Impact of Technical Assistance and Microcredit Among Rural Households in El Salvador

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Dedication

To Emilio Medina-Smith, my intellectual father and friend.

Abstract

There is an increased interest in knowing whether the provision of nonfinancial, technical services along with microcredit has a positive impact on the performance of borrowers. The combination of these services may help poor households improve their economic performance. Yet, evidence proving this proposition is scarce and results are mixed. This lack of formal evaluation is often a consequence of these services being part of integrated approaches, making the assessment of their impact difficult to disentangle from the sole impact of microcredit. This dissertation provides evidence of joint productivity impact from microcredit and technical assistance received during 1997-1999 by rural household clients of a major microcredit institution in El Salvador.

We find that the use of credit has positive effects on farm productivity. It is estimated that for every 1,000 colones of additional credit received there is a 9 percent increase in the value of farm output. These results are at the high end of the range of productivity impact reported in previous studies. When technical assistance is introduced along with credit there is also a positive impact in household productivity. In addition, we find that the pattern of consumption of these two services matters. Households with repeated loans experience smaller changes in productivity than households that borrow for the first time. It is unclear why these patterns of consumption impact productivity in different ways. However, we find that credit and technical assistance contribute to productivity through different paths: increased technical efficiency, technology adoption, and economies of scale. The role of credit and technical assistance in contributing to these productivity elements is assessed through the analysis of the households' production possibility frontier. Technical efficiency improved during these years, mainly from the effect of technical assistance. In addition, we conclude that adoption of new technologies was promoted by both credit and technical assistance. There

is also evidence that these households experience increasing returns to scale. Technical assistance may have contributed to the generation of these economies of scale by increasing farmers' skills. Credit may have helped farmers to expand their input use and take advantage of the economies of scale.

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Chapter 1

Introduction

The productivity of agricultural households is a central topic of discussion about the economic development of poor countries. According to the World Bank, a significant proportion of this population lives in rural areas and most of the rural households in these developing countries are poor, deriving their incomes from agricultural activities. Thus, there are clear reasons for researchers and practitioners to learn what interventions can improve the productivity of agricultural households. Two of these interventions are microfinance and agricultural extension services.

The ultimate goal of microfinance programs in developing countries is to alleviate poverty. The value of microcredit as an economic development tool is based on the assumption that the poorer the household, the harder it is for that household to finance productive activities from credit obtained from formal banks. Thus, society loses the potential economic contributions of micro-entrepreneurs because they are unable to be fully productive (Hulme & Mosley, 1996). Providing loans to poor households helps them to invest in income-generating assets, and improves their income levels and consumption opportunities. As earnings increase, households may be able to seek bigger loans and eventually access financial services from commercial banks. They could then invest more and therefore increase their income. This is the virtuous cycle envisioned by Muhammad Yunus, the creator of the microcredit movement (Morduch, 1999).

The evidence of the positive impact of microfinance on reducing poverty and achieving other social goals is growing as more data are collected and high-quality research is conducted. However, program leaders - as well as researchers - have identified aspects of the microfinance field that, while not yet widely discussed, may be of crucial importance to the success of microfinance. One of these questions is whether "providing credit without technical assistance and other complements is enough?" (Armendáriz & Morduch, 2010, p. 3). The term *technical assistance* (TA) here is very specific: it means *agricultural extension services*.

This question has been studied before, yet the impact of nonfinancial services, such as extension services, has not been studied thoroughly. This lack of formal evaluation is a consequence of these services often being part of integrated approaches (Ledgerwood, 1999), making the assessment of the impact difficult to disentangle from the impact of microcredit. Furthermore, the few studies which have evaluated the value of business development services (or technical assistance) in the microfinance field show mixed results. A framework integrating business services and microcredit would help improve our understanding of the role that nonfinancial services play.

1.1 Literature Review

The fundamental contribution of microcredit is the reduction of the negative impact of credit market imperfections which hamper access to financial services among the poor or certain minorities. Market imperfections arise for several reasons but mainly because of informational asymmetries and lack of collateral (Stiglitz & Weiss, 1981). These imperfections create situations where the demand for credit exceeds the supply at prevailing interest rates, i.e. some households cannot obtain credit even though they are willing to pay the prevailing interest rates or higher. Information asymmetries arise when financial institutions lack information to differentiate good clients from bad ones, increasing the risk of loan defaults and losses and causing the financial institution to raise interest rates or to indiscriminately ration the size of loans. Group lending technologies, commonly used by microcredit institutions, can prevent the problem of adverse selection; borrowers who know their own risk profiles and can thus sort themselves into groups with similar risk profiles (or at least sort out the riskier investors). In this case, the credit institution does not have to charge a higher interest rate than what it would have charged if it did not use a group lending model.

The informational asymetries and lack of collateral are two economic development issues which have several causes including weak property rights and low saving rates in developing areas (Hulme & Mosley, 1996). This situation is typical in developing countries and more evident in rural areas where it is difficult to obtain information about individual's financial history. Weak property rights, also common in developing countries, prevent potential borrowers from using their assets as collateral because they lack evidence of ownership. Fletschner, Guirkinger, and Boucher (2010) show that banks pass on to borrowers the transaction costs associated with screening applicants, monitoring borrowers and enforcing contracts. Lenders also try to reduce risk from moral hazard by tightening contractual rules and, thus, increase the cost of borrowing. Some households which could otherwise benefit from credit will opt to not borrow because of these high transactional costs.

Furthermore, credit-constrained households suffer smaller profits than non-constrained households due to lower productivity from sub-optimal allocation of productive factors such as land and labor. Lower productivity is a result of these allocative inefficiencies rather than low investments (Foltz, 2004). In turn, Briggeman, Towe, and Morehart (2009) show that the value of output is lower for farm and non-farm sole proprietors due to the presence of credit constraints; however, this study was limited to only U.S. farmers.

Morduch (1999) argues that, though some studies show credit constraints are a negative factor in the development of economic agents, debate still exists about the role microcredit can play in the alleviation of these constraints and ultimately how it can reduce the level of poverty. This skepticism is a consequence of the lack of scientific evidence about the impact of microcredits programs. However, with the proliferation of microcredit programs and the availability of data in recent years, more research is being produced on these issues, and microcredit has effectively addressed them (Armendáriz & Morduch, 2010; Wenner, Alvarado, & Galarza, 2003).

We are now more certain that improving access to credit has a positive effect on a firm's growth as measured in terms of sales and employment and adoption of technology (Hulme & Mosley, 1996). Microcredit also improves a household's consumption (Jappelli, 1990), education (Wydick, 1999), women's consumption and access to education (Pitt & Khandker, 1998; Kevane & Wydick, 2001), and the capacity to deal with crises such as health shocks (Islam & Maitra, 2012). Sebstad and Chen (1996) provide a comprehensive summary of early impact studies in the field.

Karlan and Zinman (2009) show that improving access to credit has positive effects on business and household outcomes. They emphasize that the complexity and variety of situations in which small entrepreneurs in developing countries operate, as well as the complex credit to which they are subjected, necessitate evaluation of theories about the impact of credit in different settings. For instance, male heads of households experience growth in profits after increasing their access to credit; but, this is not the case for female entrepreneurs. Yet many microfinance program target women as their primary, and sometimes only, clients.

Previous studies show the positive impact agricultural extension and training has on agricultural productivity and efficiency (Lockheed, Jamison, & Lau, 1980; Feder & Slade, 1986; Bindlish & Evenson, 1997; Bravo-Ureta et al., 2007). These studies deal with the effect of agricultural extension independent of other factors including access to credit. However, with the increased variety of microcredit models which include nonfinancial services, it is likely that these two interventions have joint impact on agricultural households.

In fact, extension services and microcredit are interconnected in most places and situations where microfinance programs operate around the world. For instance, in a survey of best practices in microlending Diaz (2008) indicates that approximately 66 percent of U.S. microlenders offer technical assistance services to their clients. In 50 percent of cases where organizations provide technical assistance, applicants must receive technical assistance in order to receive a loan.

This linkage between microcredit and technical assistance may take several forms. Sometimes microlenders provide the nonfinancial service themselves, but in other instances clients have access to technical assistance or business development services through other institutions located in the area. For example, technical assistance can be provided in the form of advice from the lender, an in-house technical assistance program, or a third-party service. In other situations the technical assistance may be related to production or farming techniques (agricultural extension) imparted by govermental agencies in the form of one-on-one counseling or group workshops. In some cases, microfinance institutions provide formal technical assistance only at the early stages of the lending process, whereas others have continuous technical assistance that lasts as long as the individual remains a client (Ledgerwood, 1999).

Ledgerwood (1999) points out, however, that the goal of technical assistance is broad and thus almost any nonfinancial service can be used to achieve it. The variety of nonfinancial services and the different modalities of delivery used by microcredit institutions make it difficult to identify whether the positive impact resulted from the microloans, the technical assistance, or both.

For example, in a study of the effects of credit on technical efficiency in Malawi, Diagne (2002) remarks that extension services should promote a more efficient use of fertilizer. Yet adverse conditions in the agricultural and credit markets may impede farmers who accept recommendations provided by extension services. The study does not demonstrate that when microcredit reduces the credit constraints faced by farmers, technical assistance may produce better impact. Even more importantly, the study does not clarify whether the provision of both services jointly is more effective than providing them separately.

The combination of technical assistance and microcredit may help poor households to achieve the ultimate goal of improving their economic performance and other outcomes. Yet evidence supporting this proposition is scarce and the results are mixed. For instance, providing loans and nonfinancial education helps improve food security and children's nutritional status in Ghana, Bolivia, and other countries, (Smith & Jain, 1998; Dunford & Denman, 2001). Yet, Dunford and Denman (2001, p. 21) state that "one should expect such impact on mothers' knowledge, practices and outcomes in any well-designed and well-implemented health/nutrition education program, whether or not it is piggy-backed on a microfinance service delivery system." In any case, joint delivery of services may not diminish the effectiveness of the interventions. In another particular study, using a randomized design Karlan and Valdivia (2011) find insignificant impact of business training on sales of small entrepreneurs in Peru. The authors also find weak evidence that "the training may have helped clients identify strategies to reduce the downward fluctuations in their sales" (p. 519).

There are other benefits to providing credit and technical assistance concurrently. Officials of the credit scheme of the Kenya Rural Enterprise Program (KREP) recognize the significance of education and training as a strategy to avoid the proliferation of similar businesses and thus saturation of markets (Buckley, 1996). Brown, Earle, and

Lup (2005), and Briggeman et al. (2009), who incorporate technical assistance in their analysis of credit constraints of small household-enterprises in Romania and the U.S., find positive microcredit impact in these outcomes, though the parameter of technical assistance is statistically insignificant. In none of these studies is the combined effect of microcredit and technical assistance evaluated.

There is also mixed evidence that diversification of effort and resources between financial and nonfinancial services by a microcredit institution may compromise effectiveness (Rhyne & Holt, 1994). Even though microcredit programs, governments, and other non-governmental organizations recognize the potential positive effects of technical assistance, microfinance practitioners still face the dilemma of whether to devote more resources to technical assistance programs or to lending. More knowledge of the impact of technical assistance programs may help microfinance institutions better allocate their resources and increase their programs' effectiveness.

The literature shows the existence of significant positive impact of microcredit on income generation. Households with access to microcredit generate significant improvements in income, revenues, profits, and employment creation in the short-run when compared to households without these loans. On the other hand, literature about the impact of technical assistance or extension services on farm productivity shows a general positive impact, although only a few authors have included technical assistance as a determinant of the performance of small firms or agricultural households participating in microcredit programs.

The previous literature has shown that microcredit and technical assistance have a positive impact on several households' outcomes, including output growth. However, the empirical problem is to attribute output growth to input growth and productivity growth (Kumbhakar & Lovell, 2000). The question that the existing literature has not addressed so far is: what is the impact of technical assistance and credit on household productivity when these two services are provided together? Furthermore, changes in productivity can be affected by technological change, improved technical efficiency, and economies of scale; thus, it is worth asking whether credit and technical assistance have any impact on productivity via these factors. This research seeks to show new evidence that agricultural extension, along with microloans to agricultural households, has a positive impact on productivity, and also determines whether this effect was generated from changes in efficiency, technology, or economies of scale.

1.2 Research Objectives

Technical assistance and credit are combined in many situations by providers of these services. Thus, it is worth asking whether providing technical assistance along with credit makes a difference in the performance of the borrowers. In this case households receive both services and the counterfactual is the state in which the household receives neither technical assistance nor credit. The question addressed is: what is the effect of technical assistance *and* credit on the productivity of rural farm-households? Furthermore, does the pattern of consumption of these services matter (i.e. receiving two consecutive loans versus receiving one loan)? What are the mechanisms through which credit and technical assistance may affect productivity?

To answer these questions the research in this thesis has the following three objectives:

1. Evaluate the impact of credit use on farm level output among households with access to microcredits.

2. Evaluate the combined output effects of technical assistance and credit use on households with access to credit.

We conduct this assessment by evaluating the separate and joint effects of credit and technical assistace on households' productivity via improvements in technical efficiency, technological change, and economies of scale.

