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Loans and Fertilizer Use: The Effect of Timing in Pineapple Production in Southern Ghana

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Abstract:

In this study, I explore if the timing of credit in the pineapple production cycle affects fertilizer use at the first crucial application period in Southern Ghana. Using unique survey data collected at six-week intervals, results of Probit and Tobit models suggest that total credit has no effect on fertilizer use, but an additional dollar of credit specifically during the time of interest significantly increases the probability of fertilizer use by 0.138% and the amount of fertilizer by 0.797%. Findings suggest that credit should be targeted during agronomically important periods for input use in order to maximize the effect of credit.

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I. Introduction:

Smallholder farmers in developing economies often struggle to purchase farm inputs at the beginning of a production cycle. Farmers need finance at the start of the season, but they do not reap revenue until harvest. This challenge is especially salient for horticulture crops such as pineapple, which takes 18 months to mature, and the timing of inputs is crucial for successful production (Conely and Udry, 2010). Economists have criticized government subsidies used to help farmers afford agricultural inputs because they introduce inefficiencies into the market and financing them can be unsustainable (Morris et. al, 2007). However, many development economists argue for fertilizer subsidies because they can create a positive cycle of growth and lead to self-sufficiency for farmers (Dorwad et. al, 2004). Duflo et. al (2011) and Brune et. al (2015) have studied other methods to incentivize farmers to use fertilizer, including small, time sensitive discounts and commitment savings accounts respectively. My research contributes to this body of literature by analyzing the effect of an analogous, but alternative approach to increasing fertilizer use: the proper timing of credit.

This study seeks to explore if the timing of credit in the pineapple production cycle affects the use of fertilizer at the first crucial period of application in Southern Ghana. I utilize a unique data set that includes the timing of fertilizer application and borrowing at six-week intervals to control for credit amounts received at various points in time in relation to planting. Results of Probit, Tobit, and OLS models suggest that an additional dollar of credit during the important time to apply fertilizer increases the probability of fertilizer use by 0.138% and the amount of fertilizer by 0.262% to 0.797%.

This paper is structured in ten sections. The next two sections describe relevant background information and literature reviewed. The following sections explain the theoretical basis, data, and empirical strategy used for the analysis. Then, I discuss the summary statistics and results, and finally I present the limitations and conclusion.

II. Background Information

Pineapple Production and the Farming System in Southern Ghana

The data for this study comes from the Akwapim South district in Southern Ghana, and economists Marcus Goldstein and Chris Udry collected the data from 1996 to 1998[1]. Throughout the 1990s, the farming system in the region underwent a transition from traditional maize and cassava intercropping to more chemical-intensive pineapple production for sale to exporters and urban consumers (Goldstein and Udry, 1999). However, pineapple farmers continue to cultivate maize and cassava plots, dispersed among pineapple plots. The entire dataset includes 221 households from four villages, and households own a total of 1,280 plots. In the study villages, 47% of farmers farm pineapple (Conley and Udry, 2010), and no village in the sample has more than half of the plots cultivated by pineapple (Goldstein and Udry, 1999). In terms of size, pineapple plots tend to be much larger. The average pineapple plot in the sample is 1 acre, while the average non-pineapple plot is only 0.6 acres (Goldstein and Udry, 1999).

In comparison to maize and cassava farming, pineapple production requires significantly more up-front costs. In the dataset, the median cost of production, including labor and non-labor inputs, is $202 per acre for pineapple plots compared to $121 per acre for non-pineapple plots (Goldstein and Udry, 1999). Labor costs include household

[1] The data is publicly available at http://www.econ.yale.edu/~cru2//ghanadata.html.

family labor valued at the local wage, but a much higher percentage of labor on pineapple plots is hired. Pineapple farmers tend to be wealthier, and this could be in part due to higher production costs and the need for start-up capital. For example, the median cost of production for pineapple plots represents 60% of GDP per capita in Ghana during the study period. While pineapple farming is more expensive, it is also more profitable. Pineapple plots in the dataset yield a median profit of $304 per acre compared to a median loss of $23 per acre for non-pineapple plots (Goldstein and Udry, 1999).

Today, the Akwapim South district is a peri-urban area located just outside of the capital city of Accra. According to the Akwapim South District Analytical Report of the 2010 Population and Housing Census, over one third of the labor force works in agriculture either formally or informally (Opoku-Addo and Abdulai, 2014). Farmers continue to grow a variety of crops including maize, cassava, plantain, pepper, and other vegetables, and the district is one of the leading producers of pineapples, mangos, and citrus fruits in Ghana (Opoku-Addo and Abdulai, 2014).

Fertilizer Use and Credit

Agronomy studies find that fertilizer use is an important determinant of pineapple productivity. Pineapple has a large nutrient demand that usually exceeds the nutrients supplied in the soil, especially nitrogen (Souza, 2005). Fertilizer trials in Kenya have shown that nitrogenous fertilizer contributes to greater fruit size growth and stronger plant foliage (Kayitesi, 2011), and trials in Nigeria have shown that additional nitrogen increases pineapple yields (Omotoso, 2013). In Southern Ghana, Abutiate and Eyeson (1973) find that nitrogen in soils is generally low, and pineapple yields and fruit weight increases with added nitrogen and potassium.

However, many pineapple farmers do not use fertilizer, use inadequate amounts of fertilizer, or conduct fertilizer application at a less than opportune time. In Benin, Hotegni et. al (2010) finds that no specific fertilizer application regime exists, and due to high costs, pineapple farmers apply fertilizer inconsistently depending on whether they can afford it at the time. The study shows that heterogeneous fertilizer application practices, including the timing and number of applications, greatly influences the quality of pineapple production in Benin. Kayitesi (2011) finds that, in Rwanda, most farmers apply less than adequate fertilizer amounts because manure from their livestock is not enough and inorganic fertilizer is too expensive. The study also states that incorrect timing of fertilizer application leads to poorer yields.

In 2016, I completed a qualitative independent study[2] interviewing six smallholder pineapple farmers in the Akwapim South district. Respondents were sampled purposively through announcements at a Village Savings and Loan Association. Half of the farmers I interviewed reported that their biggest challenge as a pineapple farmer is accessing credit to purchase inputs, and all farmers reported a lack of access to credit (Timerman, 2016). Goldstein and Udry (1999) also state that the most reported challenges for farmers in this region include increased financial demands and maintaining soil fertility. Gyimah (2015) surveys 49 pineapple farmers in the Akwapim South district and finds similar results. The study shows that a lack of access to credit is the number one reported constraint by farmers, followed by low fruit price and high fertilizer price or inaccessibility.

[2] I completed this study at Ashesi University College under the direction of Dr. Stephen Armah.

Of the three farmers I interviewed that reported a lack of credit, all of these farmers also stated that insufficient liquidity causes them to apply inputs at the wrong time. One farmer attempts to time his harvest when pineapples are scarce and prices are higher, but this strategy relies on proper timing of fertilizer application to delay fruiting (Timerman, 2016). Without liquidity at the right time, his strategy fails. Proper timing of credit could potentially increase input use, leading to higher production and incomes for smallholder horticulture farmers in this region. This study focuses on the first step: the effect of credit timing on fertilizer use.

Risk and Pineapple Production

Goldstein and Udry also collected data on shocks suffered by pineapple plots and other crops. They find no empirical evidence that pineapple farming faces a greater probability of loss than any other crop, but the magnitude of loss is greater (Goldstein and Udry, 1999). In the first year of the survey, 15% of plots suffered a shock, but pineapple plots were slightly less likely to suffer a shock. In terms of losses, farmers lost an average of $405 per acre from shocks to pineapple plots compared to an average of $81 per acre for other plots (Goldstein and Udry, 1999). Possibly, some farmers choose not to cultivate pineapple because of the added magnitude of risk, but the effect of this risk on farmers' decisions to purchase fertilizer, once they have decided to grow pineapple, is less clear. According to Conley and Udry (2010), the average fertilizer expenditure for pineapple in this dataset is $40 per acre, while the median total cost of production is $202 per acre (Goldstein and Udry, 1999). Using these statistics, average fertilizer expenditure represents about 20% of total cost. Given that fertilizer use increases production, the relatively small cost of fertilizer seems to pose little added risk. Unfortunately, my study does not control for risk preferences because the data structure is cross-sectional.

III. Literature Review: Time Inconsistency and Credit Constraints

The economic literature proposes several reasons for farmers' lack of fertilizer use, including risk aversion, high transaction costs, high learning costs, time-inconsistent behavior, and credit constraints. I focus on the last two reasons: time-inconsistency and credit constraints. Farmers with time-inconsistent behavior underestimate their ability to save for future expenses on agriculture inputs (Duflo et. al, 2011). In other words, farmers plan to save revenue from their harvest in order to buy inputs later in the season, but they fail to follow through on these plans. Credit constraints affect farmers' ability to purchase fertilizer if they lack liquidity and cannot borrow. I divide the following literature review into two sections: (1) Literature that considers the effects of timing but not the effects of credit and (2) Literature that considers the effects of credit but not the effects of timing. My study contributes to the literature by analyzing both timing and credit aspects.

Section (1): Literature that considers timing effects but not credit effects

Several studies find that farmers' behavior regarding fertilizer purchases is significantly affected by cash flow, which changes based on the time of season. Farmers have more liquidity right after harvest and less liquidity at planting time. Pineapple farmers wait three to six months after harvest before planting in order for the pineapple plants to regrow for replanting (Gatune et. al, 2013). During this three to six month period, farmers may spend their revenue from harvest on household consumption needs instead of saving revenue for input purchases later in the season. The following reviewed studies analyze the effects of timing for agriculture seasons where the time between harvesting and planting ranges from two to six months for maize (Duflo et. al, 2011; Holden and Lunduka, 2013) and three months for tobacco (Brune et. al, 2015).

