Policy Research Working Paper 8483

Sowing the Seeds for Rural Finance

The Impact of Support Services for Credit Unions in Mexico

Miriam Bruhn
Rekha Reddy
Claudia Ruiz Ortega

WORLD BANK GROUP
Development Economics
Development Research Group
June 2018

Policy Research Working Paper 8483

Abstract

This paper studies the impact of a program that provides grants for technical assistance on the interest rates and outreach of credit unions in Mexico. Credit unions financing rural borrowers received grants in different years. The study uses propensity score matching and relies additionally on the timing of the grants to identify effects. The analysis shows that the program lowered lending interest rates by up to 2.6 percentage points (from a pre-program average of 17.8 percent). This drop appears to be due to lower operating costs and better risk management, as reflected in a lower nonperforming loan ratio. The program also raised credit unions' returns on assets and significantly increased the value of their loan portfolio.

This paper is a product of the Development Research Group, Development Economics. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/research. The authors may be contacted at mbruhn@worldbank.org, rreddy5@worldbank.org and cruizortega@worldbank.org.

Sowing the Seeds for Rural Finance:

The Impact of Support Services for Credit Unions in Mexico[1]

Miriam Bruhn, *World Bank* and *IZA*

Rekha Reddy, *World Bank*

Claudia Ruiz Ortega, *World Bank*

JEL Classification: G23, O12, O16, R51

Keywords: technical assistance; access to finance; rural finance; credit unions

[1] We thank the staff of Financiera Nacional de Desarrollo Agropecuario, Rural, Forestal y Pesquero (FND), particularly Hector Manlio Pena Jiménez, Jennifer Fernández Pineda, Armando Gonzalez Barragan, and Rocío López Arredondo, for sharing their data and insights with us and the Knowledge for Change Program for supporting this project with funding. Alejandra Arrieta and Nathaniel Russell provided excellent research assistance.

1. Introduction

Despite recent progress in increasing access to finance for low-income populations, rural areas remain underserved by financial services in many countries. In developing economies, the unbanked live predominantly in rural areas (Demirguc-Kunt et al. 2015). The lack of finance creates challenges for agricultural producers and other agents in the rural economy. When formal financial services are not available, these agents resort to informal sources to meet their credit and savings needs that tend to be costlier and less reliable (Besley 1995, Fafchamps 2003, Ghate 1992, Onchan 1992, and Udry 1994 and 1990). They may also forgo investment and income-generating activities and have a more limited ability to guard against risks (Dupas and Robinson 2013, Dercon 2002, Jacoby and Skoufias 1997, Kazianga and Udry 2006, and Morduch 1999).

Rural areas typically have lower population density and more limited infrastructure, which can raise transaction costs and operating expenses for financial institutions. Often, these institutions also face other market failures in rural areas, for example related to lack of credit information and increased credit risk. In many countries, commercial banks have low credit volume in rural areas and concentrate their lending activities in urban areas instead. For some of these countries, non-bank financial institutions such as credit unions and cooperatives play a critical role in servicing the rural sector. However, small financial institutions catering to rural borrowers often lack economies of scale and tend to be constrained by poor governance, low technical capacity and limited funding sources (Branch and Evans 1999). These constraints are in turn passed on to the borrowers in the form of higher interest rates and credit rationing.

This paper asks whether providing technical assistance to rural financial institutions can help lower their interest rates and increase outreach to more borrowers. We study these effects in the context of a support program to rural financial institutions provided by the Mexican development finance institution Financiera Nacional de Desarrollo Agropecuario, Rural, Forestal y Pesquero (Rural Finance Development Agency, FND). FND's support program began in 2004 and primarily gives grants to rural financial institutions for technical assistance, which is provided through a network of accredited specialists.

Mounting evidence shows that technical assistance in the form of consulting services can increase productivity and growth of firms in a broad range of non-financial sectors (Bloom et al 2013; Bruhn, Karlan, and Schoar 2018; Anderson, Chandy, and Zia forthcoming). However, we are not aware of any study that examines the effect of technical assistance on financial institutions, which is of relevance also since it can have important spillovers to their clients.