These goals are attained by conducting an empirical analysis of the changes in productivity and efficiency of agricultural households which receive microloans from *Financiera Calpía*, one of the main microcredit institutions in El Salvador.

This study uses an original identification strategy that allows one to assess the impact - both separately and jointly - of technical assistance and credit. In addition, information about past loans was collected in the survey. This information allows one to control for the effects of credit history. This feature of the model is in line with recent proposals in the field that suggest using past borrowers as a comparison to recent borrowers, without controlling for past credit history, may produce biased results.

The remaining sections of the dissertation are organized as follows: Chapter two describes the main features of the agricultural household model, which serves as the theory of reference for the empirical analysis. The next three chapters develop the identification strategy and assessment of the impact of microcredit on productivity, and the joint impact of credit and technical assistance. Then, I explore how these services affect the technical efficiency of agricultural households. Finally, I provide conclusions and recommendations for future research.

Chapter 2

Conceptual Framework

The main economic activity of households clients of *Financiera Calpía* is farming. The majority of these households own and operate small agricultural businesses; they produce and sell their crops and animals in local markets. They also consume a fraction of the output of their farms; moreover, once they obtain a loan from a financial institution or other lender, they spend this money not only in inputs for their farms, but also in satisfying household needs such as paying for health care, food, or education. Consequently, the best theoretical framework of reference to study the impact of credit and technical assistance among rural agricultural households is the *agricultural household model* as presented by Singh, Squire, and Strauss (1986).

In this model, households are considered consumption units and productive entities at the same time. When the farm-household is constrained only by the available time and the current level of technology, and faces complete markets for labor and inputs, the household faces two independent problems: 1) maximizing profits from the family business; and, 2) allocating the household's resources toward consumption of goods and leisure. In the rest of this chapter, I summarize the main characteristics of the agricultural household model with credit; I also present a brief discussion of the potential effect of credit and technical assistance on productivity.

2.1 The Agricultural Household Model with Credit

Assume an agricultural household model where the household has a utility function that is twice differentiable and quasi-concave and is a function of consumption of goods c and leisure l. The household operates a farm that generates revenues. The production function F of this activity is assumed to be convex and twice differentiable. The household uses physical inputs V and labor L to produce output, and prices of physical inputs w^V and labor w^L are taken as given by the household. The production function also depends on a given level of technology θ and characteristics of the household υ.

The household can allocate its endowment of time E^L toward work on its farm L_f, work for a wage in the labor market L_m, or leisure activities l. The household has an endowment of inputs E^V which, for simplicity, are assumed to be used only on its own farm; thus, $E^V = V_f$ and therefore the household cannot obtain any "rent" from its inputs in the market.[1]

The household faces a credit constraint Ω. This constraint is similar to the one used by Kevane and Wydick (2001) in their model of household enterprise; these authors define Ω as a liquidity constraint that limits the amount of labor and physical inputs which can be bought $(w^L L_h + w^V V_h)$.

There are at least three sources of liquid funds: household's savings, assets that can be sold, and external credit. Households in this sample have relatively small farms, low income, and own very few assets, therefore it is reasonable to assume that they can obtain additional liquid funds only through external sources of credit. In this case, the production decisions may be affected by the level of credit that is available to the household, i.e. existence of credit constraints. In my analysis, I use a sample of current and former clients of the microcredit institution; therefore, all househlods have had access to credit.

However, credit constraints also exist when the household can not obtain all the credit it demands, even when it is willing and able to pay the prevailing interest rate; this situation is called "credit rationing." Therefore, even though I assume that all households in the sample have access to credit, one needs to ask whether the households

[1] This assumption is justified theoretically since the absence of a market for inputs does not affect the structure of the agricultural-household model (Bardhan & Udry, 1999).

are credit rationed[2]. I assume that the credit constraint is not binding, i.e. households have access to credit and are not credit rationed. This assumption allows me to focus the discussion of how credit use (as opposed to credit access or credit rationing) affects households' production decisions and productivity.

The analytical model is summarized by the following expressions:

$$\max_{c,l} U(c,l) \tag{2.1}$$

subject to

$$c + w^L L_h + w^V V_h \leq F(V, L|\theta, \upsilon) + w^L L_m, \tag{2.2}$$

$$w^L L_h + w^V V_h \leq \Omega, \tag{2.3}$$

$$E^L = L_f + L_m + l, \tag{2.4}$$

$$E^V = V_f, \tag{2.5}$$

$$c,\ l,\ L_f,\ L_m, L_h,\ V_f,\ V_h, \geq 0$$

$$\text{where,} \qquad L = L_f + L_h, \quad \text{and} \quad V = V_f + L_h \tag{2.6}$$

Substituting (2.4) - (2.6) into the budget constraint (2.2) and rearranging the resulting expression produces the budget constraint:

$$c + w^L l \leq \Pi + w^L L_m, \tag{2.7}$$

$$\text{where,} \qquad \Pi = F(V, L|\theta, \upsilon) - w^L L_h - w^V V_h \tag{2.8}$$

Equation 2.7 is called the 'full income' constraint: "the value of consumption cannot exceed the value of the household's endowment plus farm profits"(Bardhan & Udry, 1999, p. 9). If the liquidity constraint is not binding for the household's maximization problem, its production decisions are independent of its consumption decisions, i.e. the

[2] I find no evidence that households in this sample are credit rationed. For instance, less than 4 percent of the households receive loans that are smaller than the amount requested. If we assume that the amount of credit requested is a good approximation of households' demand for credit, this statistic implies that households are not credit rationed. However, note that the amount of credit requested may not necessarily be the optimal level of credit for the household. For example, the household may be asking for less than what it really needs to finance inputs for an optimal level of production. Nevertheless, one can presume that loan officers would advise the household to seek a more optimal amount (in this case a larger loan). Thus, it can be assumed that the households in this sample are not credit rationed.

separation property holds (Bardhan & Udry, 1999). and the household's maximization problem is recursive. First, the household maximizes farm profits Π and, given that level of profits, it maximizes the utility obtained from consumption and leisure.

The model with non-binding liquidity constraint can be written as:

$$\max_{c,l} U(c,l) \tag{2.9}$$

subject to

$$c + w^L l \leq \Pi^{\cdot}(w^L, w^V) + w^L L_m, \tag{2.10}$$

$$\text{where,} \qquad \Pi^{\cdot}(w^L, w^V) = \max_{L,V} F(V, L|\theta, \upsilon) - w^L L_h - w^V V_h \tag{2.11}$$

The first order conditions for the profit maximization problem are:

$$\frac{\partial \Pi}{\partial L_h} = \frac{\partial F|_{\theta,\upsilon}}{\partial L_h} - w^L = 0 \tag{2.12}$$

$$\frac{\partial \Pi}{\partial V_h} = \frac{\partial F|_{\theta,\upsilon}}{\partial V_h} - w^V = 0 \tag{2.13}$$

The first order conditions for the profit maximization problem (2.12) and (2.13) stipulate that the the amount of hired labor and physical inputs would be set so that the value of the marginal product of each factor of production is equal to its price. Given the prices of inputs, and due to the convexity of the production function, a higher marginal productivity of factors implies a lower level of inputs hired and a smaller output.

Credit use can impact productivity through several paths. To show these impacts I start by using a definition from Kumbhakar and Lovell (2000) to characterize a change in productivity as the change in output per level of inputs used in the production process. Formally, the level of output in a given period of time is denoted by q_t and the quantity of inputs used in its production by $\mathbf{x}_t$; a change in productivity can be characterized as:

$$\Delta\text{Productivity} = \frac{q_{t+1}}{\mathbf{x_{t+1}}} - \frac{q_t}{\mathbf{x_t}} \tag{2.14}$$

If $(q_t/\mathbf{x_t}) < (q_{t+1}/\mathbf{x_{t+1}})$, productivity growth ocurred.

Changes in productivity can be decomposed into technological change, technical efficiency, and returns to scale (Kumbhakar & Lovell, 2000). Increased credit may cause any or all of these changes. Increased credit allows the household to implement new production technologies which were otherwise not affordable. These new production technologies can possibly increase productivity and revenues. In this case, the change in productivity comes from technical change of the form:

$$\text{Technical Change} = q(\mathbf{x}, t+1) - q(\mathbf{x}, t), \tag{2.15}$$

where q is the production function of the household that depends on inputs, $\mathbf{x}$, and the available technology at the time period t. Technical change occurs if the production function in period $t = 1$ generates more output than the function in period t at every level of input.

Increased credit also allows the household to free some resources from less productive activities and make allocative decisions more efficiently. This would be the case for households not producing at their optimal levels given the available technology and level of input. If the production frontier is defined as the maximum output that can be obtained from any given input vector, $q(\mathbf{x}, t)$, technical efficiency is the ratio of observed output to the maximum feasible output.

$$TE_t = \frac{q_t}{q(\mathbf{x}, t)} \leq 1 \tag{2.16}$$

This implies that if $TE_t < 1$, the household is not producing at its maximum feasible level of production. Gains in technical efficiency imply that the household would produce at a level closer to its optimum. In other words, the household would move closer to its production frontier. This type of gain in efficiency is characterized as:

$$^{+}\Delta\text{Technical Efficiency} = \frac{q_{t+1}}{q(\mathbf{x}, t+1)} > \frac{q_t}{q(\mathbf{x}, t)} \tag{2.17}$$

It is also possible that households move away from their optimal level of production; weather shocks can affect crops, health shocks can affect the farmer's ability to work, etc. In these cases, the sign in (2.17) is reversed. However, having access to credit may help the household deal with these crises and reduce the negative impact of the shocks.

With increased credit, more inputs can be used in production; a proportional increase of all inputs may lead to productivity gains when increasing economies of scale are present. For example, farmers producing at low levels of output, yet with relatively large amounts of unused land, may experience economies of scale after receiving a loan that allows them to increase all their inputs. Input expansion may also lead to economies of scale when the farmer increases her productive skills, for example via technical assistance. The presence of economies of scale and their relation to credit and technical assistance is developed with more detail in Chapter 5.

The analysis in this thesis focuses on the overall gains in productivity of the households as defined in (2.14). Second, an empirical strategy is devised to assess whether technical efficiency, TE_i, is associated with factors such as technical assistance and credit.

In this context, a household may receive business development services, such as technical assistance, in addition to the microloans. The term *technical assistance* is used here in a very specific way, i.e. only as agricultural extension services in the form of seminars (as discussed in Chapter 1). Technical assistance may affect households' productivity through the same three paths described above (technical change, technical efficiency, and economies of scale). Technical assistance may provide the household with new productive skills or knowledge that allow it to shift its production frontier; it could also cause a more effective use of inputs (e.g. irrigation techniques), thus raising the productivity of cultivated land. In this case, technical assistance improves the technical efficiency of the household.

Chapter 3

Output Impact of Credit

In this research, I explore a question which microcredit institutions are interested in answering: what is the productivity impact of adding technical assistance to financial services? From the researcher's perspective, estimating the impact of credit is a difficult task that presents several potential challenges; this is why I devote a complete chapter to the estimation of the impact of credit and show the potential problems - and possible solutions - one faces when estimating the effect of credit on productivity.

I start the chapter describing the identification strategy, then I discuss some of the potential issues that this estimation could present; I complete the chapter with a set of results obtained using several specifications and a discussion about how these models suit this task.

3.1 Data and Identification Strategy

Identifying the impact of receiving credit on households' outcomes is complicated even when detailed, high quality data on the outcomes of interest and credit characteristics of participants are available. In previous studies, researchers have noted the main challenges of trying to estimate the impact of credit. For example, Tedeschi (2007) summarizes three main sources of bias: 1) credit holders may self-select into credit programs; 2) credit programs may target clients with particular characteristics, such as level of poverty, gender, or geographic location, particularly if these characteristics are unobserved; and, 3) characteristics of regions where participant households are located affect the demand and use of credit and are not controlled for. In addition, I analyze potential problems that can arise when household's credit history, (e.g. previous loans) is not controlled for in the model. In this section I review these issues in detail and present an empirical strategy to deal with them.

3.1.1 Data

The panel data used in this study are from a survey of rural clients of *Financiera Calpiá* in El Salvador, conducted by the United States Agency for Interantional Development (USAID), The World Bank, and The Ohio State University. The survey data was obtained in two rounds, one in 1998 and, the other in 2000. Each sample is drawn from the complete, known population of rural borrowers of *Financiera Calpiá*. Rural clients are defined as clients served by a rural loan officer; this definition implies that the client either lives in an area more than twenty kilometers from the nearest *Calpiá* branch or the client is engaged in some agricultural activity. The sample includes clients from all the *departmentos* (states) of the country.

The unbalanced panel data contain a total of 263 households. 217 cases are surveyed in both rounds of the survey, 22 households are present only in the first round, and 24 are only in the second round, for a total of 480 household year-paired observations for the two rounds of the survey. From these 480 cases I use 377 household year observations which reported non-negative crop yields in any of the years observed.