Duflo et. al (2011) conducts a control randomized trial of a fertilizer delivery program in Western Kenya. The free delivery provides farmers a small, time-sensitive discount. Offering this discount directly after harvest increases fertilizer use by 11.4 to 14.3%, depending on control variables included, and this effect is similar to offering a 50% subsidy just before planting. The study design eliminates concerns of credit constraints because farmers can pay for fertilizer with maize from their harvest. Duflo hypothesizes that the smaller discount after harvest is just as effective as a larger discount at planting time because farmers are time-inconsistent.

Holden and Lunduka (2013) analyze the willingness of farmers in Malawi to pay for fertilizer at various times in the season. The study shows that on average, households are willing to allocate 45% of a hypothetical cash budget for fertilizer at harvest time, compared to 60% of the budget at planting time. Both Duflo et. al (2011) and Holden and Lunduka (2013) find that farmers are willing to pay more for fertilizer at planting time. These results suggest that the timing of credit would affect fertilizer use, especially for time-inconsistent farmers.

Furthermore, studies show that discount rates are generally high in developing economies (Lunduka and Holden, 2013). This means that money today is much more valuable than money received tomorrow. High discount rates contribute to farmers' inability to save for fertilizer or buy it in advance when they have liquidity after harvest.

Descriptive statistics from Duflo et. al (2011) show that 96% of farmers bought fertilizer just before use.

Brune et. al (2015) conducted a control randomized trial of a savings account program for farmers. The program offered farmers a savings or commitment savings account to help them save money after harvest for input purchases during planting season. The effect of being offered a savings account or a commitment savings account increased input expenditure by 13.3% compared to the control group. Furthermore, the commitment savings treatment had almost a 50% greater effect on input expenditure than simply the savings treatment. The authors hypothesize that several mechanisms could be causing these results. For example, savings accounts could make farmers more eligible for loans or act as a psychological commitment device. Farmers may intend to use fertilizer, but they may need assistance to follow through on their plans. For example, Duflo et. al (2011) finds that, after a training session on fertilizer, 97.7% of farmers stated they planned to use fertilizer, but only two-thirds of farmers actually did. The results of Brune et. al (2015) suggest that increased liquidity at planting time, through commitment savings accounts, increases input expenditure. This finding indirectly suggests that credit at planting time would increase input expenditure more than credit at other times because credit also increases liquidity.

Section (2): Literature that considers credit effects but not timing effects

Many studies find that access to credit increases fertilizer use or adoption of technology, but they do not take into account the timing of credit. The economic literature measures credit in a variety of ways. Croppenstedlt et. al (2003) measures credit access in Ethiopia by the percentage of households in a farmer's village that have access to credit through a local peasant association. The study finds that a one percent increase in credit access increases the probability of fertilizer use by 0.76%. Abudulai and Huffman (2005), on the other hand, classifies farmers in Tanzania as credit constrained if they want more credit, their request for credit is rejected, or no informal or formal lenders exist. The study finds that credit non-constrained farmers are more likely on average to adopt the technology of cross-bred cows. However, Abdulai and Huffman (2005) find that farmers mostly used credit to purchase cross-bred cows, so potential endogeneity make these conclusions weaker. Both Croppenstedlt et. al (2003) and Abdulai and Huffman (2005) use cross-sectional data, and the ability to prove a causal mechanism is limited because of the inability to control for unobservable heterogeneity like entrepreneurial spirit.

Other studies attempt to account for unobserved heterogeneity by using propensity-score matching or panel data. Abate et. al (2016) measures credit access in Ethiopia as receiving credit from a farmers' association in a given production year. The study uses propensity score matching with cross-sectional data to compare borrowers to farmers without access to financial services. Results show that households with credit access are 11% more likely to use fertilizer and 32% more likely to use improved seeds. Households with credit access had significantly more education, lived closer to microfinance institutions and farmer schools, and were male-headed varied. Moser and Barret (2006) construct a seven-year panel with recall data from a cross-sectional survey, which allows for controlling for time-invariant heterogeneity. The study measures liquidity using a dummy variable for stable income and a continuous variable for total land cultivated with rice, which is a proxy for wealth. The results show that wealth and a stable source of income significantly and positively affect the probability of adopting the technology of a System of Rice Intensification in Madagascar. Liverpool and Nelson (2009) measure credit access as having taken a loan from a micro-finance institution, and use actual panel data to assess how the effect of credit differs by asset wealth for farmers in Ethiopia. The study finds that for always or transitory asset poor households, credit access had no significant effect on the probability of fertilizer use or pesticide use.

My study contributes to the literature by analyzing the effect of the timing of credit and exactly how much farmers borrowed. Other studies only measure if farmers borrowed or if they had access to credit or liquidity via some proxy variable. Most of the loans assessed in this study are informal loans taken from friends and family, while the literature tends to focus on formal microfinance. In comparison to formal loans, informal lenders face less asymmetric information problems because they know their borrowers, and informal lenders often require less collateral (Guikinger and Boucher, 2008). Furthermore, I explore the effect of credit in horticultural production, while most studies analyze staple crops such as maize or rice. This study also suffers from endogeniety and omitted variable problems inherent in cross-sectional data. However, examining the effect of timing provides a stronger causal mechanism than simply looking at credit access because the data is disaggregated to a more granular level.

IV. Theory: The agricultural household model with a credit constraint

I utilize an agricultural household model with a credit constraint to illustrate the positive effect of borrowing on fertilizer use. Agricultural households represent a unique economic unit because households are both producers and consumers of goods. In the case of perfect markets, households first make production decisions to minimize costs and then make consumption decisions to maximize utility. However, in the face of market failure, household production and consumption decisions are inseparable or made simultaneously (de Janvry and Sadoulet, 2016). My theory examines the case of credit market failure, while assuming all other markets are perfect. The household agricultural model shows that a lack of credit access at the beginning of the production cycle decreases farm investment because fertilizer use is constrained by household's ability to borrow.

I base my theory of off the work of Damon (2008) and Postolovska (2010). The agricultural household maximizes utility [1] as a function of consumption and leisure, across time periods 1 and 2, and *z* represents household specific factors. Households maximize utility subject to a time constraint [2, 3], a consumption constraint [4, 5], and a production constraint [6, 7] in each time period. The household's total time endowment equals family labor (F_t) and leisure (l_t). In the first time period, consumption equals farm revenue minus fertilizer costs plus wage earnings and amount borrowed. Wage earnings are determined by the market wage (w) times the amount of hours worked on the wage market, which equals family labor minus family-farm labor $(F_t - L_t)$. In the second time period, consumption plus repayment of the loan equals farm revenue minus fertilizer costs and wage earnings. The production constraint shows that pineapple produced is determined by farm labor and fertilizer use.

$$\max U[(C_1, l_1; z) + \beta(C_2, l_2; z)] \quad [1]$$

Subject to:

$$T_1 = F_1 + l_1 \quad [2]$$

$$T_2 = F_2 + l_2 \quad [3]$$

$$C_1 = p_1 Q_1 - \left(p_{x_1} X_1\right) + w_1(F_1 - L_1) + B \qquad [4]$$

$$C_2 + (1 + r)B = p_2 Q_2 - \left(p_{x_2} X_2\right) + w_2(F_2 - L_2) \qquad [5]$$

$$Q_1 = Q(L_1, X_1) \qquad [6]$$

$$Q_2 = Q(L_2, X_2) \qquad [7]$$

The time, consumption, and production constraints are combined into the following full income constraints [8, 9] for each time period.

$$C_1 = p_1 Q(L_1 X_1) - \left(p_{x_1} X_1\right) + w_1(T_1 - l_1) - w_1(L_1) + B \qquad [8]$$

$$C_2 + (1 + r)B = p_2 Q(L_2 X_2) - \left(p_{x_2} X_2\right) + w_2(T_2 - l_2) - w_2 L_2 \qquad [9]$$

The Lagrangian maximization problem and first order conditions for the first time period are as follows.

$$\mathcal{L} = \qquad [10]$$

$$U(C_1, l_1; z) + \beta(C_2, l_2; z) - \lambda_1 \left[C_1 - \begin{pmatrix} p_1 Q(L_1, X_1) - \left(p_{x_1} X_1\right) + w_1(T_1 - l_1) - \\ w_1(L_1) + B \end{pmatrix}\right]$$

$$- \lambda_2\left[C_2 + (1 + r)B - \left(p_2 Q(L_2, X_2) - \left(p_{x_2} X_2\right) + w_2(T_2 - l_2) - w_2 L_2\right)\right]$$

$$\frac{\partial \mathcal{L}}{\partial C_1} = \frac{\partial U}{\partial C_1} - \lambda_1 = 0 \qquad [11]$$

$$\frac{\partial \mathcal{L}}{\partial l_1} = \frac{\partial U}{\partial l_1} - \lambda_1 w_1 = 0 \qquad [12]$$

$$\frac{\partial \mathcal{L}}{\partial L_1} = \lambda_1 p_1 \frac{\partial Q}{\partial X_1} - \lambda_1 w_1 = 0 \qquad [13]$$

$$\frac{\partial \mathcal{L}}{\partial X_1} = \lambda_1 p_1 \frac{\partial Q}{\partial X_1} - \lambda_1 p_{x_1} = 0 \qquad [14]$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_1} = -C_1 + p_1 Q(L_1, X_1) - \left(p_{x_1} X_1\right) + w_1(T_1 - l_1) - w_1(L_1) + B = 0 \qquad [15]$$

As seen in equation [16], the demand for fertilizer depends on the exogenous variables of the price of pineapple, the price of fertilizer, the wage, and the amount borrowed. Holding all else constant, the derivative of fertilizer with respect to borrowing is positive.

$$X = (p_p, p_x, w, B) \tag{16}$$

$$\frac{\partial X}{\partial B} > 0 \tag{17}$$

Simple economic theory proposes that the timing of credit should not affect the amount of fertilizer used. If farmers borrow money before they need fertilizer, they should be able to save money until that time. Alternatively, farmers could purchase fertilizer and store it because fertilizer is a non-perishable good. I assume that fertilizer has a positive return on investment, and this assumption is supported by the literature (Gyimah, 2015). Therefore, as long as farmers receive credit before the necessary time for fertilizer application, it theoretically should have a positive effect on fertilizer use or investment. However, Duflo et. al (2011) shows that farmers struggle to follow through on plans to save money for inputs. My study helps shed light on the difference between theory and farmers' behavior in actuality.