The technical assistance financed through FND's support program may help financial institutions lower their lending interest rates and increase outreach for several reasons. First, the technical assistance may allow financial institutions to become more efficient, lowering operating costs. Second, it may teach financial institutions how to better screen and monitor loans, which can lower credit risk. Third, financial institutions may learn how to keep their books and financial statements in order, helping them raise funding at a lower interest rate. Depending on the market conditions, financial institutions can then pass these cost savings on to their clients in the form of better credit terms, or they might increase their profitability without any spillovers to their clients.

To trace out these channels, we first study the effects of the support program on lending interest rates and the following four key drivers of lending rates: (i) operating costs, (ii) credit risk, measured by the non-performing loan (NPL) ratio, (iii) the funding interest rate, and (iv) profits, measured by returns-on-assets (ROA). We then examine whether the program allowed financial institutions to expand by looking at the effect on their loan portfolio.

We measure the impact of FND's support program using data from the financial statements of 124 credit unions for the years 2002 through 2012. We obtained these data from the National Banking and Securities Commission (CNBV) and combined it with data from FND on the grants disbursed to credit unions. While other types of financial intermediaries also obtained grants through the program, historical financial statement data are not publicly available for these other intermediaries. A total of 65 credit unions received grants through the program between 2005 and 2008. We estimate the impact of the program on these credit unions by using a difference-in-difference estimation that relies on the comparison of never treated and ever treated credit unions over time, as well as by considering the timing of treatment.

Selection into the program is likely driven by proximity to FND offices as well as percentage of the credit union loan portfolio going to borrowers in rural areas. We do not have information on these variables and thus initially compare all treated credit unions with untreated credit unions. We then use four different matching techniques to examine the robustness of the results. Samples created through caliper matching display identical averages and trends in outcome variables in the pre-program years 2002, 2003, and 2004.

Our results suggest that the program lowered lending interest rates by up to 2.6 percentage points (from a pre-program average of 17.8 percent). This drop seems to be due to reduced operating costs and a lower NPL ratio. That is, the support program helped credit unions to make their operations more efficient and to better screen and/or monitor borrowers. We find no consistent change in the funding interest rate. However, we do see an increase in ROA as a result of the program. That is, increased operating efficiency and a lower NPL ratio are reflected in higher returns for the credit unions, but they also passed on some of these returns to their borrowers, in the form of lower interest rates.

We then study whether the reduced lending interest rate was accompanied by an increase in outreach and find that the program increased the value of the loan portfolio by about 50 percent.[2] Some grant recipients also received credit lines from FND. To make sure these credit lines are not driving the increase in outreach, we conduct two robustness checks. First, we control for borrowing from FND. Second, we restrict the sample to credit unions that did not borrow from FND during our period of observation. The estimated effects on outreach remain unchanged in these alternative specifications, suggesting that the program had a stand-alone effect and did not simply operate through increased borrowing from FND. Consistent with this conclusion, we find that even credit unions that did not borrow from FND during our period of observation increased their borrowing from members, banks, or other institutions due to the program (our data are not disaggregated enough to examine credit unions' borrowing by source).

Overall, our results suggest that high interest rates that reflect high operating costs/low efficiency and weak capacity to screen and monitor loans are an important constraint for credit unions in servicing more borrowers in rural areas. Our findings add to the literature that has examined the determinants of high intermediation costs of financial institutions in developing countries. Several studies have shown that intermediation costs are negatively correlated with a financial institution's operating efficiency and positively associated with its credit risk and cost of funding (Beck 2007; Beck and Hesse 2007; Brock and Rojas Suarez 2000; Martinez Peria and Mody 2004; Maudos and Solisa 2009).

[2] Credit unions can only lend to their members. We cannot check explicitly whether the increase in the loan portfolio implies an increase in the number of members or more borrowing to existing members, since we do not have data on the number of members. However, we have data on the value of paid-in capital, which is a proxy for number of members since each new member needs to contribute a minimum amount of capital. Using paid-in capital as an outcome variable gives similar results to using the value of the loan portfolio.