Table 3.1 contains the definition of relevant variables used throughout the analysis. The dependent variables are the value of total crop output and the value of crop output per hectare cultivated. Values for these variables are computed using average prices by type of crop and are expressed in constant local currency (*colones* of 1992). Thus, Y_{it} represents the total revenues from all types of crops sold during year t by household i, and y_{it} is the value of output divided by the total number of hectares cultivated in that period.

The main independent variables are the amount of credit C_{it} and technical assistance TA_{it}. Technical assistance is defined as agricultural extension services. The main provider of technical assistance in rural El Salvador is Centro Nacional para la Tecnologia Agropecuaria (CENTA) [National Center of Agricultural Technology].[1] CENTA is a

[1] The CENTA institutional information can be retrieved from: http://www.centa.gob.sv/.

Table 3.1: Variable Definitions

Dep. variables: (Values calculated using average price by type of crop.)
$\mathbf{Y}_{it}$: Value of total crop output (*colones* of 1992)
$\mathbf{y}_{it}$: Value of crop output per hectare (*colones* of 1992/hectares)
Independent variables:
$\mathbf{C}_{it}$: Size of loan received by household i in period t (*colones* of 1992)
$\mathbf{TA}_{it}$: Dummy variable indicating if household i received technical assistance in year t
L: Hired labor (full time equivalents = FTE)
A: Area cultivated (hectares)
l: Labor per area cultivated (FTE/hectares)
V: Input expenses (*colones* of 1992). Includes: expenses in seeds, fertilizer, irrigation, and pesticides.
Age: Age of household's head at time of interview
$\mathbf{C}_{0i}$: Present value of previous loan received before 1997 (Disc. rate = 33.2%; average rate of current loans)

public organization dedicated to scientific research in the agricultural field. It promotes and facilitates technology transfers as a tool to develop the agricultural sector in El Salvador. According to a national household survey conducted by USAID, The World Bank, and The Ohio State University[2], CENTA provided technical assistance to about 80 percent of the households receiving technical assistance in rural El Salvador in 1999. These households represent nearly 6 percent of rural households in the country.

The majority of technical assistance provided by CENTA is delivered via seminars and small group sessions held in local governmental or non-profit organization venues. Topics of CENTA seminars include techniques for growing specific crop varieties, use of new seeds, and implementation of new technologies. Instructors are technical staff from CENTA, most of whom are agricultural engineers. Seminars are free and usually held in sites close to the households' locations.

Given the significant role CENTA plays in the provision of technical assistance in El Salvador, I use the model implemented by CENTA as my benchmark definition of technical assistance. Note, however, that about 20 percent of the rural households in the country with technical assistance receive it from unspecified private sources. Thus,

[2] (OSU Rural Finance Program, n.d.)

when referring to a household as having received technical assistance, this implies it attended at least one of the seminars provided by CENTA or received some other form of assistance from a private source, such as training from a vendor. Also note there is no formal connection between CENTA and *Financiera Calpiá*, nor is there any technical assistance requirement to apply or receive loans from *Financiera Calpiá*. Thus, with this sample I cannot evaluate the relationship between credit and technical assistance when the training is a requirement for accessing the loans (see Karlan & Valdivia, 2011 for an analysis of these types of impact.)

The inputs included in the analysis are cultivated land A, measured in hectares, hired labor L, and the total expenses in seeds, fertilizer, pesticides, and irrigation V. Hired labor is measured in terms of full time equivalent workers (FTE) using the standard criteria of 40 hours per week and 52 weeks per year for a full time worker.

Table 3.2 contains summary statistics for these variables. The variables take on

Table 3.2: Summary Statistics

Variable	**Mean**	**(Std. Dev.)**	**Min.**	**Max.**	**N**
Y (*colones*)	12,745	(38,955)	0	485,630	377
y (*colones*)	3,364	(6,371)	0	70,381	377
C (*colones*)	7,136	(11,853)	0	109,000	377
C_0 (*colones*)	2,217	(9,113)	0	75,000	377
TA	0.21	(0.41)	0	1	377
A (*hectares*)	3.54	(3.99)	0	28	377
L (FTE)	0.13	(0.45)	0	7.31	377
l (FTE/hect.)	0.04	(0.09)	0	0.72	377
V (*colones*)	3,745	(7,865)	0	86,751	349
Gender (1 = female)	0.12	(0.33)	0	1	377
Age (*years*)	46.3	(12.96)	17	85	377

values that are within the expected ranges and there are no missing values, except for the value of inputs V_{it} for which there are 28 missing values. Revenues and credit take on very high maximum values (485,630 and 109,000 colones) relative to the mean for these variables (12,745 and 7,136)[3]; however, I find no significant effect of outliers in the analysis.

[3] For reference, the average total revenues of 12,745 colones is equivalent to approximately $1,600 USD using the official exchange rate in 1999 reported by the Central Bank of El Salvador.

About 21 percent of households receive technical assistance, Households cultivate an average 3.5 hectares and hire very little non-household labor, about 0.13 FTEs, which is equivalent to approximately 5 hours of hired labor per week. The survey does not contain detailed data on hours worked by household members on their farms during 1997, so we can only include data on hired labor in the analysis. Households spend in inputs nearly 3,745 colones; this represents slightly more than half the average size of the loans received and about 25 percent of the average revenues. The average age of household head is 46 years and 12 percent are female.

3.1.2 Identification Strategy

To illustrate the identification and estimation strategy, assume that the initial model of interest is given by:

$$E(Y_{it}|\alpha_i, \mathbf{x}_{it}, C_{it}) = \alpha_i + \beta\mathbf{x}_{it} + \gamma C_{it} \tag{3.1}$$

where Y_{it} is the outcome of interest (in this case the value of crop output) and C_{it} is the amount of credit received by household i in period t. The vector $\mathbf{x}_{it}$ includes input expenses V_{it} and age of the household's head. In addition, the model allows for the presence of individual time invariant characteristics, α_i. The marginal impact of credit is given by $\gamma = \partial E(Y_{it}|\alpha_i, \mathbf{x}_{it}, C_{it},)/\partial C_{it}$. The variable C_{it} is time-varying and continuous since credit is measured as the amount of money borrowed by households. Thus, the parameter γ in model (3.1) can be estimated using *fixed-effects* (FE) methods. The FE controls for time-invariant unobserved characteristics that may be associated with credit or other regressors. The parameters β and γ are estimated without bias using FE as long as $E(\varepsilon_{it}|\alpha_{it}, \mathbf{x}_{it}, C_{it}) = 0$, where ε_{it} is the idiosyncratic error that includes unobserved time-variant household traits that affect productivity. In other words, the model allows for the treatment and other covariates to be correlated with the time-invariant factors, yet it requires the regressors be uncorrelated with the error term.

The first potential source of bias is the possibility that credit holders self-select themselves into credit programs, implying there are unobservable characteristics of the borrowers that make them seek credit, more likely to receive credit, and more (or less) productive. This is the typical problem of endogeneity of the treatment due to unobservable variables. When the unobserved variables causing endogeneity are time-invariant, such as the character or entrepreneurial ability of the borrower, the estimation of γ_1 using FE avoids selection bias. However, if the endogeneity is associated with time-variant factors, 2SLS with instrumental variables must be used if valid instruments are available. I explore both options by using FE and FE-2SLS estimations; I also compare the FE results to cross section estimations.

The second source of bias arises from the possibility of non-random allocation of loans by the credit program. This issue occurs when credit programs target specific types of households, sometimes located in particular geographic areas. For example, a program might specifically provide loans to poor households with low productivity. In the case of *Financiera Calpía* this may not be an issue since the program serves households from almost all geographic regions in El Salvador and does not hold particular client-targeting strategies beyond the usual observed credit worthiness indicators, e.g. cash flows, repayment history, etc.

The third source of bias occurs if borrowers and non-borrowers come from geographic areas that have systematic differences - prices of goods and services, land fertility, and areas where poverty is high, for example. These geographic characteristics may affect the demand and use of credit. Since most of the households in the sample remain in the same location for the period studied, location traits are time invariant and the FE estimation will correct any potential bias from these characteristics. To the extent the estimation technique does not control for time invariant factors, I include specific geographic dummy variables to control for differences associated with location.

In addition, there are some other considerations to keep in mind due to the nature of the households in the sample. The households used in the estimation come from a random sample of current and former clients of the microcredit program. I observe the amount of credit received during the two years of the survey, 1997 and 1999. However, regardless of the amount of credit received during these years, these households may have received loans before 1997. A potential problem with this is that past loans (C_{it-1}) may be correlated to shocks to current productivity.

The impact of previous loans on current outcome is related to how the loans were used, the amount of the loans, and when they were received. If the loan was used as working capital, or to buy inputs that were used and depleted during a production cycle (e.g. seeds and fertilizer) the amount of the loan is correlated only with output in the same period when it was received. In this case, the effects of the amount of credit on future outlays of output is minimal. On the other hand, bigger loans are usually used for capital investments and their impact could occur over several years of production. In general, it is reasonable to assume that a more recent loan may have a bigger impact on a household's productivity than a loan received 10 prior.

The absence of data on output and other variables for the years when the previous loans were received prevents me to implement a FE with all lagged values of loans (see Ottaviano & Lage, 2007 for an implementation in the microcredit field). An alternative way to introduce credit history in the FE regression consists of expressing previous loans in present value terms and including this discounted value in the FE regression. Discounting is computed from the year when the previous loan was received to 1997 and using the average interest rate of current loans as the discount rate. Discounting the previous loan is used to generate a proxy for how the loan was used in the past; the assumption is that the loan's opportunity cost - in this case captured by the discount rate - is a proxy for the impact of the loan on household production. This impact is discounted over time so the older the loan, the smaller its impact on current outcome. Forming a interaction term between previous and current loans and substituting into (3.1), the model becomes:

$$E(Y_{it}|\alpha_i, \mathbf{x}_{it}, C_{it}) = \alpha_i + \beta\mathbf{x}_{it} + \gamma_1 C_{it} + \gamma_2(C_{0i} \cdot C_{it}) \tag{3.2}$$

Where C_{0i} is the present valued amount of the previous loan and the total impact of credit on output, controlling for credit history, is given by $\gamma_1 + \gamma_2$. The coefficient γ_2 captures non-linearities in the effect of current loans associated with the reception of loans in the past. For example, if γ_2 is negative, the marginal impact of current loans diminishes as the present value of past loans increases, i.e. given a constant amount of the previous loan, its present value decreases as it is received more recently.

This result would seem counter intuitive because one could expect that large loans would have permanent effects on productivity regardless of how long ago they were received. However, this is not the case if households are using the loans to acquire inputs and expand their production, but are not experiencing a shift in their production functions. In other words, assuming that the households have similar concave production functions, the expansion of output and consequence of previous loans results in a movement along the household's production function toward higher production levels and a smaller incremental changes in output associated with additional amount of inputs. In this case, first time borrowers experience a bigger increase in productivity than households with previous loans because long time borrowers are already at higher points of their production functions.

To illustrate this point, I show in Table 3.3 differences between first time borrowers and households with large previous loans:

Table 3.3: Credit History Summary Statistics

Mean (*colones*)	First time borrowers	Borrowers with large previous loans
Value of crop output (*colones*)	12,419	18,562
Area cultivated (hectares)	3.53	3.64
Labor (full time equivalent workers)	0.12	0.25
Technical Assistance	0.22	0.15
Age	46.52	42.25
Previous Loan (*colones*)	-	36,058***
Current Loan (*colones*)	6,859	12,075*
Current loan use:		
Inputs	0.71	0.8
Equipment	0.02	0.10**
Land	0.01	0**
Labor	0.06	0.20*
	N	357

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 3.3 I observe that borrowers with large previous loans have larger outlays of output than first time borrowers (18,562 - 12,419) and run slightly bigger farms in terms of area cultivated (3.64 - 3.53). Both groups of households hire very little labor, with previous borrowers hiring slightly more full time employees than first time borrowers (0.25-0.12). Previous borrowers receive current loans almost twice the size of loans by first time borrowers (6,859 - 12,075). Previous borrowers are more likely to use their large loans to buy equipment and pay for hired labor, which is expected due to the size of the loans.

One can see that previous borrowers run larger farms and produce more outputs. The FE regression of model 3.2 controls for the factors that are time-invariant (and unobserved time-invariant factors); thus, assuming that technology remains constant across these households, it seems reasonable to interpret a negative sign of the coefficient of the interaction term $C_{0i} \cdot C_{it}$ as movements along a concave production function rather than permanent shifts in the curve.

The second part of my strategy to control for the timing of the receipt of loans is similar to a procedure introduced by Tedeschi (2007). Tedeschi asks: Is it reasonable to use former borrowers as a comparison group when estimating the impact of credit? There are two possible sources of the bias when comparing households without recent loans to households with recent loans. First, a bad economic shock motivates a household to seek credit in the period following a negative economic shock. In this case, one risks overestimating the impact of credit because credit holders were at a low level of productivity before the loan was received and credit may just be helping them to get back to their normal productivity levels. Thus, the change in productivity for credit holders with bad previous years may be unusually larger than the change in productivity of noncredit holders or credit holders who did not experienced a “bad” productive year.