V. Data Description: Agricultural Innovation and Resource Management in Ghana

The dataset used for this study is titled "Agricultural Innovation and Resource Management in Ghana". Researchers originally collected the data to understand social learning about fertilizer use and the transition to pineapple farming in Southern Ghana (Goldstein and Udry, 1999). The survey consists of 15 rounds of data collected approximately six weeks apart, starting in late November of 1996 and ending in early August of 1998. In each round, farmers are asked about their farming activities, input use, and borrowing. Four village areas were chosen purposively for representing a variety of agricultural and economic characteristics (Goldstein and Udry, 1999). Only three of the four villages have pineapple farmers. Married couples were sampled randomly from the villages to create the final sample. The entire household roster of the survey data includes 221 households with a total of 1,624 individuals.

I use pineapple plantings as the unit of analysis. In the data, 294 observations of pineapple plantings exist, but I drop three observations due to missing data on input use and 28 observations due to a lack of household demographic information. About half of the plantings lack data for loan amounts received before and after plantings because they take place at the beginning and end of the survey. Omitting these observations decreases the sample size to 150 plantings owned by 59 households. Then, I drop 10 observations associated with outlier loan values of $1,000, $2,000, and $5,000, and an additional 10 observations associated with household savings of $5,000 or values of stored chemicals of $3,300. In short, I omitted 20 plantings associated with five households that are wealthier or received very large amounts of loans. The final sample includes 130 plantings representing 54 households and 85 plots.

The observations of plantings are fairly evenly distributed over time because in Southern Ghana there is no specific time of year for planting pineapple (Goldstein and Udry, 1999). Table 1 displays the percentage of plantings in each round. Round 10 has the largest percentage of plantings with 16.15% and Round 5 has the smallest with 8.46%.

VI. Empirical Model and Strategy

The timing of loans is analyzed in terms of before, during, and after the first necessary time to apply fertilizer in the pineapple production cycle. The agronomy literature on pineapple production unanimously recommends fertilizer be applied within the first three months after planting, and one to two more times within nine months after planting. (Abutiate and Eyeson, 1973; Souza, 2005; Omotoso, 2013). Timing is measured in terms of periods of the survey data. Time zero (t_0) is marked as the survey period in which pineapple is planted. The necessary first time to apply fertilizer is designated as during the period of planting or within two periods after the period of planting, ($t_0 - t_2$). The dependent variable, fertilizer use ($y_{i,t_0 - t_2}$), represents a continuous variable for the amount of fertilizer applied during this time or a dummy variable for fertilizer use during this time.

First, I specify a completely aggregated model without including the effect of timing. This model provides a comparison with other models that do account for timing. The dependent variable of interest is the total amount of credit received over all time periods ($t_{-2} - t_{+4}$). The letter V represents a vector of control variables, including household socio-economic characteristics and village. Household demographic variables include household size, age of the household head, and education of the household head, which are controlled for in accordance with other studies (Croppenstedlt et. al, 2003; Abdulai and Huffman, 2005; Abate et. al, 2016).

Aggregated timing model:

$$y_{i,t_0-t_2} = \beta_0 + \beta_1 \left(Credit_{Total_{t_{-2}-\, t_{+4}}}{}_i \right) + \beta_4 V_i + \varepsilon_i$$

In the simple timing model below, receiving credit is counted as 'before' the necessary time period of fertilizer application if it is received within two periods before the period of planting $\left(Credit_{Before_{t_{-2}-t_{-1}}}\right)$, and receiving credit is counted as 'after' the necessary time period of fertilizer application if it is received the third or fourth period after planting $\left(Credit_{After_{t_3-t_4}}\right)$. The variables $Credit_{Before_{t_{-2}-t_{-1}}}$, $Credit_{During_{t_0-t_2}}$, and $Credit_{After_{t_3-t_4}}$ are estimated as continuous variables for the amount of credit received[3]. The effect of credit before (β_1) and during (β_2) is hypothesized to be positive, while the effect of credit after (β_3) is hypothesized to be not significant.

Simple timing model:

$$y_{i,t_0-t_2} = \beta_0 + \beta_1\left(Credit_{Before_{t_{-2}-t_{-1}}}\right) + \beta_2\left(Credit_{During_{t_0-t_2}}\right) + \beta_3\left(Credit_{After_{t_3-t_4}}\right) + \beta_4 V_i + \varepsilon_i$$

A third specification is conducted using disaggregated specifications for time where *C* stands for Credit. The disaggregated specification further explores the effect of the granularity of timing.

Disaggregated timing model:

$$y_i = \beta_0 + \beta_{1-7}\sum_{t=-2}^{t=4} C_{t_i} + \beta_8 V_i + \varepsilon_i$$

In terms of empirical strategy, I first use a Probit model to estimate the effect of credit on the probability of using fertilizer during the time period of interest. The dependent variable for the Probit model equals one if the planting is fertilized during the

[3] I also tested specifications using loan dummy variables for each time period, but none were significant.

timeframe of interest and equals zero if it not. Secondly, I use Tobit and OLS models to estimate the effect of credit on the amount of fertilizer used. I measure fertilizer use by mini bags per 10,000 pineapple plants or suckers. A pineapple plant is called a sucker, and one sucker produces one pineapple. The average number of suckers per planting is 7,250 suckers, which represents about one third of an acre. The distribution of fertilizer use heavily skews right because 71% of plantings never received fertilizer at this time.

I take the inverse hyperbolic sine[4] of fertilizer amount in order to transform the distribution to have a smaller range. This technique is similar to a logarithmic transformation, but it allows for zero values (Burbidge et. al, 1998; Bellemare et. al, 2013). I use a Tobit model to account for the the highly skewed distribution of the dependent variable. However, a Tobit model is not ideal for this data because the zero values are not artificially or randomly censored at zero; they are observed zero values. The OLS model is also not ideal due to the skewed distribution, even with the inverse hyperbolic sine transformation. As seen in the residual plot in Figure B, the errors of this model are highly systematic for observations with a dependent variable equal to zero.

VII. Summary Statistics: Initial exploration of credit timing and fertilizer use

Initial summary statistics suggest that plantings associated with credit during the designated important time to apply fertilizer are more likely to receive fertilizer at this time. As seen in Table 2, 32.2% of plantings associated with credit during the important time to receive fertilizer actually received fertilizer, while only 28.2% of plantings associated with credit before and 27.2% of plantings associated with credit after received fertilizer. Additionally, Table 3 shows that, of plantings that received fertilizer at this

[4] Inverse Hyperbolic Sine of $\mathrm{X} = \log(\mathrm{X} + \sqrt{X^2 + 1})$

time, 76.3% of plots are associated with credit during this time, compared to 66.3% of plots that did not receiver fertilizer. However, according to t-tests, neither the percent of plantings receiving fertilizer or the percent of plantings associated with credit are statistically different by credit or fertilizer status respectively.

Summary statistics also suggest that receiving a greater amount of credit in the 'during' period increases the likelihood of applying fertilizer. Table 4 shows that plantings that received fertilizer at the time of interest are associated with an average value of $67.49 in loans at this time, compared to an average of $26.09 for plantings that were not fertilized. A t-test shows that credit amounts associated with plantings in the 'during' period ($t_0 - t_2$) are statically different by fertilizer status. The next sections explain summary statistics in depth for the main variables of interest and household demographic characteristics that are included as control variables.

Fertilizer use:

In the final sample, 55.38% of plantings ever received fertilizer, but only 29% of plantings received fertilizer during the important first window for application. Therefore, less than half of the plantings that were fertilized did not get fertilizer within the first two periods after planting. I hypothesize that liquidity constraints are preventing farmers from applying fertilizer earlier. In terms of fertilizer amount, the average unit applied is 0.53 with a standard deviation of 0.97. Specifications using fertilizer amount have two less observations because two plantings in the data lacked the number of suckers.

Loans:

According to Goldstein and Udry (1999) credit markets are surprisingly active and well integrated into larger markets in the study area. Of the 54 households in my sample, only 4 households never take a loan. On average, a household has 57 days to pay back a loan, but this data only exists for 46 households. The days to pay back the average loan by household vary widely from 8 to 533 days, with a standard deviation of 78 days.