Our findings also relate to the literature on matching grants, which evaluates interventions in which funds are provided to institutions or firms for technical assistance. This literature has faced many difficulties in studying the effectiveness of such grants (Campos et al 2014). Bruhn, Karlan, and Schoar (2018) may be the only paper so far to illustrate that matching grants for consulting services can have a positive effect on productivity and firm growth, suggesting that these grants do not simply subsidize services that firms would have hired in any case. Our paper adds to this evidence by showing that grants that cover 100 percent of the cost of technical assistance can promote the growth of credit unions.

The rest of this paper is organized as follows. Section 2 provides background information on rural finance in Mexico and on FND's support program. Section 3 describes the data. Section 4 discusses the identification strategy. Section 5 presents the results and section 6 concludes.

2. Institutional Background

2.1. Rural Finance in Mexico

Mexico has relatively low credit depth in general: credit to the private sector in Mexico was at 27 percent of GDP in 2016, less than the average for the Latin America and Caribbean region (LCR, 44 percent) and Mexico's upper-middle-income country peers (51 percent). The supply of financial services in rural Mexico is low. The Mexican financial system is bank dominated, with many smaller financial institutions serving more remote areas. In rural areas, banks are focused on larger and more profitable agribusiness clients. Bank branches make up just 15 percent of total branches in rural areas, in comparison to 88 percent of total branches in urban areas (CNBV 2017). Non-bank financial institutions such as non-deposit taking financial institutions (SOFOMES), popular savings credit institutions (SOCAPs) and credit unions primarily serve smaller enterprises and lower-income households. Many of these institutions lack economies of scale and some are constrained by limited funding sources and low technical capacity. However, they play a significant role in providing access to finance, particularly in rural areas where banks' operational costs may be high. Mexico also has six development banks, six government trusts, and four development finance institutions to support key sectors such as the rural economy.

2.2 FND and the Capacity Building Support Program

FND is a development finance institution that plays a key role in channeling finance to the rural economy in Mexico. It lends directly to producers in agriculture, livestock, fisheries, forestry, and other rural activities, and provides second-tier financing and capacity building support to rural financial intermediaries.[3] The most recent Mexican agricultural census (2007) showed that FND was the most common source of agricultural credit, reaching 17 percent of rural production units.

FND has worked with more than 500 financial intermediaries, including credit unions, cooperatives, SOFOMES, and producers' associations, as an important part of its strategy to increase access to credit in rural areas. Leveraging the distribution networks of these financial intermediaries helps not only increase FND's outreach but also to support the sustainable long-term development of private sector supply of rural finance, as these intermediaries can more easily service smaller loan amounts and low-income borrowers. As per its mandate, FND can provide financing to projects located within rural areas (both on the first and second tier).

Before a financial institution can receive an FND loan, it needs to go through an extensive accreditation process which includes questions about the institution's objectives as well as a

[3] Before 2014, FND was known as Financiera Rural. Its establishment occurred when Banrural, an agricultural development bank that provided subsidized credit for agriculture, was liquidated in 2002.

detailed review of products, financial statements, organizational structure and governance, quality of financial reporting, systems, and manuals for operation and risk management. To help improve institutional performance and outreach, FND uses public funds from the national budget (administered by the Ministry of Finance, SHCP) to provide a capacity building support program (*Programa de Apoyos*). This program provides grants for capacity building projects to financial intermediaries with the goal of getting them ready to receive FND loans and more broadly to develop sound rural financial institutions that can responsibly reach more rural borrowers.[4]

Funds from FND's support program are allocated to financial intermediaries on a first-come, first-served basis as described each year in the operating rules for FND's support program which are published in Mexico's *Diario Oficial*. The support program is not widely advertised and financial institutions that have interacted with FND for loans or that are located closer to FND offices may be more likely to find out about the program.

This paper focuses on the impact of the support program on credit unions. Credit unions are member-based institutions that by law can offer credit only to their members. Credit unions are a common source of finance in rural areas, serving 8.8 percent of agricultural units (Agricultural Census 2007). They are supervised by the CNBV. Credit unions make up 20 percent of the financial intermediaries that have received grants through the support program. We do not study other types of financial intermediaries, such as cooperatives, SOFOMES, and producers' associations, due to a lack of data. Most of these other entities are not supervised by the CNBV, and we are not aware of a repository of their financial data.