Second, there may be other potential factors which make households with previous loans different from households without previous loans that also affect productivity. Some of these factors may be unobserved by the researcher, such as the innate ability of the farmer, which may also lead the household to self-select into the credit program. The question is why did the household decide to obtain a loan more recently and not before? For instance, are more productive farmers seeking credit more recently or have they been receiving loans for several years? If the factors affecting the timing of the loan are constant over time (e.g. genetic or intrinsic skills), a fixed effects procedure would difference them out. However, some of these factors may be both time-variant and unobserved by the researcher. The fixed effect model is not able to control for these types of factors and a 2SLS is more appropriate. I explore this approach in the next section.

One can check if credit status is a source of bias using the first round of the survey (1997) and information on the borrowing status of the client. The first step is to introduce a set of dummy variables to describe the household's borrowing status, as determined by the time when the loans are received. The borrowing status of a household is defined as *always* when the household received loans during 1997 and 1999. $Newborrowers$ are households which received their first loans in 1999, while *dropped* clients received a loan in 1997 or 1998, but not in 1999. The *never* variable takes the value *one* if the household did not receive any loan during the 1997-1999 period.

Table 3.4 shows the summary statistics of these variables. About 67 percent of the households have loans between 1997 and 1999 (*always*), 3 percent are classified as *new borrowers*, 18 percent of households do not receive more credit after 1998 (*dropped*), and about 11 percent do not receive a loan since 1996 (*never*).

Table 3.4: Credit Status Summary Statistics

Variable	**Mean**	**(Std. Dev.)**
Always	0.671	(0.470)
New borrowers	0.034	(0.182)
Dropped	0.185	(0.389)
Never	0.108	(0.311)
N	377	

We use the following regression to assess the presence of the bias:

$$Y_i^{97} = \alpha + \beta X_i + \gamma_1 Always_i + \gamma_2 Dropped_i + \gamma_3 New_i + \varepsilon_i \qquad (3.3)$$

To check for self-selection bias, I pay special attention to the coefficient γ_3. If γ_3 is negative, *new-borrowers* have significantly lower revenues than the baseline group of households without loans in recent periods and there is a strong suspicion that *new-borrowers* with a bad productive year self-select into the credit program. Yet, if γ_3 is positive and statistically significant, more productive farmers would be more likely to seek credit. In both cases, the use of former borrowers as a control group may cause overestimation of the impact of credit.

Table 3.5: OLS Test of Selection Bias

VARIABLES	Value of crop production, 1997 (logs)
Borrowing status	
Always	0.490
	(0.721)
New	0.801
	(0.823))
Drop	0.991
	(0.733))
Household characteristics	
Gender	0.300
	(0.469)
Age	0.033
	(0.071)
Age^2	-0.000
	(0.000)
Write	-0.158
	(0.368)
Farm characteristics	
Hired labor (FTE)	0.536**
	(0.286)
Area cultivated (Hectares)	0.243***
	(0.045)
Constant	5.096***
	(1.748)
Observations	207
R-squared	0.229
Prob > F	0.0003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.5 shows the results of the regression model (3.3). The coefficient γ_3 is not statistically significant so I cannot reject the hypothesis that *new borrowers* have significantly different farm productivity than the *never* group in 1997. However, one cannot discard self-selection bias based solely on this result. First, even though the parameter is not statistically significant, it is large. Second, the small sample size may be causing large standard errors, therefore it is more difficult to reject the null hypothesis that the parameter is different from zero. Therefore, one should interpret the results of this test with caution.

3.2 Results

3.2.1 Fixed Effects

The starting point for estimating the impact of credit on household productivity is model (3.2). I estimate the model using FE regressions for two dependent variables: value of crop output (FE1, FE2) and value of crop output per hectare cultivated (FE3, FE4); I also report a specification of the model without controlling for previous loans. These regressions are estimated using households that did not receive technical assistance in any of the years of the survey. Results from these estimations are shown in Table 3.6.

Table 3.6: Fixed Effects Estimations of the Impact of Credit

Dep. variables:	Value of total crop output (logs of *colones* of 1992)		Value of crop output per hectare (logs of *colones* of 1992/hectare)	
	FE1	FE2	FE3	FE4
C	0.000116***	0.000119***	0.000087***	0.000089***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
C_0xC		-0.000000		-0.000000
		(0.0000)		(0.0000)
L (FTE)	0.437237	0.441309		
	(0.3417)	(0.3450)		
A (hectares)	0.149817*	0.151751*		
	(0.0900)	(0.0915)		
V	0.000012	0.000010		
	(0.0001)	(0.0001)		
v (inputs per hectare)			0.001005**	0.001004**
			(0.0004)	(0.0004)
l (FET/hectare)			5.145291**	5.156661**
			(2.1071)	(2.1133)
Age	0.418932*	0.416176*	0.335797*	0.334318*
	(0.2193)	(0.2197)	(0.2027)	(0.2031)
Age^2	-0.004248*	-0.004222*	-0.003303*	-0.003289*
	(0.0022)	(0.0022)	(0.0020)	(0.0020)
Cons	-3.518739	-3.4623	-3.1403	-3.1070
	(5.1486)	(5.1545)	(4.7252)	(4.7347)
R-square	0.269	0.266	0.252	0.250
N	243	243	266	266
p(Chi^2)	0.000	0.000	0.000	0.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The regressors are jointly significant in all models because the overall F statistic has probabilities lower than 5 percent. The relevant variables associated with credit (C and C_0xC) are all individually significant, as well as the area cultivated and the coefficients of *age* and *age square*. When credit history is not controlled for (regression FE1), credit shows a positive effect on the value of crop output of an 11.6 percent increase for every 1,000 colones of additional credit (0.000116). In regression FE2 the impact of credit is 11.9 percent for every 1,000 of additional credit (0.000119); the coefficient of the interaction term of previous loans with current loans (C_0xC) is negative, very small, and not significant.

The negative sign of (C_0xC) indicates that the marginal impact of current loans decreases as the household receives larger previous loans (or has received it more recently). As discussed before, this may indicate movements along the concave production function of the households. On the other hand, the coefficient is very small, so the impact of previous loans is almost negligible. The coefficient of credit remain fairly similar when the credit history is included in the regression; this indicates that omitting credit history in the model does not have a significant impact in the estimation of the impact of credit on total value of output.

The remaining coefficients in models FE1 and FE2 are significant and show the expected signs, with the exception of the coefficient of labor, which is not significant at any of the standard levels. This may be because these farms are relatively small and can be operated by only a few workers, mainly the household's members, so the observed increases in productivity may be achieved without hiring external labor but with increasing the amount of the household's time allocated to working in the farm. An additional hectare cultivated implies an increase in value of output of 15 percent (0.1517) in the regression with credit history (FE2). The variables *age* and age^2 are individually significant in both regressions. Older heads of household seem to be more productive, yet the change in productivity decreases with age, as evidenced by the negative sign of the coefficient of age^2.

The impact of credit on crop output per hectare (regressions FE3 and FE4) are slightly smaller than on the total output. Credit generates a percentage change in output per hectare of 9 percent for every 1,000 colones of additional credit (0.000087) when credit history is not included (FE3); whereas when previous loans are included

(FE4), the impact of credit increases to 8.9 percent (0.000089).

3.2.2 Fixed Effects - Instrumental Variables

It is likely that the same time-variant household characteristics that determine households' productivity also determine the amount of credit received. This may be a source of endogeneity in model 3.2 that is not corrected by fixed effect estimation. I implement a fixed-effect model with instrumental variables (FE-IV) to account for the potential endogeneity of credit.

Letting C_{it} be the amount of credit received by household i in period t, let $\mathbf{z}_{it}$ be the excluded exogenous regressors (instruments) and let u_{it} and v_{it} be zero mean error terms. The FE-IV procedure performs a *within* 2SLS regression of the mean differenced outcome of interest $y_{it} - \bar{y}_{it}$ on an intercept and $\mathbf{x}_{it} - \bar{\mathbf{x}}_{it}$ with the instruments $\mathbf{z}_{it} - \bar{\mathbf{z}}_{it}$. The FE-IV model is estimated assuming that observations are independent across households but not necessarily within households across years, where the instrumental variables $\mathbf{z}_{it}$ are correlated with credit, C_{it}, but uncorrelated with the error term, u_{it}.

The two instruments $\mathbf{z}_{it}$ are: 1) the number of days that passed since the application for the loan and the disbursement of the funds; and, 2) the loan origination fees paid by the borrower. The justification for these instruments is that the number of days to disbursement is not associated with the productivity of the households, yet it is closely related to the amount borrowed. This relation occurs because the larger the loan, the more time it takes the lender to conduct the underwriting process, so larger loans are correlated with more days between application and disbursement. However, when the lender has an option to expedite the process of disbursement if a nominal fee is paid up front, households with more liquid funds will likely gain more availability of cash and may tend to have their loans disbursed faster than households with less cash at hand; if more productive households also have more liquid funds, then the instrument may be related to productivity. Further, if the household is a repeat borrower from the financial organization, the lender may already have information about the household and so may spend less time underwriting. If more productive households are also repeat borrowers, the chosen instrument may not be adequate. However, I find no information that these situations occur in *Financiera Calpía*, so I can presume that the instrument is suitable for my purpose.

The other instrument is the amount of the origination fee charged to the borrower. The origination fee is usually a fixed percentage of the amount of the loan and depends on the cost structure and policies of the financial institution. The fee is expressed in percentage terms so it should not be correlated to the level of productivity of the borrower. However, a financial institution may waive part or all of the fee for certain households, i.e. those which are poorer. If this is the case, the instrument would be also correlated to productivity and does not meet the conditions for a good instrument. However, I am not aware of such policy in the case of *Financiera Calpiía* and I expect that the origination fee is a good instrument. Both instruments are interacted with the amount of credit and credit history and included as instruments for the original interaction terms in the model.

Table 3.7: Summary Statistics of Instruments for IV-FE

Variable	**Mean**	**(Std. Dev.)**	**Min.**	**Max.**
Days to disbursement	8.44	(12.26)	0	95
Origination fee (% of loan)	0.03	(0.03)	0	0.2
N		377		

Table 3.7 contains the summary statistics of the two instruments. On average, loans are disbursed in 8.4 days with some loans disbursed nearly three months past application. I have no information about why some loans take longer than others to be disbursed, but I can presume that this may be related to administrative issues and not to the productivity of the households. On average, households pay about 3 percent of the amount of the loan in fees.

The coefficient of credit indicates a magnitude of the impact on the the value of total output and output per hectare of 0.000367 and 0.000188 respectively, both coefficients being significant (Table 3.9). The coefficient of the interaction terms of the credit history and current credit (C_0xC) are statistically significant in the regression of total output, yet in both regressions their values are very small, similarly to the results from the FE estimation.

In the bottom section of table 3.9 I provide the *Hansen J statistic* to test for overidentification of the model. The null hypothesis of the test is not rejected, indicating that the chosen instrumental variables instruments are valid instruments. The first

Table 3.8: Panel-IV Estimations

	FEIV1	FEIV2
	b/se	b/se
C	0.000367*	0.000188**
	(0.0001)	(0.0001)
C_0xC	-0.000000*	-0.000000
	(0.0000)	(0.0000)
L (FTE)	0.371958	
	(0.3653)	
A (hectares)	0.063683	
	(0.1511)	
V	-0.000242	
	(0.0002)	
Age	0.248950	0.220865
	(0.2476)	(0.2047)
Age^2	-0.002596	-0.002172
	(0.0025)	(0.0020)
l (FTE/hectares)		5.619169**
		(2.1478)
v (inputs per hect.)		0.000856*
		(0.0004)
R-square	-1.157	-0.699
N	214	236
p(Chi^2)	0.000	0.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9: Impact of Credit on Farm Productivity (2SLS with Panel Fixed Effects)

Instrumented: C_{it}, $C_{0ixC_{it}}$		
Instruments: Days to disbursement, origination fee		
Dep. variables: (logs of *colones*)	Total value of crops	Value of crops per hectare
C	0.000367*	0.000188**
	(0.0001)	(0.0001)
PVC0xC	-0.000000*	-0.000000
	(0.0000)	(0.0000)
L	0.371958	
	(0.3653)	
A	0.063683	
	(0.1511)	
V	-0.000242	
	(0.0002)	
l (FTE/hect.)		5.619169**
		(2.1478)
v (input expens./hect)		0.000856*
		(0.0004)
Age	0.248950	0.220865
	(0.2476)	(0.2047)
Age^2	-0.002596	-0.002172
	(0.0025)	(0.0020)
R-square	0.19	0.19
N	236	236
p(Chi^2)	0.000	0.000
Hansen J statistic (overidentification test of all instruments): H_0: instrument are valid		
Chi^2 (3) P-val =	0.12	0.36
First-stage regression summary statistics		
F(7,106):	214	236
Prob > F	0.0000	0.0000
Partial R^2 of excluded instruments:	0.12	0.26
Test of excluded instruments:		
F(4, 106):	5.52	3.55
Prob >	0.0005	0.009

* p<0.05, ** p<0.01, *** p<0.001

stage results show that he instruments are correlated with credit (R^2=.12 and .26) and that they are jointly significant.