I specify loans as a continuous variable for the amount received in a given time period[5]. Table 6 shows the fairly even distribution of loan amounts in US dollars for each time period. The average credit amount ranges from $20.80 in the 'after' time period to $35.70 in the 'before' period and $38.20 in the 'during' time period. Loans are also distributed fairly evenly over time. The percent of plantings associated with loans in the 'before' period is 50%, compared with 69% and 50% in the 'during' and 'after' periods respectively. I also control for loan frequency, which represents the number of time periods in which a household took a loan. There are six time periods, so the variable for loan frequency ranges from 0 to 6. The average loan frequency is 2.82 with a standard deviation of 1.93.

The data provides farmers' responses to the survey question, "What will you use the loan for?" Most households did not take loans for farming purposes, but listed other reasons such as trading, medical needs, school fees, funerals, and travel. Graph A shows that the percentage of loans taken for farming purposes is also evenly distributed over time, which suggests that farmers are not consistently or uniformly taking loans for farming purposes at a specific stage in the pineapple production cycle. The percentage is given in terms of the number of loans taken in each period.

Household demographic characteristics:

The final sample includes 54 households. I first present demographic statistics by comparing households that ever applied fertilizer during the first important time or not.

[5] I also tested specifications for loans as dummy variables, but none were significant.

As seen in Table 8, households that ever applied fertilizer have on average greater savings and a greater value of assets and stored chemicals. However, the average savings and value of assets are not statistically different by household fertilizer status. This means that households that apply fertilizer may not actually differ on average from households that do not apply fertilizer, but the small sample size makes finding statistical difference challenging.

In contrast, the trend changes slightly when comparing demographic characteristics by plantings that received fertilizer in the first important window or not. Table 8 shows that plantings that received fertilizer are associated with households with a slightly lesser value of assets but still greater savings and a greater value of stored chemicals. Most demographic characteristics fail to be statistically different by fertilizer status, but this could again be due to the small sample.

Overall, the average household in the sample has a size of about 8 people. The average head of household is about 40 years of age and with an average of four years of education. The average household savings is $77.68 and the average value of assets is $845.83.

VIII. Results and Discussion:

Results for the completely aggregated timing model show that aggregated credit has no effect on fertilizer use. As seen in Table 8, when credit is defined as total credit received over time, it appears to have no significant influence on fertilizer use. However, the simple timing model and disaggregated timing model show that credit during the important period significantly increases fertilizer use and the probability of fertilizer use.

This contrast supports my claim that assessing the effect of credit by including timing proves to be important.

Table 9 displays the results of the simple timing model with credit amount before, during, and after. Marginal effects of the Probit model (Figure C) suggest than an additional dollar of credit during the first crucial time to apply fertilizer increases the probability of fertilizer use at this time by 0.138%. The average loan amount in the 'during' period is about $40, and interestingly, the average expenditure on fertilizer for pineapple production is $40 per acre (Conley and Udry, 2010). If a planting is associated with a loan increase of $40 or $100 in the 'during' period, results suggest the probability of fertilizer use increases by 5.52% or 13.8% respectively. Results of the disaggregated Probit model in Table 10 (Figure D) support the results of the simple timing model. The regression shows that an additional dollar increase in credit in period t_1 increases the probability of fertilizer use by 0.158%, significant at the 10% level.

In terms of fertilizer amount, results of the Tobit model in Table 9 (Figure E) suggest that a $1 increase in loans in the 'during' period increases fertilizer amount by 0.80%, or a $40 increase in loans increases fertilizer amount by 32%. The OLS model finds a similar, but smaller effect with a loan increase of one dollar increasing fertilizer amount by 0.26% or a $40 loan increasing fertilizer amount by 10.4%. Both Tobit and OLS models find significant coefficients on credit 'during' at the 5% level[6]. In terms of the disaggregated models in Table 10 (Figure F), results are only significant at the 10% level. The Tobit regression suggests that a one-dollar increase in credit in period t_2

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[5] When the specification of credit in the 'during' period is redefined to include time period t_{-1}, credit in the 'during' period no longer significantly affects fertilizer use.

increases fertilizer amount by 1.6%, while the OLS regression suggests a much smaller 0.51% increase.

Interestingly, the sign on credit received in the 'before' period is negative, although not significant, in all simple timing models. In the disaggregated models, the coefficient on $t_{-1}$is also consistently negative. Specifically, results suggest that an additional dollar of credit decreases the probability of fertilizer use by 0.47% and the amount of fertilizer by 3.23%, significant at the 10% level. Increased liquidity before the important time to apply fertilizer may not positively affect fertilizer use due to high discount rates commonly found in developing economies. However, the fact that credit in the 'before' period is negatively associated with fertilizer is surprising. Perhaps households that take a loan one time period before planting cannot take an additional loan during planting time, which negatively affects fertilizer use.

Robustness check: Clustered standard errors by household

Clustered standard errors are used to adjust for unobserved heterogeneity at the household level, especially because households own multiple plantings. There are 55 households in the sample, and households own 5.8 plantings on average. The results of the Probit and OLS specifications with clustered errors are shown in Column (2) and (4) of Tables 9 and 10 (Figures D and F). Standard errors cannot be clustered in the Tobit model. For the simple timing model, clustered standard errors decrease the significance of credit in the 'during' period in the Probit model, but increase its significance in the OLS model. In the disaggregated timing model, clustered standard errors increase the significance of credit in periods: t_{-1}, t_1, and t_2. Clustered errors also make previously insignificant coefficients now significant. These coefficients include credit in period t_2 in the Probit model and credit in periods t_{-1} and t_1 in the OLS model. The signs of these now significant variables are in accordance with the original results.

Robustness check: Including dropped outliers

I conduct a robustness check including 10 outliers with household savings or values of stored chemicals \$3,000 or \$5,000. The results with dropped outliers are displayed in Tables 11 and 12 (Figures G – J). Compared to the original simple timing model, the effect of credit during the important time to apply fertilizer remains at the same level of significance but has a greater magnitude. Specifically, an additional dollar of credit in the 'during' period increases the probability of fertilizer use by 0.149% compared to 0.138% in the original model. The Tobit model suggests that an additional dollar of credit increases the amount of fertilizer by 0.879% compared to 0.797% in the original model. In the disaggregated model, including outliers causes the coefficient on credit in period t_{-1} to no longer be significant, but the sign is still negative. In the Probit and OLS models, credit in period t_1 remains significant but has a greater magnitude, and in the Tobit model, credit in period t_2 remains significant but has a lesser magnitude. Although results vary slightly from the primary findings, the argument that credit during the important window to apply fertilizer significantly increases fertilizer use still holds when including outliers.

IX. Limitations:

The conclusions of this study are limited by cross-sectional data that prohibit controlling for heterogeneous time invariant unobservable factors such as entrepreneurial spirit. For example, perhaps farmers that take loans during the important time to apply fertilizer are also more entrepreneurial on average. Then, my analysis could have incorrectly attributed increase in fertilizer use to the timing of loans, when in fact the increase in fertilizer use is actually due to farmers' entrepreneurial aptitude. The effect of credit on fertilizer use could be insignificant or much more diminished after accounting for unobserved factors such as entrepreneurialism. The best data would allow for observing fertilizer use during the important first window for application both before and after randomized dispersal of credit.

Other potential omitted variable biases exist as well. Variables such as off-farm income and gifts received at the household level were not controlled for because the survey did not include these variables for each time period. The effect of this bias is unknown. Controlling for these variables could diminish the effect or significance of credit because off-farm income and gifts represent other sources of liquidity that could increase fertilizer use, making credit less influential. However, controlling for these variables could increase the effect of credit if off-farm income and gifts are regular sources of household income that do not affect the expenditure constraint on farm inputs.

The study is also limited by potential endogeneity. For example, farmers may plan when to take credit based on when they plan to apply fertilizer, which means that the timing of fertilizer could also affect the timing of credit. However, during the important time to apply fertilizer, the percentage of loans reported for specifically farming purposes ranges from only 10% to 17% depending on time period. A randomized control trial would be needed to erase concerns of endogeneity. It is possible that without problems of endogeniety and omitted variables there would be no effect of credit timing because the truly causal factors are being controlled for in the regression. While the findings of this study are limited by the data, the results are supported by similar findings in the literature.

X. Conclusion:

I find that credit during the important first time to apply fertilizer in the pineapple production cycle significantly affects fertilizer use at this time. This conclusion supports the findings of other studies, including Croppenstedlt et. al (2003), Abdulai and Huffman (2005), and Abate et. al (2016), that state credit access or being non-liquidity constrained is associated with higher fertilizer use or technology adoption. Results also suggest that credit received just before the first window for fertilizer application decreases the probability and amount of fertilizer at this time. My findings are constrained by observational data and further studies should randomize the variables of credit overtime. The literature currently lacks randomized control trials assessing horticultural production, which especially relies on the correct timing of inputs. Although credit plays an important factor, it should not be seen as a silver bullet to improving fertilizer use. Farmers may not have the knowledge to use fertilizer effectively or traveling to buy fertilizer may be infeasible or incredibly time consuming.

Future studies should also assess the effect of credit on fertilizer use among women. Men significantly dominate pineapple farming and tend to have greater access to credit. According to Goldstein and Udry (1999), 90% of plots cultivated by women in the survey grow cassava and maize, and women's plots receive less fertilizer on average. Furthermore, men in the dataset borrowed a median amount of $50, while women only borrowed a median amount of $20.

In conclusion, programs aimed at supporting farmers with credit should consider offering loans during agronomically important times for input use in the production cycle in order to maximize the effect of credit. Pineapple farmers plant at varied times throughout the year, so this important time could be different for every farmer, and credit programs would require a degree of flexibility and adaptability. This study shows that accounting for the effect of timing proves to be important when analyzing the impact of credit on fertilizer use.