[4] Some development finance institutions in other countries have similar programs although they still represent a relatively small share of development finance institutions' activities. A recent CGAP survey of selected development finance institutions found that 92 percent of their financial inclusion commitments are for financing retail financial institutions, while 4 percent is allocated towards capacity building grants (Moretto and Scola 2017).

The support program started in 2004 and continues until today. We have data for the period up to 2012. Table 1 displays the number of credit unions that obtained a grant through the program in each year (2004 through 2012) broken down by the year when the credit union first received a grant through the program. Here, we only include the 69 credit unions for which we have complete financial data. Out of these 69 credit unions, 32 unions obtained a grant for the first time in 2005 and most of these went on to also receive grants in the following years. Another 18 credit unions received a grant for the first time in 2006 and again many of these also received grants in later years. In the years 2007 and 2008, 7 and 8 more credit unions received a grant for the first time, respectively. Only one additional credit union received a grant for the first time in each of the years 2009, 2010, and 2011.

Table 2 relates grants through the support program to FND loans. For each year when a credit union first obtained a grant the table displays the year in which a credit union obtained a loan from FND for the first time. Out of the 69 credit unions, 32 did not receive an FND loan between 2002 and 2012. More than half of the other 37 credit unions had already received an FND loan before obtaining a grant through the support program. In our analysis, we control for obtaining an FND loan to estimate the separate effect of the support program on credit unions' outreach.

The support program provides grants for distinct types of projects. We group these projects into three categories. The first category is technical assistance, which is provided through a network of accredited specialists with extensive experience in supporting financial institutions focused on lower-income populations. Examples of technical assistance include credit risk management, trainings to increase the skills and capacity of management and staff and IT systems selection. The second category includes equipment (i.e. computers, copiers and desks) to support the opening of branches and/or expansion of operational capacity in rural areas. The third category refers to financial support in the form of capitalization, guarantees to support credit access and interest rate subsidies. The median grant amounts were about 70,000 Mexican pesos (4,000 USD) for technical assistance, 340,000 pesos (19,000 USD) for equipment and 1,600,000 pesos (89,000 USD) for capitalization.

Table 3 lists the number of grants disbursed in each year by type of project. About 64 percent of the grants disbursed between 2004 and 2012 were for technical assistance, followed by 23 percent for capitalization and 13 percent for equipment. All 69 credit unions in our sample obtained a grant for technical assistance at some point between 2004 and 2012. Of these, 46 also received a grant for either equipment or capitalization. In our analysis, we are not able to separate the effects of distinct types of grants since most credit unions received more than one type of grant often in the same year. However, since most grants were for technical assistance, a robustness check suggests that this is the primary channel through which the program operates.[5]

3. Data

We combine two data sets in our study. The first data set contains administrative information from FND about all credit unions that obtained a grant through FND's support program in each year between 2004 and 2012. The data set lists the year, type and monetary value of each grant. It also includes the year in which credit unions opened a credit line with FND.

Our second data set comes from the CNBV and contains quarterly financial statements of the 172 credit unions operating in Mexico from September 2002 to December 2012. Since credit unions are supervised by the CNBV, they are required by law to publish their financial statements

[5] We conducted a robustness check where we replicate our analysis for the 20 credit unions in our full sample that obtained only grants for technical assistance (i.e. no other grants). The effect sizes are similar, but the results are not always statistically significant since the standard errors are larger in this smaller sample.

on a quarterly basis. Of the 172 credit unions in the CNBV data, we drop the 22 credit unions that had already closed by the time the FND support program began in 2004. We also drop another 22 credit unions whose financial information is missing for the pre-program period or is only reported in one of the pre-program years 2002, 2003, and 2004. In addition, we drop the one credit union that received a grant through the program in 2004 to have three years of pre-program data for all credit unions. Finally, we drop the three credit unions that received a grant through the program for the first time in 2009, 2010, or 2011 since these years are further removed from the pre-program years 2002 through 2004 that we use in the matching exercise described in section 4.[6]

Our final CNBV data set thus consists of 124 credit unions covering the years 2002 through 2012. From the quarterly CNBV data, we keep only December of each year and merge it with the FND data at the credit union and year level.

Based on the CNBV data, we generate seven variables to assess the impact of FND's support program on lending interest rates, their components, and outreach.