Comparing the FE-IV results with those given by the FE regressions, the coefficient of credit (C) is nearly three times larger in absolute value in the regressions of the total value of output (0.000367 IV vs. 0.000119 FE) and almost double in the per hectare regressions (0.000188 IV-FE vs 0.00089 FE). The coefficient of the other regressors are not so different from the FE regressions. The IV-FE standard errors are three times larger than in the FE. Thus, the IV-FE regression leads to substantial loss in estimator efficiency.

3.3 Conclusions

The estimations in this chapter show that credit has a positive effect on the productivity of the agricultural households. Credit can boost productivity as much as 9 percent per hectare even after controlling for previous loans and time-invariant factors. Furthermore, the estimations indicate that the amount of credit received is not endogenous to the productivity and that the FE procedure is appropriate in this case. However, I found it is important to include the reception of previous loans in the model to avoid underestimation of the impact of credit.

The loss in efficiency of the IV-FE is notable in these results; furthermore, it is likely that any potential endogeneity of credit may be caused by time-invariant factors which are controlled for in the FE regressions. Consequently, I believe that there is no reason to prefer the FE-IV approach over the FE. However, it is difficult to assess if the intrumental variable model is the correct one and, if the fixed effects model is understimating the true impact of credit.

Chapter 4

Output Impact of Credit and Technical Assistance

In the previous chapters I found that credit improves productivity of households. However, in many real world situations microcredit providers, in their search for ways to help borrowers improve their economic performance, usually favor and even require that their clients receive technical assistance. Thus, it is important to turn attention to the joint impact of technical assistance and credit. Does receiving technical assistance improve the positive effect that credit has on productivity? To answer this question I propose a strategy to identify the impact of these two services, then present the results from analyzing the productivity of *Financiera Calpía* clients.

4.1 Identification of the Impact of Technical Assistance and Credit

The strategy to assess this impact is to include technical assistance in the structural model of the impact of credit (3.1) and add an interaction term with credit and technical assistance as in (4.1).

$$E(Y_{it}|\alpha_{it}, \mathbf{x}_{it}, C_{it}, TA_{it}) = \alpha_i + \beta\mathbf{x}_{it} + \gamma_1 C_{it} + \gamma_2 TA_{it} + \gamma_3(C_{it} \cdot TA_{it}) \tag{4.1}$$

In this model, the parameter γ_3 associated with the interaction term $C_{it} \cdot TA_{it}$ can be written as: $\partial E(Y_{it}|.)/\partial C_{it} \partial TA_{it}$. This parameter is the marginal joint impact of credit and technical assistance. Because productivity is measured in logs of the value of crop output, γ_3 is the percentage change in productivity associated with an additional unit of credit of households with technical assistance compared to the impact of credit of households without technical assistance. The total impact of technical assistance is: $\partial E(Y_{it}|.)/\partial TA_{it} \cdot \Delta TA_{it} = \gamma_1 + \gamma_3 C_{it}$, and the total impact of credit is: $\partial E(Y_{it}|.)/\partial C_{it} \cdot \Delta C_{it} = \gamma_2 + \gamma_3 TA_{it}$.

There is little understanding of how the impact of credit and technical assistance differ when these services are received repeatedly, as opposed to being received once. In this regard, a problem with model 4.1 arises: neither OLS or FE models can assess whether the impact of technical assistance and credit varies with the number of times credit or technical assistance is received, nor with the period of time in which these services are received. For example, one is interested in knowing whether the productivity of households that received technical assistance and credit in the two periods observed differs from the productivity of households receiving technical assistance and credit only in the second period; the parameter γ_3 does not differentiate between these two cases.

To incorporate these aspects of the impact on output, I start by analyzing the occurrence of technical assistance and credit in the data of *Financiera Calpía's* clients. The interaction term $TA_{it} \cdot C_{it}$ includes sixteen possible combinations of technical assistance and credit over the two periods observed. This may complicate the identification of the joint impact and make the interpretation of γ_3 ambiguous. Thus, I discard households with $TA_{i1} = 1$ and $TA_{i2} = 0$, or with $C_{i1} > 0$ and $C_{i2} = 0$ (note that purposely discarding observations may lead to a form of sample selection bias). This might be a problem if the selection criterion is a function of the treatments and the treatment is endogenous (Wooldridge, 2002). In this case it is clear that the selection criterion is a function of receiving technical assistance and receiving credit; however, the risk of biasing the results by purposely dropping observations is preferred over obtaining parameters with ambiguous interpretations which may not be useful at all.

To identify which of the possible combinations of technical assistance and credit over the two periods can be compared to each other, I define dummy variables for each of the possible transitions of technical assistance and credit. In Table 4.1, I report these identification variables. Each case is defined depending on the occurrence of technical assistance and credit during 1997 and 1999, as shown in the first part of the table, with ones indicating that the treatment was received in that year and zeros otherwise.

Table 4.1: Variables for Identifying the Joint Impact of Technical Assistance and Credit

1997		1999			Identification	
TA	Credit	TA	Credit	TA & credit status	variables	n
1	1	1	1	*AlwaysTA-AlwaysCredit*	$ATAC_i$	24
0	1	1	1	*NewTA-Always Credit*	$NWTAC_i$	22
0	1	0	1	*NeverTA-AlwaysCredit*	$NTAC_i$	146
0	0	0	1	*NeverTA-NewCredit*	$NTNWC_i$	15
0	0	0	0	*NeverTA-NeverCredit*	$NTNC_i$	21
1	0	1	1	*AlwaysTA-NewCredit*	$ATNWC_i$	0
0	0	1	1	*NewTA-NewCredit*	$NTNWC_i$	3
1	0	1	0	*AlwaysTA-NeverCredit*	$ATNC_i$	2
0	0	1	0	*NewTA-NeverCredit*	$NWTNC_i$	2
						235

The first possible occurrence of credit and technical assistance is called *AlwaysTA-AlwaysCredit* and it is identified with the dummy variable $ATAC_i$. This variable contains households with technical assistance and credit in both periods. The second variable contains households with technical assistance only in 1999 and credit if both periods identified with the dummy $NWTAC_i$. The rest of the variables are formed in the same way. Over the two periods observed there are nine transitions of technical assistance and credit that I can compare with a total of 235 observations, yet some cases have very few observations. As a result, I limit the outcomes I analyze to those with sufficiently numerous observations. I can identify five outcomes that are relevant to the objectives of this research. Table 4.2 illustrates these outcomes and the cases used to identify them.

Case 1

The first outcome identified is the impact of technical assistance when the households receive this service during both periods, compared to households that never receive technical assistance. The groups to be compared are: *AlwaysCredit-AlwaysTA* and *AlwaysCredit-NeverTA*. Note that I am controlling for the reception of credit in both periods.

Table 4.2: Identified Impact of Technical Assistance and Credit by Treatment Status

Outcome	Groups to compare	Variable	n
Case 1. Impact of repeated TA	*AlwaysTA-AlwaysCredit*	$ATAC_i$	24
	NeverTA-AlwaysCredit	$NTAC_i$	146
Case 2. Impact of one-time TA	*NewTA-AlwaysCredit*	$NWTAC_i$	22
	NeverTA-AlwaysCredit	$NTAC_i$	146
Case 3. Impact of repeated credit	*NeverTA-AlwaysCredit-*	$NTAC_i$	146
	NeverTA-NeverCredit	$NTNC_i$	21
Case 4. Impact of one-time credit	*NeverTA-NewCredit*	$NTNC_i$	15
	NeverTA-NeverCredit	$NTNC_i$	21
Case 5. Impact of repeated TA and credit	*AlwaysTA-AlwaysCredit*	$ATAC_i$	24
	NeverTA-NeverCredit	$NTNC_i$	21

Case 2

The second outcome of interest is the impact of technical assistance when it is received just once. Here the comparison is between households with technical assistance in 1999 and households without technical assistance, with both groups always receiving credit.

Case 3

The third outcome is the impact of repeated loans. In this case I control for technical assistance using households without technical assistance in both periods, and I compare those that always receive credit to households without credit.

Case 4

The fourth outcome captures the differences in productivity between households without technical assistance who have received credit just once to households without technical assistance and credit.

Case 5

The last outcome of interest is the joint impact of technical assistance and credit. This impact is identified by comparing the productivity of households with technical assistance and credit in both periods to households without these services in 1997 and 1999.

Note that the dummy variables identifying the groups in these cases vary only across households and not across years, thus their coefficients capture the impact of credit and technical assistance on productivity in both years studied even when the service was received only in one of the years. For example, when analyzing Case 2 (the impact of receiving technical assistance only in 1999), the coefficient of NWTAC_i captures the impact of technical assistance that was received only in 1999 on revenues in both years (1997 and 1999), even though it is expected that technical assistance in 1999 has no effect on productivity in 1997. Thus, the coefficient may be underestimating the impact of training received in 1999 because the impact is "averaged" over two periods.

4.2 Estimation Methods

4.2.1 Ordinary Least Squares Model

I estimate the impact summarized in Table 4.2 implementing two OLS regressions using the structural model 4.1, but include a set of dummy variables to identify the outcomes of interest associated with the occurrence of C_{it}, TA_{it}, and $(C_{it} \cdot TA_{it})$. The model shows the expected value of productivity associated with the dummy identification variables d_{ki}, where the subscript k indicates whether the household belongs to the treated group in case $k = 1, \ldots 5$ described in Table 4.2; the model is:

$$Y_{it} = \alpha_i + \eta_k \sum_{k=1}^{4} d_{ki} + \beta \mathbf{x}_{it} + \varepsilon_{it} \tag{4.2}$$

where I omit households without technical assistance or credit in both periods, d_{5i}, as the benchmark for the interpretation of the remaining dummy variables. I keep defining Y_{it} as the log of the value of crop output (or, alternatively, output per hectare, y_{it}) and $\mathbf{x}_{it}$ as a vector of observed households' characteristics. Implementing the model with OLS (with clustered robust errors by households to account for the pooled nature of the sample) allows us to interpret the parameters η_k as the differences in proportional change of the value of crop output between households in case $d_{k\neq 5,i}$ and households in the baseline case, d_{5i}.

I assess and verify the significance of the five cases of interest is this model as follows: in Case 1, the impact of repeated technical assistance is the difference between parameters η_1 and η_3; here, the hypotheses to be tested are H_{01}: $\eta_1 = \eta_3$ and $\eta_1, \eta_3 \geq 0$. The difference between η_1 and η_3 provides an estimation of the impact of technical assistance when it is received repeatedly versus when it is not received at all.

We can also test if $\eta_1 = \eta_2$. If η_1 is greater and significantly different than η_2, households with technical assistance in both periods are more productive than households with technical assistance only in one period (controlling for the reception of credit). This may be an indication that technical assistance is more effective when provided continuously.

In Case 2, I estimate the impact of receiving technical assistance one time. The case is assessed by comparing parameters η_2, and η_3. The estimated difference between these two parameters is the impact of receiving technical assistance once versus receiving no technical assistance at all.

In Case 3, I estimate the impact of repeated credit by comparing η_3 to η_4, and η_3 to η_5. In all these groups, households do not receive technical assistance at all in order to isolate the impact of credit. If η_3 is significantly greater than 0 and positive in the regression (since η_5 represents the omitted group), then the impact on productivity increases as credit is received repeatedly when compared to not receiving any loans. If η_3 is greater and significantly different from η_4, the impact of repeated credit on productivity is greater than the impact of receiving credit only once.

In Case 4, I evaluate whether $\eta_4 \neq 0$ in order to assess the impact of receiving credit once compared to changes in productivity of households without credit during the period studied. Finally, in Case 5, I evaluate the joint impact of receiving technical assistance and credit. Here I check if the estimated coefficient η_1 is significantly different from 0 and positive.

4.2.2 Fixed Effects Model

The dummy variables d_{ki} do not vary within households across the two periods observed. Thus, they are differenced out if a FE regression is used to estimate 4.2. Furthermore, the interpretation of the coefficients η_k in the OLS model refers to differences in productivity across households that received the treatments. This may be convenient to analyze the impact of technical assistance because this treatment is measured using a dichotomous variable; yet the model does not provide measures of the impact of receiving an additional amount of credit. However, one can include a set of interaction terms between the dummy identification variables d_{ki} and the amount of credit received to assess the marginal impact of the amount of credit received. Since credit varies across periods for each household, the FE procedure can produce the coefficients of these interaction terms. These FE coefficients capture the change over time in productivity associated with changes in credit for the groups identified by d_{ki}. In this way I am able to control for any time-invariant traits that simultaneously determine the timing of the reception of the treatments and the productivity of the households. Following this strategy, I write the FE model:

$$E(Y_{it}|\alpha_{it}, \mathbf{x}_{it}, C_{it}, TA_{it}) = \alpha_i + \beta\mathbf{x}_{it} + \sum_{k=1}^{4} \upsilon_k(d_{ki}) \cdot C_{it} \tag{4.3}$$

The parameters υ_k are the differences in the proportional change in the value of crop output associated with an additional unit of credit between households in case $d_{k\neq 5,i}$ and households in the base line case, d_{5i}. The five outcomes of interest are identified using the parameters υ_k and the same hypotheses defined in the OLS model. Table 4.3 summarizes the hypotheses to be tested using the OLS and FE procedures.