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Figures:

Figure A

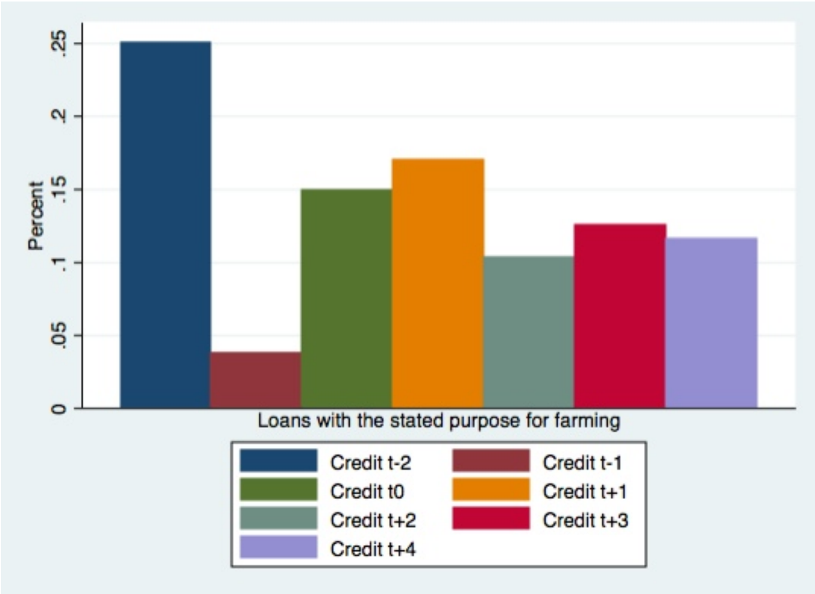


Figure B:

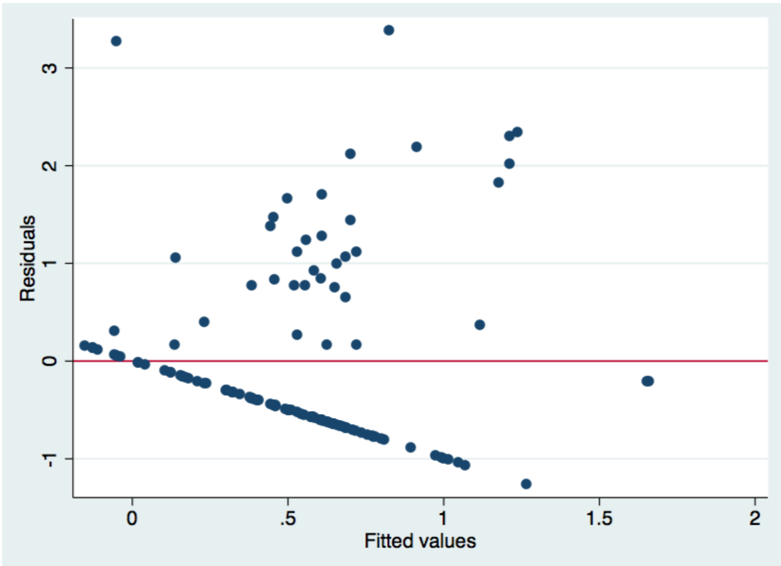


Figure C:

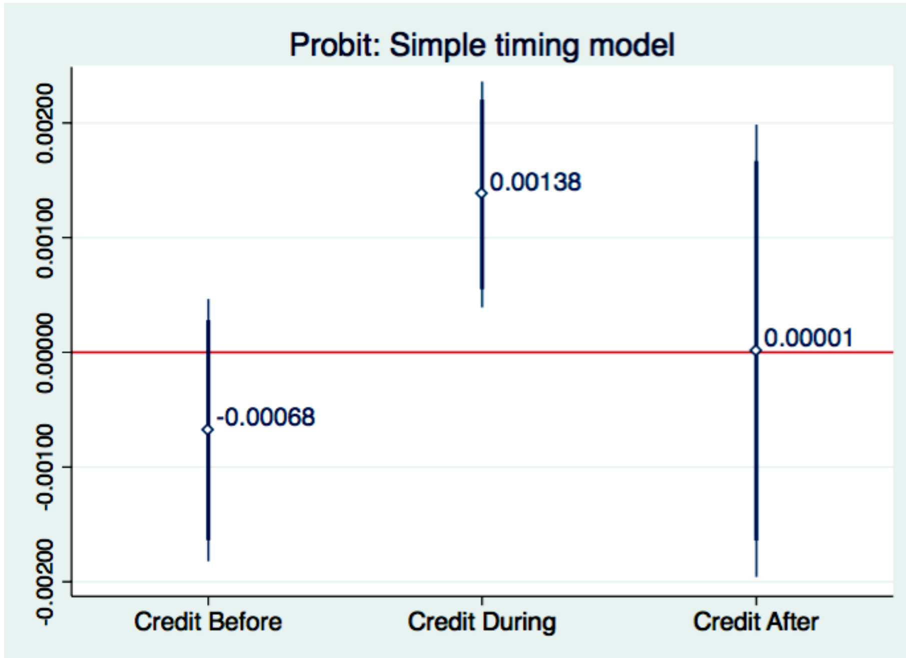
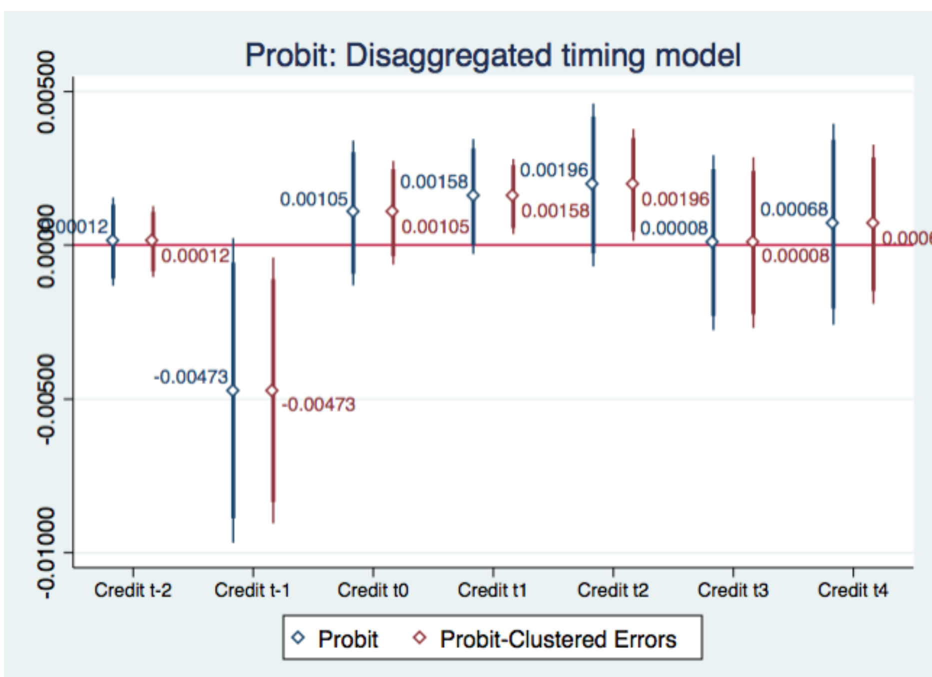


Figure D:



Note: For coefficient plots, the thick line represents the 90% confidence interval and the thin line represents the 95% confidence interval

Figure E

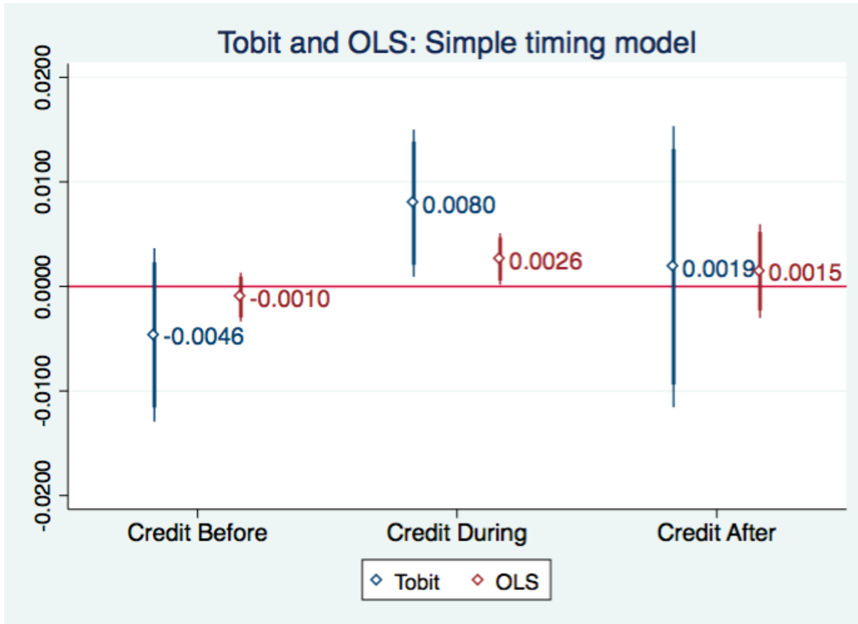
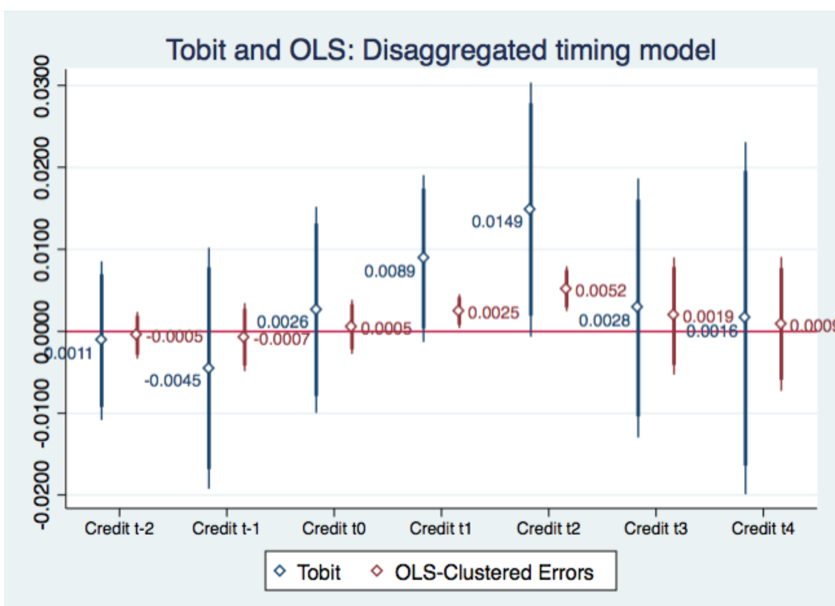