We calculate the lending interest rate by dividing annualized interest income by the average size of the loan portfolio. We then define four components that are likely to drive lending interest rates. First, the operating cost ratio, calculated by dividing annualized operating expenses by average annual total assets. A lower ratio signals more efficiency in the form of lower operating costs for the same size. Second, the NPL ratio, which we calculate by dividing the value of non-performing loans by the total loan portfolio. Third, the funding interest rate, which is calculated as the ratio of interest expenses to average liabilities. Fourth, the return-to-assets (ROA) ratio, which is a frequently used measure of financial institutions' profitability and performance. We calculate ROA by dividing annualized net income by average annual total assets.

[6] Results are similar when we do not drop these three credit unions.

To study outreach, we look at the value of the total loan portfolio, which we calculate as the sum of all outstanding loans, including performing and non-performing loans. We also study loans from credit union members, banks or other institutions, which we obtained directly from the financial statements.

Finally, we noticed that a significant fraction of credit unions in our sample end up closing during the eight years in our data. We thus check whether the support program had an effect on survival of credit unions since this has implications for sample selection and how we deal with the observations for closed credit unions.

Table 4 shows summary statistics of our variables for the pre-program period for the 124 credit unions in our sample. All credit unions remained open in the pre-program years, as we drop credit unions that closed before 2005. Credit unions in our sample charged an average interest rate of 16.9 percent. The operating cost ratio was 8.2 percent on average. The average NPL ratio was 19 percent, with a substantially lower median of 4.4 percent. The average funding interest rate was 7.3 percent. ROA was -1.5 percent on average, but the median credit union was not making losses, with an ROA of 0.3. There is large heterogeneity across credit unions in terms of the loan portfolio: while the median value of the loan portfolio was around 25 million Mexican pesos (about 1.4 million USD), the average credit union lent more than double that amount. Finally, credit unions borrowed on average about 69 million Mexican pesos (close to 4 million USD).

4. Identification Strategy

We use a difference-in-difference framework to estimate the effects of the program. The estimating equation is

$$y_{it} = \alpha_i + \beta_t + \gamma Treatment_{it} + \varepsilon_{it} \qquad (1)$$

where y_{it} is an outcome variable of interest for credit union i and year t, α_i is a credit union fixed effect, and β_t is a year fixed effect. The variable $Treatment_{it}$ is equal to one for a given credit union i in the year t where it received the first grant through the program and for all years thereafter. It is equal to zero for all years before the credit union received the first grant through the program. For credit unions that did not participate in the program by 2012 (the last year in our data), $Treatment_{it}$ is equal to zero in all years. ε_{it} is an error term, clustered at the credit union level. The coefficient γ represents the treatment effect of the program on outcome y_{it}. Equation 1 thus identifies the treatment effect γ by relying on the comparison of never treated and ever treated credit unions over time, as well as by considering the timing of treatment.

We estimate equation 1 in different samples, starting with a full sample that we then refine through different propensity score matching (PSM) techniques (Dehejia and Wahba 2002). In the full sample, we keep all 124 credit unions in the CNBV data that have non-missing observations in the pre-program period 2002 to 2004 and that either received the program at some point between 2005 and 2008 or did not receive the program by 2012. We call the 65 credit unions that received the program between 2005 and 2008 the full treatment group and the 59 credit unions that did not receive the program by 2012 the full control group.

If the full control group is a valid comparison group for the treatment group depends on how selection into the program happened. For example, equation 1 would overestimate the effects of the program on the volume of the loan portfolio if credit unions that expected to grow their loan portfolio received the program right before this growth was to happen. In practice, we do not know what determined if a credit union applied to the program. Although, as described in section 2, we do know that the program was not widely advertised, and it is likely that credit unions located closer to FND offices had more information about the program. Also, credit unions that had a higher fraction of their loan portfolio located in rural areas were more likely to participate in the program.[7]

While we cannot say for certain what determined selection into the program, we can compare pre-program outcomes for the credit unions in the treatment and control group. Column 1 of table 5 shows the pre-2005 averages of our outcome variables for the 65 credit unions in the full treatment group. Column 2 shows the normalized differences between the averages of the credit unions in the full treatment group and the full control group and column 3 shows the p-values corresponding to these differences. Credit unions in the full treatment and control groups have similar values of their loan portfolio and loans from members, banks or other institutions. However, they differ in their lending interest rate and its components. On average, credit unions in the full control group have a higher NPL ratio than credit unions in the full treatment group and they pay a lower interest rate for their funding. These differences in means do not *per se* invalidate our identification strategy, but they do suggest that the full control group may not be a good comparison group for the full treatment group.