Table 4.3: Hypotheses for the Evaluation of the Impact on Output of Technical Assistance and Credit

Outcome	**Hypothesis (H_0)**	
	OLS	FE
Case 1. Impact of repeated TA	$\eta_1 = \eta_3$	$\upsilon_1 = \upsilon_3$
	$\eta_1 = \eta_2$	$\upsilon_1 = \upsilon_2$
Case 2. Impact of one-time TA	$\eta_2 = \eta_3$	$\upsilon_2 = \upsilon_3$
Case 3. Impact of repeated credit	$\eta_3 = \eta_5$	$\upsilon_3 = \upsilon_5$
	$\eta_3 = \eta_4$	$\upsilon_3 = \upsilon_4$
Case 4. Impact of one-time credit	$\eta_4 = \eta_5$	$\upsilon_4 = \upsilon_5$
Case 5. Impact of repeated TA and credit	$\eta_1 = \eta_5$	$\upsilon_1 = \upsilon_5$

4.3 Results

I start by showing the differences in productivity and other household characteristics across the groups formed according to the occurrence of technical assistance and credit, as defined in the previous section. Table 4.4 contains the mean value and standard deviation of several variables of interest for each of the identification groups identified in the pooled sample of clients of *Calpía*.

Table 4.4: Summary Statistics by Technical Assistance and Credit Status

	AlwaysCredit-AlwaysTA	**NewCredit-NeverTA**	**NeverCredit-NeverTA**	**AwaysCredit-NewTA**	**AlwaysCredit-NeverTA**
Variable	mean / (S.D.)	mean / (S.D.)	mean / (S.D.)	mean / (S.D.)	mean / (S.D.)
Value of crop outputs (colones)	10,123	6,026	4,782	48,110	12,867
	(9,576)	(13,236)	(6,630)	(112,008)	(39,729)
Value of crop outputs per	4,088	3,130	4,187	4,427	3,403
hectare cultivated	(4,670)	(6,282)	(9,990)	(7,218)	(7,890)
Area (hectares)	3.4	2.39	2.68	7.38	3.57
	(3.55)	(3.01)	(3.55)	(7.85)	(4.11)
Labor (FTE)	0.17	0.01	0.2	0.31	0.17
	(0.21)	(0.03)	(0.06)	(0.47)	(0.67)
l (FTE/hectare)	0.08	0.01	0.03	0.06	0.04
	(0.14)	(0.4)	(0.12)	(0.1)	(0.01)
Equipment	0.67	0.6	0.71	1	0.74
	(0.48)	(0.51)	(0.46)	(0)	(0.44)
Fertilizer	0.79	0.13	0.3	0.55	0.59
	(0.39)	(0.35)	(0.46)	(0.51)	(0.47)
C	7,383	2,176	0	14,954	8,673
	(8,122)	(2,730)	(-)	(13,521)	(13,785)
C_0	312	0	0	0	1,185
	(1,060)	(-)	(-)	(-)	(13,785)
Gender	0.08	0.07	0.14	0.18	0.1
	(0.28)	(0.26)	(0.36	(0.39)	(0.3)
Literacy	0.83	0.8	0.57	0.68	0.66
	(0.38)	(0.41)	(0.51)	(0.48)	(0.48)
Age	43.42	42.33	45.52	41.55	45.4
	(9.67)	(15.03)	(11.68)	(8.30)	(12.2)
N	24	15	21	22	146

In the first row of Table 4.4 the average value of crop output (*Ycrops*) varies remarkably across these groups. Households without credit or technical assistance (*NeverCredit-NeverTA*) show the lowest level of crop output across all the groups (4,782 colones), while the *AlwaysCredit-NewTA* group shows the highest level of value of crop output (48,110 colones), nearly ten times the value of the *NeverCredit-NeverTA* group. However, when the output is expressed in per hectare terms (second row), the differences across the groups become smaller, indicating that household's productivity levels are more or less similar across these groups after controlling for the scale of the farms, though the high standard deviation (SD) of the *NeverCredit-NeverTA* should be noted.

Households in the group *AlwaysCredit-NewTA* cultivate on average more than double the number of hectares of any other group. This group also hires more labor and owns more farming equipment. Households with *AlwaysCredit-NewTA* borrow on average 14,954 colones, almost double the amount borrowed on average by households with *AlwaysCredit-NeverTA*. This indicates that technical assistance is associated with higher amounts of credit. One possible explanation for this relation is that households that receive technical assistance acquire skills that allow them to use more capital or different technology; once the households become aware of their new abilities, they seek more credit to take advantage of their increased human capital. The opposite can also be true - a household that obtains a loan may seek technical assistance to be able to acquire the skills required to take full advantage of the additional productive resources that can be purchased with the loan.

Another difference between these groups is the low level of literacy among the heads of household which have never received both credit or technical assistance. Only 57 percent of these heads of household write and read, nearly 10 percentage points lower than the proportion of literates in the *AlwaysCredit-NeverTA* and *AlwaysCredit-NewTA* groups, and at least 20 percent points lower than the other groups. This difference may be expected since less literate farmers may be discouraged from seeking technical assistance if they think that the training includes reading materials.

Table 4.5: Pooled OLS Estimations of the Joint Impact of Technical Assistance and Credit

Dep. Variable: Value of crop output per hectare cultivated (Log of constant local currency)	OLS1 b/se	OLS2 b/se	FE b/se
ATAC	0.907697		
	(0.7504)		
NWTAC	0.709756		
	(0.6994)		
NTAC	0.267733		
	(0.6315)		
NTNWC	0.606082		
	(0.7766)		
ATACxC		-0.000016	-0.000192**
		(0.0000)	(0.0001)
NWTACxC		0.000033*	0.000074
		(0.0000)	(0.0001)
NTACxC		0.000003	0.000015***
		(0.0000)	(0.0000)
NTNWCxC		0.000361***	0.001104
		(0.0001)	(0.0009)
l (FTE/hectares)	3.221796***	3.639071*	4.6422**
	(1.3355)	(1.2578)	(1.7985)
v (input exp. per hect.)	0.001037***	.0010449***	0.001177***
	(0.0002)	(0.0002)	(0.0002)
Age	0.018139	0.024336	-0.3196988
	(0.0800)	(0.0776)	(0.2845)
Age^2	-0.000039	-0.000154	0.0031692
	(0.0008)	(0.0008)	(0.0028)
Cons	4.374919**	4.591751**	12.3189*
	(1.9533)	(1.7992)	(7/1478)
R^2	0.224	0.234	0.168
N	228	228	228
p(Chi^2)	0.000	0.000	0.000
* p<0.10, ** p<0.05, * p<0.01			

Variable definitions:
$ATAC_i$: *AlwaysTA-AlwaysCredit*
$NWTAC_i$: *NewTA-AlwaysCredit*
$NTAC_i$: *NeverTA-AlwaysCredit*
$NTNWC_i$: *NeverTA-NewCredit*
$NTNC_i$: *NeverTA-NeverCredit* (omitted group)

Table 4.5 contains the results of implementing models 4.2 and 4.3. I also include a variation of the OLS model (OLS2) using the interaction term between the amount of credit received and the status of the treatments (d_k). This second specification adds some depth to the interpretation of the model because it provides estimates of the differences in the impact per unit of credit received between households with different occurrences of technical assistance and credit over time. It also allows us to compare results from the OLS and the FE more directly.

The regressors in the first OLS specification (OLS1) are jointly statistically significant as evidenced by the *p-value* of 0.000. At the same time, only the regressors of l and v are significant. The coefficients associated with credit and technical assistance are all very large, ranging from 0.26 (NTAC) to 0.90 (ATAC), whereas the rest of the regressors are fairly similar to the coefficients in the OLS2 and FE regressions.

The second OLS model (OLS2) includes the interaction terms of the participation variables with the amount of credit received. This model performs better than the OLS1 becuase all coefficients are jointly significant (p-Chi^2 < 0.000), the coefficients show lower values, and the standard errors are relatively low. Most of the coefficients which associate with credit and technical assistance are significant. In the FE regression the coefficients are jointly significant (p-Chi^2 < 0.000), with the interaction terms ATACxC and NTACxC significant at the standard levels (-0.000192, 000015).

The coefficient of hired labor per hectare is significant and large in all regressions; as well as the coefficient of the value of v. The coefficient of *age* and *age square* have the expected alternate signs (with the exception of the FE regression) that show the non-linearity of the effect of aging on productivity, yet these regressors are not significant.

Comparing these three regressions, specification OLS1 seems to perform less efficiently than the other two models. The OLS1 show larger standard errors of the participation variables and the coefficients of the participation variables are large relative to the other two specifications. These results indicate that the dummy variables are picking up other factors associated with the reception of these services and that the OLS1 model is less efficient than the OLS2 and FE regressions. For these reasons, one could consider that OLS1 is the least preferred of the three regressions.

The coefficients of the FE regression are larger than the OLS2. This implies that the when the time-invariant factors associated with productivity (and possibly with credit and technical assistance) are not controlled for (as in OLS2), the impact of credit and technical assistance is underestimated. One could prefer the FE regression over the OLS2 if it is suspected that time-invariant variables are playing a role in the model.

In the following sections I evaluate each of the five cases of interest based on the results of these three regressions.

4.3.1 Case 1: Impact of Repeated Technical Assistance

The first outcome identified is the impact of technical assistance when the households receive this service during both periods, as compared to households that never receive technical assistance. The groups compared are *AlwaysTA-AlwaysCredit* and *NeverTA-AlwaysCredit*, where I control for credit reception in both periods. I also compare the treated group to households with *NewTA-AlwaysCredit* to assess if the impact of receiving technical assistance twice is different from receiving technical assistance only once.

Table 4.6: Case 1. Impact of Repeated TA

	AlwaysTA-AlwaysCredit $ATAC_i$	*NewTA-AlwaysCredit* $NWTAC_i$	*NeverTA-AlwaysCredit* $NTAC_i$
OLS1	0.907697	0.709756	0.267733
	$ATAC_i \cdot C$	$NWTAC_i \cdot C$	$NTAC_i \cdot C$
OLS2	-0.000016	0.000033	0.000003
FE	-0.000192	0.000074	0.000015

* p<.10, ** p<.05, , *** p<.01

In regression OLS1 (Table 4.6), the additional impact of receiving *AlwaysTA* over *NeverTA* is approximately 64 percentage points (0.907697-0.267733); this difference is not significant at any of the standard levels of confidence.

In the OLS2 regression, the impact of an additional 1,000 colones of credit on productivity of households receiving ATAC·C is negative and smaller than the increase in productivity of households that never receive technical assistance (NTAC·C), (-0.000016 - 0.000003); this difference is not statistically significant.

In the FE regression, the coefficient of households in the *AlwaysTA-AlwaysCredit* group (ATAC·C) are significantly different from the coefficients of the regressor of

NeverTA-AlwaysCredit (NTAC·C). However, the coefficient of ATAC is negative (-0.000192); thus, households with *AlwaysTA-AlwaysCredit* show smaller changes in productivity than households with *NeverTA-AlwaysCredit*. This result is somewhat counter intuitive because one could expect that the more technical assistance received, the larger the positive changes in productivity associated with more credit received by the household.

Households receiving technical assistance twice experience a positive change in productivity of about 20 percentage points higher than those households receiving technical assistance only once as evidenced by the positive difference between the parameters ATAC and NWTAC in the OLS1 regression (0.907697 - 0.709756).

The regression OLS1 shows that the impact of technical assistance is positive and increases when training is received repeatedly instead on receiving training for the first time or never receive technical assistance at all.

4.3.2 Case 2: Impact of One-Time Technical Assistance

The second outcome of interest is the impact of technical assistance when it is received just once. Here, the comparison is between households with technical assistance in 1999 (NWTAC) and households without technical assistance (NTAC), with both groups always receiving credit.

Table 4.7: Case 2. One-Time Technical Assistance

	NewTA-AlwaysCredit $NWTAC_i$	*NeverTA-AlwaysCredit* $NTAC_i$
OLS1	0.709756	0.267733
	$NWTAC_i \cdot C$	$NTAC_i \cdot C$
OLS2	0.000033	0.000003
FE	0.000074	0.000015

* p<.10, ** p<.05, , *** p<.01

The changes in productivity of households in the group NWTAC is 44 percent larger than the changes in productivity of households without technical assistance (NTAC) in the OLS1 model in Table 4.7 (0.709756 - 0.267733).

In models OLS2 and FE, households that received technical assistance once (NWTAC

$\cdot$ C) experience changes in productivity about 3 percentage points larger than households without it (NTAC·C) (0.000033 - 0.000003). Similarly, the FE regression shows a difference of nearly 60 percentage points in favor of households with technical assistance once over households without technical assistance. Note that these differences are not significant.