Figure F



Note: For coefficient plots, the thick line represents the 90% confidence interval and the thin line represents the 95% confidence interval

Figure G:
Robustness Check – Including Dropped Outliers

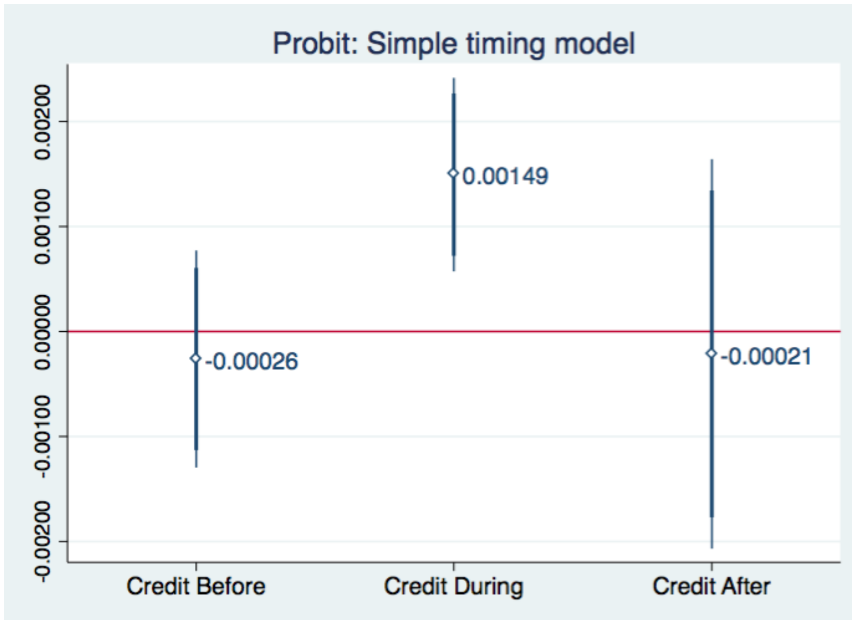
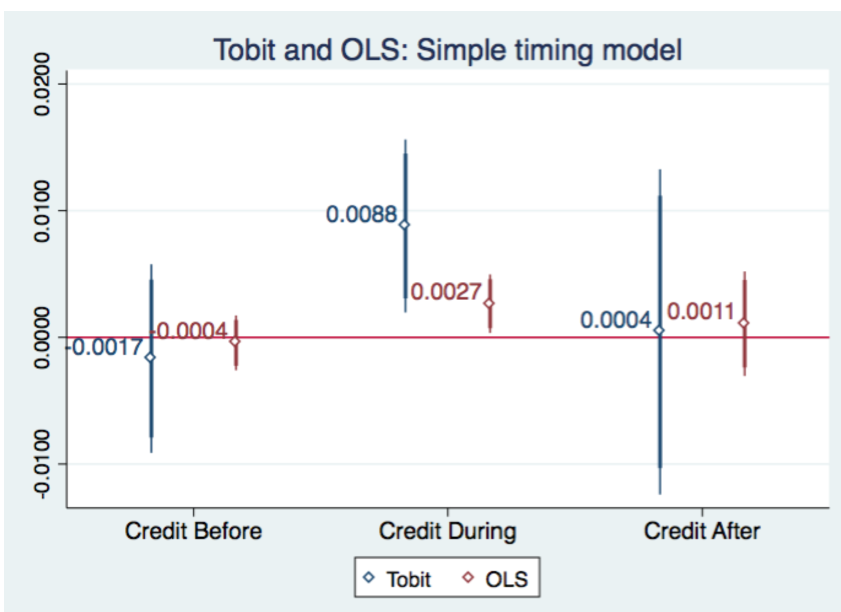


Figure H:
Robustness Check – Including Dropped Outliers



Note: For coefficient plots, the thick line represents the 90% confidence interval and the thin line represents the 95% confidence interval

Figure I
Robustness Check – Including Dropped Outliers

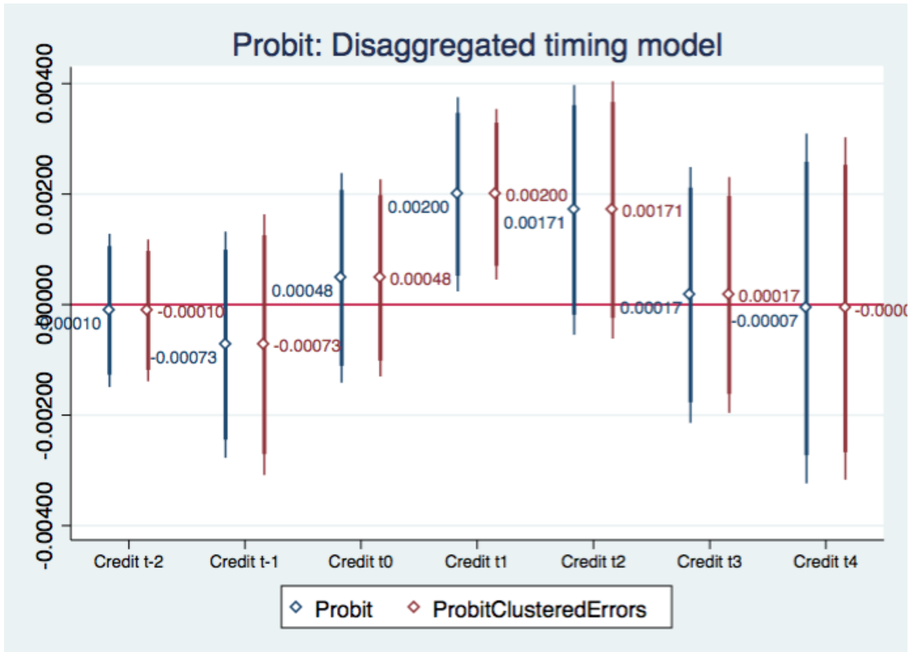
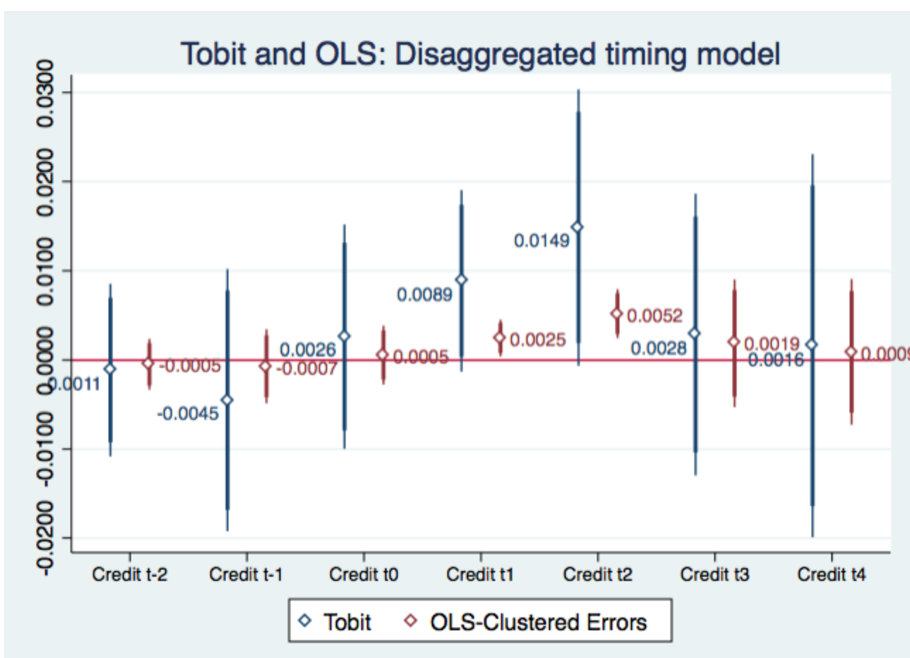


Figure J
Robustness Check – Including Dropped Outliers



Note: For coefficient plots, the thick line represents the 90% confidence interval and the thin line represents the 95% confidence interval

Tables:

Table 1: Percent of Plantings by Survey Round

Survey Round	Number of Plantings	Percent
4	14	10.77
5	11	8.46
6	18	13.85
7	18	13.85
8	17	13.08
9	15	11.54
10	21	16.15
11	16	12.31
Total	130	100