We now examine the identification assumptions for equation 1 in more detail. These assumptions are that, (i) if the credit unions in the treatment group had not participated in the program, their outcomes variables would have followed a trend parallel to those of the credit unions in the control group, and (ii) the timing of treatment in the treatment group is exogenous to the outcomes variables. While we cannot explicitly test these assumptions, we can check whether the outcomes for treatment and control group credit unions followed a parallel trend in the pre-2005 period. If this was the case, it is more plausible that the outcomes would have continued to

[7] We do not have data on the location of credit union branches or the location of their loan portfolio to use these criteria in our identification strategy.

follow a parallel trend in the post-2005 period. Table 6 shows the results from the following regression that tests the parallel trends assumption in the pre-2005 period

$$y_{it} = \alpha + \beta * Trend_t + \gamma Treatment_i * Trend_t + \varepsilon_{it} \tag{2}$$

where y_{it} is an outcome variable of interest for credit union i and quarter t and α is the constant term. $Trend_t$ is a linear time trend and $Treatment_i$ is equal to 1 for the credit unions in the full treatment group and is equal to 0 for the credit unions in the full control group. ε_{it} is an error term, clustered at the credit union level. If the coefficient γ is not statistically different from zero, we can conclude that outcome y_{it} followed a parallel trend for treatment and control group credit unions in the pre-2005 period. Table 6 reports the p-values for the coefficient γ. Column 1 shows that the pre-2005 trends in the NPL ratio, as well as the funding interest rate, were statistically significantly different across the full treatment group and the full control group.

To obtain treatment and control groups that are more comparable we use four different PSM techniques, yielding four different samples that allow us to check the robustness of our results. For the first two samples, we obtain the propensity score by running a probit regression of a dummy variable for being in the full treatment group vs the full control group on the averages of and changes in all our outcome variables (the seven variables listed in table 4), i.e., 14 variables in total. The averages are across the years 2002, 2003, and 2004, and the changes are those from 2002 to 2004, i.e. 2004 values minus 2002 values.[8] We match on outcome variables, instead of other background characteristics, since previous research finds that past values of an outcome of interest are the ones that are most strongly correlated with future outcomes (Bruhn and McKenzie 2009). That is, matching on past values of the outcome variables is likely to yield the most comparable groups of credit unions in the post-program period.

[8] If the value for any year is missing, we calculate the average over the two non-missing values. For the changes, we replace 2002 with 2003 if 2002 is missing and we replace 2004 with 2003 if 2004 is missing.

Figure 1 plots the propensity scores for the full treatment and full control groups. Based on these scores, we generate two different samples. The first sample keeps only credit unions on the common support of the propensity score, covering 60 credit unions in the treatment group and 36 credit unions in the control group. The second sample uses caliper matching without replacement using the logit of the propensity score and calipers of width equal to 0.2 of the standard deviations of this variable, as recommended in Austin (2011 and 2014).[9] This small caliper is quite restrictive in our setting since we start with a relatively small sample and only keep 29 credit unions in each group. We thus expect to have low power to detect effects in this sample, but we still show the results since this matching technique is likely to yield the most comparable treatment and control groups.

For the remaining two samples, we obtain a different propensity score for each outcome. That is, we run a probit regression of a dummy variable for being in the full treatment group vs the full control group on the 2002, 2003, and 2004 values of the respective outcome variable we are looking at. This technique is bound to give a closer match on the respective outcome variable of interest. Here, we match on all three years of data to replicate the pre-2005 trend most closely.[10] As before, we create one sample that keeps only credit unions on the common support of this propensity score and another sample based on caliper matching as described above. This procedure yields a different number of credit unions in each group for each outcome. These numbers are reported in columns 3 and 5 of tables 10 to 16.