The difference between the coefficients of NWTAC·C and NTAC·C is larger in the FE regression than in the OLS1 and OLS2 models. Thus, it may be the case that when time-invariant factors are not controlled for, e.g. in the OLS2 regression, the impact of technical assistance (when received for the first time) may be undestimated. In any case, any estimations using new technical assistance receivers should be interpreted with caution and complemented with estimations of the impact of using repeat participants.

4.3.3 Case 3: Impact of Repeated Credit

The third outcome is the impact of repeated loans. In this case, I control for technical assistance using households without technical assistance in both periods, and I compare those that always receive credit (NTAC) to households without credit (NTNC).

Table 4.8: Case 3. Impact of Repeated Credit

	NeverTA-AlwaysCredit $NTAC_i$	*NeverTA-NewCredit* $NTNWC_i$
OLS1	0.267733	0.606082
	$NTAC_i \cdot C$	$NTNWC_i \cdot C$
OLS2	0.000003	0.000361***
FE	0.000015***	0.001104

* p<.10, ** p<.05, , *** p<.01

The comparison group in this case is the omitted group *NeverTA-NeverCredit*; thus, one can assess the significance of the coefficient of NTAC directly from Table 4.5. I summarize the results relevant for Case 3 in Table 4.8. The OLS1 regression shows an increase in productivity in the NTAC group of 26 percent over the productivity of the households without credit (NTNC); however, this difference is not significant.

The OLS2 results show that every 1,000 colones of additional credit increases productivity of households with *NeverTA-AlwaysCredit* (NTAC·C) by less than one percent

(0.000003); yet the coefficient is not significant.

The FE regression coefficient of NTAC·C is 0.000015, implying a change in productivity of 1.5 per 1,000 colones of additional credit when credit is received repeatedly; this coefficient is significant at the 1 percent level.

In Case 3, I also compare households with repeated credit to households with credit in one period (NTAC versus NTNWC). In all three models, I find that the change in productivity of households with repeated credit is smaller than the change in productivity of households that received credit only in 1999. This result is similar to the effect of credit history found in Chapter 3 where households that received a previous loan before 1997 experienced smaller changes in productivity than households without credit history.

The results from Case 3 show that this pattern of impact of credit history also applies to situations when the two loans are separated by short periods of time, i.e. by one to two years. So, does every additional loan have a smaller impact than the previous loans? It is hard to say from these results. As discussed before, one possible explanation for this result is that each additional loan allows the household to increase the inputs used in production and so move along its production function. If the production function shows decreasing marginal productivity, then the additional loans will be associated with lower marginal productivity.

4.3.4 Case 4: Impact of One-Time Credit

The fourth outcome captures the differences in productivity between households without technical assistance which have received credit once (NTNWC) and households without technical assistance and credit (NTNC). The impact of receiving credit for the first time can be evaluated directly form Table 4.5; I find that the coefficient of NTNWC in regression OLS1 is 0.606082 and not significant; thus, households that received their first loan in 1999 are more productive than households without credit. The coefficient NTNWC·C in the OLS2 regression is statistically significant and has the expected positive sign, with a value of 0.000361. This implies an average change of 36 percent in the value of crop output per hectare associated with each additional 1,000 colones of the first credit received.

The FE regression produces a coefficient for NTNWC·C of 0.001104; this implies a large effect of 110% increase in productivity for every 1,000 colones of credit for households that receive their first loan. However, this result is not significant.

4.3.5 Case 5: Joint Impact of Technical Assistance and Credit

The last outcome of interest is the joint impact of technical assistance and credit. This impact is identified by comparing the productivity of households with technical assistance and credit in both periods (ATAC) to households without these services in both periods (NTNC). I assess this impact by evaluating the parameter associated with the variables NTAC and NTACxC in Table 4.5. The NTAC coefficient is 0.907697 in the OLS1 regression, which indicates that households with *AlwaysTA-AlwaysCredit* are more productive than households without these services by at least 90 percent.

In regression OLS2, the coefficient of ATAC·C is -0.000016, which implies a change in the value of crop output per hectare for every 1,000 colones of credit of nearly 2 percent less than in households in the comparison group (NTNC·C). The coefficient is not significant at any of the standard levels of confidence.

The FE regression also produces a negative coefficient for ATAC·C, (-0.000192) showing a change in productivity nearly 10 percent lower than households without credit and technical assistance.

4.4 Conclusions

The results in this chapter confirm the results found in Chapter 3 that, in general, credit improves productivity. I also confirm that the first time credit is received, larger changes in productivity are produced than when credit is received twice (Cases 3 and 4). I find positive impact of repeated credit (and no TA) of 2 percent (FE - Case 3), while receiving credit for the first time improves productivity by 36 percent (Model OLS2 - Case 4).

I also find that the OLS1 regression captures the impact of technical assistance more efficiently than the OLS2 and FE regressions. This is so because the OLS1 regression controls for the reception of the loans (or credit access) but does not measure the marginal impact of increasing the loan size. However, the OLS1 coefficientS are not statistically significant.

Chapter 5

Impact of Credit and Technical Assistance on Technical Efficiency

In the previous chapters I showed evidence that credit and technical assistance have positive impact on productivity. However, productivity can be attributed to three factors: changes in technical efficiency, technological change, and economies of scale (Kumbhakar & Lovell, 2000). In this chapter, I evaluate whether these factors are present and whether credit and technical assistance contribute to them. I start the chapter summarizing the main definitions used in the analysis. I then, describe the empirical strategy and, finally, I present the results and conclusions of the estimations.

5.1 Identification and Empirical Strategy

A change in productivity was defined in Chapter 2 as the change in output q_t per level of inputs $\mathbf{x}_t$ used in the production process; a change in productivity can be characterized as:

$$\Delta\text{Productivity} = \frac{q_{t+1}}{\mathbf{x_{t+1}}} - \frac{q_t}{\mathbf{x_t}} \tag{5.1}$$

If $(q_t/\mathbf{x_t}) < (q_{t+1}/\mathbf{x_{t+1}})$, productivity growth ocurred. Changes in productivity are decomposed into: 1) changes in technical efficiency, 2) technological change and 3) returns to scale.

Changes in Technical Efficiency

The *production frontier* is defined as the maximum output that can be obtained from any given input vector $q(\mathbf{x}, t)$; *technical efficiency* is the ratio of observed output q_t to the maximum feasible output, and gains in efficiency are characterized as:

$$^{+}\Delta\text{Technical Efficiency} = \frac{q_{t+1}}{q(\mathbf{x}, t+1)} > \frac{q_t}{q(\mathbf{x}, t)} \tag{5.2}$$

Thus far I have assumed that the households are behaving optimally, i.e. they are choosing inputs to produce the maximum level of output generated at given prices, inputs, and technology. In this context, the only possible deviation from the output of the production function is from randomly distributed statistical noise (Aigner, Lovell, & Schmidt, 1977; Meeusen & Broek, 1977). However, there is no reason to believe *a priori* that all households are producing at this optimum level. If I assume that some households are not optimizing their production, I can turn the analysis of productivity using the production function toward an analysis of productivity using the production frontier of the households.

Further, I ask whether receiving technical assistance and credit can help households that are not producing at their frontiers to move closer to their optimal levels. Increased credit can help a household to allocate its inputs more efficiently (*increased allocative efficiency*) by allowing the purchase of inputs that are more cost-efficient, i.e. generate more output per unit of input cost.

Credit can also improve productivity via increased technical efficiency by allowing the household to specialize in crops which yield a more competitive advantage. Credit may also reduce the use of less efficient practices, such as mixed cropping (Diagne, 2002).

Another example of the positive effect of credit on efficiency occurs when household heads are skillful managers and supervising activities are relatively expensive; in this case, credit is used to hire more external labor enabling the household head to focus on using her own time for managerial activities and thus improving their farm's efficiency (Kevane & Wydick, 2001).

It is also possible that households move away from their optimal level of production; weather shocks can affect crops, health shocks can affect the farmer's ability to work, etc. In these cases, the sign in (5.2) is reversed. Having access to credit and technical assistance may help the household deal with these crises and reduce the negative impact of the shocks. For example, available credit can be used as insurance against negative productive shocks. Similarly, farmers who receive technical assistance and acquire productive skills may be more prepared for bad times.

To evaluate the impact of credit and technical assistance on technical efficiency, I use a stochastic production function (Aigner et al., 1977; Meeusen & Broek, 1977) as the framework of reference. Diagne (2002) has used this approach to show the impact of access to credit on technical efficiency. He shows that access to credit improves technical efficiency of maize and tobacco producers in Malawi. Instead, I focus on the impact of the level of credit used and not on the possibility that some households may not borrow even when willing to pay prevailing interest rates, which by definition is “lack of access to credit.” The difference between these two conditions may be important depending on the scope and goals of the research. Diagne argues that access to credit - as opposed to the level of credit - affects technology adoptions and therefore technical efficiency. On the other hand, I show that the level of credit can be an important determinant of technical efficiency. Furthermore, I show that technical assistance can enhance the positive effects of credit on the technical efficiency of crop producers who already have access to credit. My estimation approach also differs from Diagne's because I use a specification of the stochastic frontier and a measure of technical efficiency that allow me to capture technical efficiency changes which occur over time; this approach also allows me to take full advantage of the panel data.

Technological Change

Technological change is assumed to be exogenous to household's decisions. For example, new production technologies are generated through research and development conducted by public and private entities such as universities and private corporations. Households may be exposed to these new technologies and motivated to adopt them through several ways; for example, when they receive technical assistance[1] or when they buy a new productive asset with embedded new technology. Thus, the term *technological change* is used here to imply technology adoption and not the exogenous development

[1] Birkhaeuser and Evenson (1991) remark that technical assistance may create positive spillovers; households which don't receive technical assistance may also adopt new technologies after being motivated by neighbors who received the assistance and implemented the new technologies.

of new technologies. In this context, evidence of the adoption of technological change of a given household can be written as:

$$\text{Technological Change} = q(\mathbf{x}, t+1) - q(\mathbf{x}, t), \tag{5.3}$$

where q is the production function of the household that depends on inputs $\mathbf{x}$, and the available technology at the time period t. Technological change (or adoption of new and more productive technology) occurs if the production function in period $t+1$ generates more output than the function in period t at every level of input. Thus, adoption of a new technology can improve household's productivity.

Examples of adoption of a new technology as a result of increased credit are the purchase of more advanced fertilizers or new type of seeds which would not have been affordable without credit. Increased credit may also reduce the risk associated with implementation of new technologies by ways of serving as insurance in case that the implementation fails, thus motivating the household to adopt more productive but riskier technologies.

Technical assistance can also motivate technology adoption. Households can be trained to implement new technologies and production techniques which can generate shifts in their production functions. In fact, the main goal of CENTA, the main provider of agricultural extension in el Salvador, is to promote technology adoption. CENTA's seminars and workshops are designed to introduce new varieties of crops to farmers and to teach them more productive growing techniques.

Economies of Scale

Changes in productivity can come from economies of scale. If constant returns to scale are present, a proportional change in all inputs generates an output change of the same proportion; thus, according to 5.1, there is no impact on productivity. Under decreasing economies of scale, an increase in inputs may lead to a less than proportional change in output, thus decreasing productivity over time; while under increasing scales, an expansion of inputs is associated with a more than proportional change in output and an increase in productivity.

Increasing scale economies are likely to occur in farms operating in developing countries when managerial skills are improved or when transactional costs are present (Eastwood, Lipton, & Newell, 2010). Whenever more skillful farmers choose to run larger farms (a proportional increase in all inputs), economies of scale will appear because the more productive farmers are able to obtain more than proportional changes in output from a given increase in inputs, while less skillful farmers may obtain less than proportional changes in output from a similar proportional change in all inputs.

When scale economies are present, both credit and technical assistance contribute to output growth and increase productivity by allowing the expansion of the amount of input and by increasing the productive skills of the farmer.

5.2 Estimation of Technical Efficiency

The stochastic production function is the maximum output that the household can generate given fixed quantities of inputs and technology (Aigner et al., 1977; Meeusen & Broek, 1977). To derive this function, I start from the production function (5.4), including only the measurable inputs, $\mathbf{x}_{ji}$, and a component of random production shock, ε_i:

$$q_{it} = q(\mathbf{x}_{jit}) \exp(\varepsilon_{it}) \tag{5.4}$$

This function is used under the assumption that the households are producing at their most efficient level. To introduce the possibility that some households may produce less than their optimal level, I add a parameter that measures the level of efficiency of the household to the production function (5.4). I denote the efficiency parameter as ϵ_{it}:

$$q_{it} = q(\mathbf{x}_{jit}) \exp(\varepsilon_{it})\epsilon_{it} \tag{5.5}$$

By assumption, the output is strictly positive. Thus, ϵ_{it}, must be in the interval (0,1]. The model implies that a household can produce only up to its production possibilities frontier (e.g. when $\epsilon_{it} = 1$), and when $\epsilon_{it} < 1$, the production is below the optimal levels.