Table 2: Percent of plantings receiving fertilizer by credit timing association

Credit timing	Number of plantings associated with credit timing	Percent of plantings that received fertilizer at the first important time period (St. dev)	Difference
Credit Before	78	0.282 (0.452)	0.026 (0.082)
Credit During	**90**	**0.322** **(0.470)**	**0.097** **(0.087)**
Credit After	66	0.272 (0.449)	0.040 (0.080)

Table 3: Percent of plantings associated with credit by fertilizer status

Credit Status	Planting fertilized at the first important time period	Planting NOT fertilized at the first important time period	Difference (St. dev)
Percent of plantings associated with Credit Before (St. dev)	0.579 (0.500)	0.609 (0.491)	0.030 (0.095)
Percent of plantings associated with Credit During (St. dev)	**0.763 (0.431)**	**0.663 (0.475)**	**0.100 (0.089)**
Percent of plantings associated with Credit After (St. dev)	0.474 (0.506)	0.521 (0.502)	0.048 (0.097)
Number of Plantings	38	92	

Table 4: Mean credit by fertilizer status

Credit Status	Planting fertilized at the first important time period	Planting NOT fertilized at the first important time period	Difference (St. dev)
Mean amount of Credit Before associated with plantings (St. dev)	$27.21 (62.33)	$39.21 (82.35)	$12.00 (14.87)
Mean amount of Credit During associated with plantings (St. dev)	**$67.49 (98.79)**	**$26.09 (61.71)**	**$41.40** (14.34)**
Mean amount of Credit After associated with plantings (St. dev)	$24.70 (49.47)	$19.19 (43.48)	$5.51 (8.73)
Number of Plantings	38	92	

** Significant at 5% level

Table 5: Summary Statistics

Variable (unit)	N	Mean	Std. Dev.	Min	Max
Fertilizer:					
Apply Fertilizer (=1)	130	0.29	0.46	0	1
Fertilizer (mini bags)	128	0.53	0.97	0.00	4.20
Credit over time:					
Credit before (=1)	130	0.60	0.49	0	1
Credit during (=1)	130	0.69	0.46	0	1
Credit after (=1)	130	0.51	0.50	0	1
Credit $_{t-2}$ (=1)	130	0.48	0.50	0	1
Credit $_{t-1}$ (=1)	130	0.40	0.49	0	1
Credit $_{t0}$ (=1)	130	0.36	0.48	0	1
Credit $_{t1}$ (=1)	130	0.42	0.50	0	1
Credit $_{t2}$ (=1)	130	0.45	0.50	0	1
Credit $_{t3}$ (=1)	130	0.38	0.49	0	1
Credit $_{t4}$ (=1)	130	0.33	0.47	0	1
Credit amounts:					
Credit before ($)	130	35.70	76.99	0	382.5
Credit during ($)	130	38.20	76.44	0	457.5
Credit after ($)	130	20.80	45.19	0	212
Credit $_{t-2}$ ($)	130	20.25	54.21	0	350
Credit $_{t-1}$ ($)	130	15.45	41.11	0	207.5
Credit $_{t0}$ ($)	130	9.96	37.11	0	350
Credit $_{t1}$ ($)	130	15.68	45.91	0	350
Credit $_{t2}$($)	130	12.55	32.47	0	207.5
Credit $_{t3}$ ($)	130	12.12	34.77	0	207.5
Credit $_{t4}$ ($)	130	8.68	25.40	0	182.5
Household demographics:					
HH size (People)	130	7.68	3.42	2	19
Education HH Head (Years)	130	4.03	2.32	0	10
Age HH Head (Years)	130	39.37	8.96	24	66
HH savings ($)	130	77.48	130.39	0	750
HH stored chemicals ($)	130	69.62	104.84	0	465
HH value of assets ($)	130	845.83	1108.25	0	5965.25
Village 1 (=1)	130	0.19	0.40	0	1
Village 2 (=1)	130	0.26	0.44	0	1
Loan frequency	130	2.82	1.93	0	7

Table 6: Comparative demographic statistics by household fertilizer status

	Households that EVER applied fertilizer at the important first time N = 23		Households that NEVER applied fertilizer at the important first time N = 31		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Diff
HH size	7.6	3.3	6.6	3.5	0.96
Education HH Head (Years)	3.8	2.4	3.9	2.5	0.12
Age HH Head (Years)	40.8	10.7	37.9	9.5	2.96
HH savings ($)	100.2	175.1	46.6	93.8	53.63
HH stored chemicals ($)	87.7	117.2	30.3	52.7	57.42**
HH value of assets ($)	874.5	1235.8	764.6	1251.7	109.99
Village 1 (=1)	0.3	0.4	0.1	0.3	0.16
Village 2 (=1)	0.3	0.4	0.5	0.5	0.19

** Significant at 5% level

Table 7: Comparative demographics statistics by planting fertilizer status

	Plantings that received fertilizer at the important first time N = 49		Plantings did NOT receive fertilizer at the important first time N = 115		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Diff
HH size	8.1	3.0	7.5	3.6	0.59
Education HH Head (Years)	3.7	2.0	4.2	2.5	0.45
Age HH Head (Years)	40.4	9.5	39.0	8.8	1.41
HH savings ($)	89.6	149.1	72.5	122.4	17.3
HH stored chemicals ($)	96.8	118.9	58.4	96.9	38.45*
HH value of assets ($)	804.5	993.2	862.9	1157.2	58.36
Village 1 (=1)	0.2	0.4	0.2	0.4	0.02
Village 2 (=1)	0.2	0.4	0.3	0.5	0.11

* Significant at 10% level

Table 8
Aggregated timing model: Fertilizer Use ~ Loan Amount

VARIABLES	(1) Probit[1]	(2) Tobit	(3) OLS
Credit Total ($)	0.00043	0.00306	0.00102
	(0.00035)	(0.00241)	(0.00081)
HH size	-0.00496	-0.11469	-0.06635*
	(0.01593)	(0.10976)	(0.03554)
Education HH Head	-0.02438	-0.19036	-0.05905
	(0.01908)	(0.13619)	(0.03810)
Age HH Head	-0.00076	0.02294	0.02031
	(0.00625)	(0.04285)	(0.01339)
HH savings	0.00012	0.00105	-0.00001
	(0.00034)	(0.00236)	(0.00074)
HH stored chemicals	0.00078*	0.00411	0.00082
	(0.00042)	(0.00301)	(0.00098)
HH value of assets	-0.00006	-0.00034	-0.00008
	(0.00005)	(0.00035)	(0.00009)
Village 1	-0.02036	-0.36645	-0.25338
	(0.14248)	(0.99191)	(0.30927)
Village 2	-0.18424	-1.51932*	-0.47064*
	(0.12456)	(0.89614)	(0.26538)
Loan Frequency	-0.02181	-0.16961	-0.05458
	(0.02699)	(0.18884)	(0.06001)
Constant		0.00965	0.71516
		(2.02060)	(0.60404)
Observations	130	128	128
R-squared			0.09987

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] Probit estimates presented as marginal effects

Table 9
Simple timing model: Fertilizer Use ~ Loan Amount

VARIABLES	(1) Probit[1]	(2) Probit: Clustered Errors	(3) Tobit	(4) OLS	(5) OLS: Clustered Errors
Credit before ($)	-0.00068	-0.00068	-0.00464	-0.00102	-0.00102
	(0.00058)	(0.00063)	(0.00419)	(0.00118)	(0.00084)
Credit during ($)	**0.00138*** **	**0.00138** **	**0.00797** **	**0.00262** **	**0.00262*** **
	(0.00050)	**(0.00061)**	**(0.00356)**	**(0.00125)**	**(0.00083)**
Credit after ($)	0.00001	0.00001	0.00189	0.00146	0.00146
	(0.00101)	(0.00090)	(0.00679)	(0.00227)	(0.00285)
HH size	-0.00676	-0.00676	-0.12674	-0.07209**	-0.07209*
	(0.01584)	(0.01464)	(0.10839)	(0.03568)	(0.03654)
Education	-0.02694	-0.02694	-0.21008	-0.06691*	-0.06691
	(0.01849)	(0.01845)	(0.13375)	(0.03773)	(0.04418)
Age	-0.00196	-0.00196	0.01573	0.01657	0.01657
	(0.00604)	(0.00724)	(0.04170)	(0.01328)	(0.01683)
Savings	0.00023	0.00023	0.00181	0.00029	0.00029
	(0.00033)	(0.00029)	(0.00229)	(0.00074)	(0.00057)
Stored chemicals	0.00075*	0.00075***	0.00418	0.00081	0.00081
	(0.00040)	(0.00029)	(0.00294)	(0.00097)	(0.00066)
Value of assets	-0.00005	-0.00005	-0.00033	-0.00008	-0.00008
	(0.00005)	(0.00005)	(0.00033)	(0.00009)	(0.00009)
Village 1	-0.03889	-0.03889	-0.45290	-0.29479	-0.29479
	(0.13788)	(0.14911)	(0.96475)	(0.30570)	(0.30772)
Village 2	-0.20703*	-0.20703	-1.59883*	-0.53975**	-0.53975*
	(0.12170)	(0.14446)	(0.88286)	(0.26321)	(0.29770)
Loan Frequency	-0.02760	-0.02760	-0.19472	-0.07660	-0.07660
	(0.02656)	(0.03048)	(0.18786)	(0.06007)	(0.08285)
Constant			0.61777	1.01033	1.01033
			(1.97408)	(0.61003)	(0.65931)
Observations	130	130	128	128	128
R-squared				0.14123	0.14123

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] Probit estimates presented as marginal effects