[9] Austin (2014) used Monte Carlo simulations to compare 12 algorithms for propensity score matching in terms of bias, variability, and MSE of the resulting estimates. He concludes that nearest neighbor caliper matching without replacement performs best in most situations. Austin (2011) conducted simulations to determine the optimal caliper width for propensity score matching.

[10] For the first two samples where we match on more variables, we do not use all years of data separately and match on the average and growth rate instead to reduce the number of matching variables.

Tables 5 and 6 summarize the differences in pre-2005 averages and trends for each sample. Columns 4 through 11 in table 5 first show the normalized difference between the average outcome in the treatment group and control group obtained with each method. Table 6 shows the p-value corresponding to that difference. Columns 2 through 5 in table 6 show the p-values for the coefficient γ in equation 2 obtained by running a regression in each different sample. The common support samples show statistically significant differences in the pre-program average of some of the variables, as displayed in columns 4 through 7 of table 5, but not in the trends of these variables (see columns 2 and 3 of table 6). The two samples obtained with caliper matching show neither differences in pre-program averages nor pre-program trends across the treatment and control groups (except for one difference in the average value of the loan portfolio with p-value 0.094).

When we discuss our results in section 5, we also present figures that provide a visual check of the parallel trends assumption, displaying average values of the outcome variables for treatment and control credit unions in each sample, before and after 2005.

Finally, we try to assess whether the timing of treatment was exogenous to our outcome variables. We do this by dividing the 65 credit unions that received a grant through the program between 2005 and 2008 into early and late receivers. We define early receivers as the 32 credit unions that received a grant through the program for the first time in 2005 and late receivers as the 33 credit unions that received a grant for the first time in 2006, 2007, or 2008. We replicate tables 5 and 6 to check for differences in pre-program means and trends across early and late receivers.

Here, we do not use data for 2002 through 2004 for all credit unions. Instead, for each credit union we use the three years of data before receiving a grant through the program for the first time. For example, for credit unions that received a grant for the first time in 2006, we use 2003, 2004, and 2005. For credit unions that received a grant for the first time in 2008 we use

2005, 2006, and 2007. Table 7 shows that the 32 credit unions that received a grant for the first time in 2005 had similar characteristics averaged over the three years prior to receiving the grant to those 33 credit unions that received a grant for the first time in 2006, 2007, or 2008. Pre-trends in outcomes across these two groups as analyzed through equation 2 were also similar (table 8).

5. Results

5.a. Survival

We first examine whether the support program had an effect on the survival of credit unions (table 9). The estimates in table 9 are obtained by estimating equation 1 with an outcome variable that is equal to 0 if a credit union is still operating in that year and equal to 1 if the credit union closed. In this table, we only have three different samples since all our credit unions survived during the pre-program years 2002, 2003, and 2004, so that matching on the outcome variable survival only leads to the full sample. The estimates from all three samples show that the program significantly increased the probability of survival. We thus make assumptions for filling in the observations for closed credit unions, as explained in the following section.

5.b. Lending interest rate and channels

The fact that not all credit unions survive during our period of study implies that we face sample selection for studying the effect of the program on the lending interest rates since the lending interest rates are not observed for credit unions that closed. We address this issue by filling in the years after a credit union closed with values based on two different assumptions.

First, we assume the lending interest rate would have stayed the same as in the last year where we observed the credit union. We view this as a best-case scenario and consider the results obtained with this assumption as a lower bound of the effect of the program on lending interest rates.[11] That is, we believe that credit unions would likely have raised their interest rates had they remained in operation instead of closing. Presumably they closed because of low returns and would thus have had to try to increase revenues by raising interest rates. Our second and alternative assumption is that the lending interest rates would have been the highest observed for the same credit union. We view this as a worst-case scenario and consider the results obtained with this assumption to be an upper bound of the effect. We use analogous assumptions for the other four variables that we do not observe for closed credit unions: the operating cost ratio, the NPL ratio, the funding interest rate, and ROA.

In table 10 we examine whether the program changed the average interest rate charged to borrowers using the five different samples described in section 4. All but one specification suggest that the program lowered lending interest rates, but the effect is only statistically significant in three specifications. We interpret the consistency of signs the coefficients as weak evidence that the program lowered lending interest rates.