Substituting q for the value of crop output (Y_{it}) and taking the natural log of (5.5) yields:

$$\ln Y_{it} = \beta_j \ln(\mathbf{x}_{jit}) + \varepsilon_{it} + \ln(\epsilon_{it}) \tag{5.6}$$

Defining $u_{it} = -\ln \epsilon_{it}$, restricted to $u_{it} > 0$, and assuming k inputs, the regression to be fitted is:

$$\ln Y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j \ln(x_{jit}) + \varepsilon_{it} - u_{it} \tag{5.7}$$

There are three specifications of the distribution of the inefficiency term, u_i, that are commonly used (Green, 2003). In the exponential case, the u_i are independently exponentially distributed with variance σ_u^2. In the half normal case, the u_i are independently half-normally distributed, $N^+(0, \sigma_u^2)$; and in the case of the truncated half normal, the u_i are independently distributed with truncation point at 0.

I am implementing a parameterization of the inefficiency term that include time effects (Battese & Coelli, 1995), in which u_{it} is specified to be a truncated half normal, $N^+(\mu, \sigma_u^2)$, with truncation point at 0, where μ is the mean of the truncated-normal distribution of the efficiency parameter. I choose this specification because it allows me to model the conditional mean of the inefficiency term, μ, as a linear function of technical assistance and credit and other covariates. In this way, I am able to analyze how the inefficiency factor varies over time across households with different levels of technical assistance and credit. More precisely, I have that $\mu = \delta \mathbf{z}_{it}$. Technical efficiency (TE) is $E[exp(-u_{it}|e_{it})]$, and

$$\text{TE} = \delta \mathbf{z}_{ti}, \tag{5.8}$$

where $\mathbf{z}_i$ is the vector of exogenous covariates suspected to influence the productive technical efficiency of the households which include technical assistance and credit. The vector of coefficients, δ, captures the effects of the covariates on efficiency. Because $E[exp(-u_{it}|e_{it})]$ and $u_{it} = -\epsilon_{it}$, a positive coefficient δ implies that the covariate (e.g. credit or technical assistance) reduces the inefficiency of the household. In this time-variant decay specification, $u_{it} = \exp\{-\eta(t - T_i)\}u_i$, where T_i is the last period in the panel (T=1999), η is the decay parameter.

The procedure is carried out in two stages. First, (5.7) is estimated by Maximum Likelihood Estimation (MLE) using panel data. During the first stage, u and TE are estimated. In the second stage, the estimated TE_{it} is modeled as a function of the factors that are suspected to affect efficiency, and the δ's in (5.8) are estimated. In this step equation (5.8) is estimated using:

$$TE = \delta_1(TA_{it}) + \delta_2(C_{it}) + \delta_k \mathbf{z}_{kti} \tag{5.9}$$

5.3 Results

The estimated parameters, standard errors, and MLES from models (5.7), (5.8), and (5.9) are presented in Table 5.1.

Table 5.1: MLE-Stochastic Frontier

	MLE
	b/se
Equation 1: Value of crop output (logs):	Y_i
	colones
L (Log of FTE)	0.304
	(0.442)
A (log of hectares)	1.241***
	(0.150)
v (Log of input expenses)	0.592***
	(0.039)
t	1.311***
	(0.238)
cons	2.269***
	(0.277)
μ	-529.432
	(.)
η	-2.226
	(0.795)
$\ln \sigma_s^2$	6.544***
	(0.134)
Inverse logit of γ	5.723***
	(0.178)
$\sigma_s^2 = \sigma_\varepsilon^2 + \sigma_u^2$: Total error variance	695.044
	(93.118)
$\gamma = \sigma_u^2/\sigma_\varepsilon^2$	0.996
	(0.0005)
σ_u^2	692.77
	(93.167)
σ_ε^2	2.265
	(0.199)
Equation 2: Effects on Technical Efficiency	
C	$1.01\text{x}10^{-6}$
	(0.000)
TA	0.070**
	(0.025)
Age	0.002
	(0.000)
Age^2	-0.000
	(0.000)
Cons	0.569***
	(0.100)
R^2	0.017
N	377
p(Chi^2)	0.059

* p<0.10, ** p<.05, *** p<0.01

The inefficiency frontier model (5.7-5.9) accounts for both technical change and time-varying inefficiency effects. The variable t in (5.7) is a time trend that indicates if the observation refers to year 1997 or 1999. The time trend accounts for Hicksian neutral technological change. The distributional assumptions on the inefficiency effects permit the identification of the effects of technical change, in addition to the intercept parameter in the stochastic frontier (Battese & Coelli, 1995).

The coefficients of the stochastic frontier have the expected sign. The coefficient of L is 0.30, indicating an elasticity of hired labor of 30 percent, yet the coefficient is not significant. Area cultivated and the value of other inputs are positive and highly significant as expected (1.241 and 0.592). I reject the null hypothesis of constant returns to scale, that is: the sum of the elasticities of the inputs equals 1 (prob $\text{Chi}^2 = 0.0008$); in fact the sum equals 2.12, indicating very large returns to scale. Increasing economies of scale is typical in developing countries especially when farmers acquire more managerial and productive skills and the observed farmers tend to work more on lands of higher quality (Eastwood et al., 2010).

The time trend is positive and significant (1.31), indicating that output outlays grew over the period 1997-1999 and that technological change occurred during this period.

The coefficient η is negative and large, yet it is not significant, so the inefficiency factor is declining over time. The estimate for the variance parameter, γ, is close to 1, which indicates that the inefficiency effects are likely to be highly significant in the analysis of the value of output of the farmers.

In the technical efficiency equation, the coefficient of credit is positive yet close to 0 ($2.77\text{x}10^{-6}$); the coefficient is not significant. Thus, credit improves the efficiency of these households very little. This indicates that if credit is contributing to improvements in productivity, it is not via increased efficiency but most likely through returns to scale or technological change. Given the fact that most of the loans are used to purchase inputs such as seed and irrigation, it is reasonable to conclude that credit generates improvements in productivity by allowing households to purchase more inputs and experience increased economies of scale.

On the other hand, the coefficient of technical assistance is 0.07 and significant; this value implies an impact of 7 percent increase in technical efficiency after receiving technical assistance. The average TE across households is 0.48 with standard deviation of 0.35, indicating that households are producing at relatively low levels of efficiency with respect to their production frontiers. Receiving technical assistance can boost efficiency by 7 percent, or about a fifth of one standard deviation of the efficiency term.

The positive coefficient of *age* and the negative regressor *age square* indicate that households become more efficient as their age increases (and more experience is gained), yet efficiency gains slow down as they get older.

5.4 Conclusions

The results of the stochastic frontier model indicate that technological progress happened during the years studied, ergo the production frontier is shifting away from the origin. At the same time, I find that technical assistance improves households' technical efficiency, while credit does not contribute to productivity via increased technical efficiency. It is plausible to conclude that at least part of the technological progress experienced by these households was the result of improvement in efficiency caused by technical assistance and that the role of credit on improvements in productivity may be associated with increasing economies of scale.

Chapter 6

Conclusions and Recommendations for Future Research

Practitioners and researchers in the microfinance field have an increased interest in learning whether providing complementary, non-financial services along with credits have any impact on borrower performance. The main goal of this dissertation is to provide evidence of this joint impact of microcredits and technical assistance on a household's productivity. To achieve this goal, I used data from the microcredit institution *Financiera Calpía*, one of the main microcredit institutions in El Salvador, about its rural clients.

In the first part of the analysis, I focus on the output impact of credit; I show that credit has the positive effect on productivity of a 9 percent increase in the value of output outlays for every 1,000 colones of additional credit received by a household. About 50 percent of *Financiera Calpía's* clients receive loans smaller than 3,000 colones, which implies that each of these loans could generate an increase in output per hectare of 27 percent. These results fall into the higher range of impact found in those studies that found impact between 1 and 39 percent (Hulme & Mosley, 1996; Armendáriz & Morduch, 2010). *Financiera Calpía's* clients are not considered extremely poor relative to Salvadorian standards during the 1997-1999 period. Thus, the relatively high impact of credit is consistent with Mosley's (1996) idea that microcredits have bigger impact on richer households.

When technical assistance is introduced along with credit in the estimations, it has a positive impact in household productivity. For example, I find that households which received loans in consecutive years and receive technical assistance for the first time experience significant improvements in productivity compared to households without any loan or technical assistance.

It is clear that both services contribute to productivity growth. However, I find that patterns of consumption of these services matter (e.g. receiving credit repeatedly and receiving a loan for the first time) and generate output impact of different magnitudes.

In the case of the impact of patterns of credit, it is very likely that the loans provided by *Financiera Calpía* are producing movements along the production function of these households. Consistently across all the estimations, I find that households with previous loans (or repeated loans) experience smaller changes in productivity than do households borrowing for the first time. It is not clear from the current literature if the impact of each additional loan declines as more loans are received. This situation is known as the *plateau effect* of microcredits, but the issue has not yet been studied in detail. My results show that borrowers with more loans experience smaller changes in productivity than do households with fewer loans. Thus, I believe that the *plateau effect* may occur only under some circumstances; for example, in cases where rural farmers use loans to expand their operations yet do not implement permanent changes in their production technologies. Further exploration of the long run impact of microcredits on productivity and enterprise growth may be worth pursuing.

I find that credit and technical assistance contribute to productivity through different paths. Changes in productivity can be decomposed into changes in technical efficiency, technological change, and returns to scale. I find evidence that technical efficiency improved during the period studied; in addition, technological change occurred (technology adoption), and significant increasing returns to scale are present. The role of credit and technical assistance in contributing to these productivity elements is clarified through the analysis.

Credit has very little effect on efficiency, yet I find significant contributions of credit to on general productivity. In addition, households use a large proportion of their loans to purchase inputs. These results lead me to conclude that credit contributes to productivity mostly because of the existence of returns to scale or other unobserved paths such as effects on health or education.

I find that that technical assistance improves productivity between 70 and 90 percent. I can presume that this productivity boost comes mostly from increased efficiency and technology adoption caused by technical assistance. I find evidence that technical assistance improves households' technical efficiency by about 30 percent of a standard deviation. The training provided to the households focuses on learning new and more efficient production techniques thus it is expected that households receiving technical assistance experience some improvements in efficiency and adopt new technologies.

The presence of economies of scale may be associated with the effects of technical assistance on the productive and managerial skills of the farmers who use increased credit to expand their farm production and at the same time increase productivity.

The inclusion of borrowers' credit history in the estimation of credit impact is an important contribution to the field. Some authors have started to think about this issue, Tedeschi (2007) and Ottaviano and Lage (2007) for example. My results provide evidence that comparing recent borrowers to non-borrowers, yet omitting the presence of previous loans, leads to biased results. The direction and magnitude of the bias depends on how the loans are used, the size of the loans, the amount of time that elapsed between loans, and the possible effects of credit on changes in a household's production technology. In the case of *Financiera Calpía's* clients, my estimations show that when previous loans are not accounted for, the impact of credit is slightly smaller than when credit history is included in the model.

Estimations of the type of impact studied in this research are sensitive to estimation methods and the characteristics of the case analyzed. From my estimations I find that empirical methods which control for unobserved time invariant factors, such as fixed effects, are preferred. However, because of the importance of credit history, larger longitudinal data sets are required in order to have a more complete picture of this long term phenomenon. One natural environment where this factor is controlled for is microcredit programs that offer small repetitive loans (a very common lending model in the microfinance field). In this type of program, borrowers receive many loans during their participation in the program and data about the credit history of participants and their outcomes over relatively long periods of time can be collected.

A topic that can enhance the scope of my research is the impact of the loans on the accumulation of human capital in the form of health improvement and other household activities. Most households receiving microcredit treat the loans as fungible resources; a relaxation of the credit constraint may increase the “full income” of a household and impact the shadow prices of other household activities.

Is allocating already scarce resources of microcredit providers to the design and provision of technical assistance along with microcredit worth it? The answer, at least from the perspective of households, is “yes.” However, it is difficult to generalize the joint positive effects of credit and technical assistance from the results found in this research; one reason is that providers implement a variety of models to deliver these services together and/or separately, within many particular economic environments, and under a variety of institutional conditions (Karlan & Valdivia, 2011). Thus, producing more studies that compare the impact across several microcredit institutions may also improve our understanding of this issue. Furthermore, this issue is important from the provider’s perspective since it addresses the question of whether allocating already scarce resources to design and providing technical assistance along with microcredit is worth it. (Ledgerwood, 1999). A cost-benefit analysis of this question may be a valuable contribution to the field.

The idea that microcredit institutions should provide not only financial services but also other complementary services such as training or coaching is already gaining popularity among practitioners who intuitively recognize the importance of giving their client complementary services. Yet, the field would benefit from more formal evidence that these non-financial services generate real and meaningful improvements in their clients’ productivity and ultimately in their own efforts to reduce poverty. I believe that results from this dissertation will help in this regard and hopefully motivate further efforts to advance the microfinance field toward more efficient and effective delivery models.

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