Table 10
Disaggregated timing model: Fertilizer Use ~ Loan Amount

VARIABLES	(1) Probit[1]	(2) Probit[1]: Clustered Errors	(3) Tobit	(4) OLS	(5) OLS: Clustered Errors
Credit $_{t-2}$ ($)	0.00012	0.00012	0.00052	0.00021	0.00021
	(0.00073)	(0.00059)	(0.00503)	(0.00169)	(0.00126)
Credit $_{t-1}$ ($)	**-0.00473***	**-0.00473****	**-0.03233***	-0.00317	**-0.00317****
	(0.00253)	**(0.00220)**	**(0.01827)**	(0.00234)	**(0.00128)**
Credit $_{t0}$ ($)	0.00105	0.00105	0.00419	0.00106	0.00106
	(0.00120)	(0.00086)	(0.00683)	(0.00261)	(0.00180)
Credit $_{t1}$ ($)	**0.00158***	**0.00158****	0.00654	0.00203	**0.00203****
	(0.00095)	**(0.00062)**	(0.00526)	(0.00204)	**(0.00099)**
Credit $_{t2}$ ($)	0.00196	**0.00196****	**0.01689***	**0.00509***	**0.00509*****
	(0.00135)	**(0.00093)**	**(0.00903)**	**(0.00297)**	**(0.00125)**
Credit $_{t3}$ ($)	0.00008	0.00008	0.00375	0.00241	0.00241
	(0.00145)	(0.00142)	(0.00936)	(0.00287)	(0.00405)
Credit $_{t4}$ ($)	0.00068	0.00068	0.00670	0.00169	0.00169
	(0.00167)	(0.00132)	(0.01096)	(0.00402)	(0.00352)
HH size	-0.00208	-0.00208	-0.10371	-0.07066*	-0.07066*
	(0.01602)	(0.01355)	(0.11063)	(0.03682)	(0.03611)
Education	-0.02485	-0.02485	-0.20705	-0.06653*	-0.06653
	(0.01816)	(0.01859)	(0.13320)	(0.03816)	(0.04504)
Age	-0.00381	-0.00381	0.00657	0.01647	0.01647
	(0.00617)	(0.00734)	(0.04347)	(0.01401)	(0.01804)
Savings	0.00028	0.00028	0.00198	0.00024	0.00024
	(0.00032)	(0.00024)	(0.00228)	(0.00076)	(0.00057)
Stored chemicals	0.00119**	0.00119***	0.00689*	0.00084	0.00084
	(0.00046)	(0.00044)	(0.00359)	(0.00103)	(0.00079)
Value of assets	-0.00006	-0.00006	-0.00039	-0.00008	-0.00008
	(0.00005)	(0.00005)	(0.00034)	(0.00009)	(0.00009)
Village 1	-0.04520	-0.04520	-0.45809	-0.27949	-0.27949
	(0.13907)	(0.14034)	(0.97870)	(0.31374)	(0.32456)
Village 2	-0.16437	-0.16437	-1.31238	-0.53259*	-0.53259*
	(0.12397)	(0.14664)	(0.91038)	(0.27120)	(0.31561)
Loan Frequency	-0.02552	-0.02552	-0.19015	-0.07760	-0.07760
	(0.02691)	(0.03016)	(0.19396)	(0.06230)	(0.08737)
Constant			0.60274	0.99212	0.99212
			(2.06329)	(0.64345)	(0.68486)
Observations	130	130	128	128	128
R-squared				0.15652	0.15652

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] Probit estimates presented as marginal effects

Table 11
Robustness Check – Including Outliers
Simple timing model: Fertilizer Use ~ Loan Amount

VARIABLES	(1) Probit[1]	(2) Probit[1]: Clustered Errors	(3) Tobit	(4) OLS	(5) OLS: Clustered Errors
Credit before ($)	-0.00026	-0.00026	-0.00168	-0.00043	-0.00043
	(0.00053)	(0.00054)	(0.00376)	(0.00109)	(0.00086)
Credit during ($)	**0.00149*** **	**0.00149*** **	**0.00879** **	**0.00266** **	**0.00266*** **
	(0.00047)	**(0.00057)**	**(0.00345)**	**(0.00117)**	**(0.00080)**
Credit after ($)	-0.00021	-0.00021	0.00043	0.00108	0.00108
	(0.00095)	(0.00088)	(0.00649)	(0.00209)	(0.00262)
HH size	-0.01355	-0.01355	-0.16700	-0.07949**	-0.07949**
	(0.01494)	(0.01550)	(0.10456)	(0.03373)	(0.03736)
Education	-0.02246	-0.02246	-0.18066	-0.06357*	-0.06357
	(0.01751)	(0.01660)	(0.12814)	(0.03717)	(0.04405)
Age	0.00383	0.00383	0.05142	0.02286*	0.02286
	(0.00535)	(0.00692)	(0.03715)	(0.01173)	(0.01605)
Savings	0.00006	0.00006	0.00054	0.00020	0.00020*
	(0.00005)	(0.00005)	(0.00038)	(0.00012)	(0.00010)
Stored chemicals	-0.00001	-0.00001	-0.00030	-0.00004	-0.00004
	(0.00013)	(0.00010)	(0.00095)	(0.00020)	(0.00013)
Value of assets	-0.00006	-0.00006	-0.00039	-0.00009	-0.00009
	(0.00005)	(0.00005)	(0.00032)	(0.00009)	(0.00009)
Village 1	0.06740	0.06740	0.21729	-0.17123	-0.17123
	(0.12114)	(0.13678)	(0.86416)	(0.27162)	(0.28607)
Village 2	-0.13509	-0.13509	-1.11609	-0.47938*	-0.47938
	(0.11388)	(0.13818)	(0.81251)	(0.25287)	(0.29762)
Loan Frequency	-0.02017	-0.02017	-0.13932	-0.06501	-0.06501
	(0.02603)	(0.03077)	(0.18342)	(0.05824)	(0.08038)
Constant			-0.63611	0.79162	0.79162
			(1.86133)	(0.57590)	(0.64374)
Observations	140	140	138	138	138
R-squared				0.13097	0.13097

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] Probit estimates presented as marginal effects

Table 12:
Robustness Check – Including Outliers
Disaggregated timing model: Fertilizer Use ~ Loan Amount

VARIABLES	(1) Probit[1]	(2) Probit[1]: Clustered Errors	(3) Tobit	(4) OLS	(5) OLS: Clustered Errors
Credit $_{t-2}$ ($)	-0.00010	-0.00010	-0.00114	-0.00050	-0.00050
	(0.00071)	(0.00065)	(0.00489)	(0.00159)	(0.00141)
Credit $_{t-1}$ ($)	-0.00073	-0.00073	-0.00452	-0.00072	-0.00072
	(0.00104)	(0.00120)	(0.00744)	(0.00207)	(0.00207)
Credit $_{t0}$ ($)	0.00048	0.00048	0.00260	0.00054	0.00054
	(0.00097)	(0.00091)	(0.00635)	(0.00235)	(0.00164)
Credit $_{t1}$ ($)	**0.00200****	**0.00200****	**0.00887***	0.00245	**0.00245****
	(0.00090)	**(0.00079)**	**(0.00514)**	(0.00192)	**(0.00102)**
Credit $_{t2}$ ($)	0.00171	0.00171	**0.01485***	**0.00518***	**0.00518*****
	(0.00115)	(0.00119)	**(0.00783)**	**(0.00281)**	**(0.00137)**
Credit $_{t3}$ ($)	0.00017	0.00017	0.00283	0.00186	0.00186
	(0.00118)	(0.00109)	(0.00798)	(0.00254)	(0.00357)
Credit $_{t4}$ ($)	-0.00007	-0.00007	0.00158	0.00090	0.00090
	(0.00162)	(0.00158)	(0.01085)	(0.00393)	(0.00408)
HH size	-0.01436	-0.01436	-0.17675*	-0.08090**	-0.08090**
	(0.01512)	(0.01406)	(0.10548)	(0.03447)	(0.03514)
Education	-0.02181	-0.02181	-0.18491	-0.06475*	-0.06475
	(0.01746)	(0.01652)	(0.12802)	(0.03765)	(0.04511)
Age	0.00470	0.00470	0.05726	0.02418**	0.02418
	(0.00544)	(0.00707)	(0.03784)	(0.01210)	(0.01645)
HH savings	0.00007	0.00007	0.00061	0.00021*	0.00021**
	(0.00006)	(0.00004)	(0.00039)	(0.00012)	(0.00009)
Stored chemicals	0.00001	0.00001	-0.00023	-0.00004	-0.00004
	(0.00013)	(0.00010)	(0.00097)	(0.00021)	(0.00012)
Value of assets	-0.00007	-0.00007	-0.00042	-0.00009	-0.00009
	(0.00005)	(0.00005)	(0.00033)	(0.00009)	(0.00009)
Village 1	0.09005	0.09005	0.35530	-0.15122	-0.15122
	(0.12212)	(0.13391)	(0.86977)	(0.27673)	(0.29281)
Village 2	-0.11728	-0.11728	-1.05654	-0.47737*	-0.47737
	(0.11598)	(0.14286)	(0.82690)	(0.26095)	(0.30443)
Loan Frequency	-0.01539	-0.01539	-0.11668	-0.06076	-0.06076
	(0.02664)	(0.03193)	(0.18745)	(0.06055)	(0.08633)
Constant			-0.88560	0.72996	0.72996
			(1.92213)	(0.60483)	(0.66855)
Observations	140	140	138	138	138
R-squared				0.14263	0.14263

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] Probit estimates presented as marginal effects