Figure 2 displays interest rates of credit unions in the treatment and control group over time, for our five different samples, using the upper bound assumption. Overall, the graphs show that lending interest rates in the treatment and control groups followed similar trends before program start. After program start, the interest rates dropped more steeply in the treatment group than the control group. Based on the evidence in table 10 and figure 2, we conclude that the program lowered lending interest rates by up to 2.6 percentage points, compared to an average pre-program interest rate of about 17.8 percent (column 1 of table 7).

[11] If instead we use the best-case assumption that the lending interest rate would have been the average observed for the same credit union, we obtain comparable results.

We now study the components that are likely to drive interest rates and that could have been affected by the program, starting with operating efficiency.[12] The results in table 11 show that the program lowered the operating cost ratio by up to 1.5 percentage points, compared to a pre-program mean of 7.7 percent (column 1 of table 7).

Table 12 shows the impact estimates for the NPL ratio. The estimated effect is negative in all specifications, but it is only statistically significant in one specification. We interpret this as suggestive evidence that the program lowered the NPL ratio.

The results for the borrowing interest rates are mixed (table 13). One specification shows a significant positive effect of the program on the borrowing interest rates, while three of the upper bound estimates show a significant negative effect.

Next, we examine the effects of the program on ROA (table 14) and find evidence that the program increased ROA by up to 4.6 percentage points, corresponding to about two-thirds of a standard deviation (table 4).

Overall, we conclude that the program increased operating efficiency, suggesting that the technical assistance helped credit unions streamline their operations. We also find some evidence of reduced risk in the loan portfolio, as reflected in a lower NPL ratio. The program thus seems to have improved the way in which credit unions screen and monitor borrowers. The lower operating costs and lower NPL ratio are reflected in higher ROA, providing higher returns to credit unions, but part of this gain was passed on to the borrowers in the form of lower lending interest rates.

[12] Operating costs tend to make up the largest part of the intermediation costs of financial institutions in most countries (Beck 2007) and they are often particularly relevant for smaller institutions. The effects of the program on operating efficiency may thus vary by size of the credit union. For smaller credit unions, operating costs tend to represent a higher share of their total costs, implying that the benefits from an intervention that raises their operating efficiency should be greater. We conducted a test along these lines in our data. Following suggestions from FND, we classified credit unions as small or large based on whether their capital from partners one year before participating in the program was below or above 20 million pesos. We do not find different effects of the program on operating efficiency by size of the credit union, which may be due to the relatively small sample size.

5.c. Outreach

Table 15 shows the effects of the program on the value of the loan portfolio (for credit unions that close, the value of the loan portfolio is zero). The effect is large and positive in all five samples in panel A, although it is not statistically significant in the caliper matched sample that relies on all variables in the matching procedure. The size of the effect varies from 35 million to 73 million pesos (about 2 million to 4 million USD). These values are large compared to the pre-program mean of 66 million pesos (about 3.6 million USD), corresponding to 53 to 111 percent.

Figure 3 illustrates the effect of the program on the loan portfolio. The average value of the loan portfolio increases over time for credit unions in the treatment group while it remains relatively constant for credit unions in the control group. The time when the loan portfolio starts to increase in the treatment group coincides with the first treatment year (2005).

We interpret the increase in the loan portfolio as an increase in outreach, i.e. credit unions lending to more borrowers. Since credit unions can only lend to their members this interpretation implies that treatment credit unions increased their membership. We do not have data on number of members. However, we do have data on the value of paid-in capital, which is a proxy for number of members since each new member needs to contribute a minimum amount of capital. Using paid-in capital as an outcome variable gives similar results to using the value of the loan portfolio.

We now ask whether the program had a standalone effect on outreach or whether the effect operated through borrowing from FND. That is, the program may have allowed credit unions to obtain FND funding for the first time or to increase their borrowing from FND, which could have led to increased survival and a higher loan portfolio. In panel B of table 15 we thus add a variable to estimating equation 1 that controls for FND borrowing. This variable is equal to one in the first year a credit union obtained a loan from FND and in all following years and equal to zero in all years before a credit union obtained a loan from FND for the first time (or for all years for the credit unions that did not obtain an FND loan by 2012).[13] Comparing the results in panels A and B of table 15 shows that the estimated effect of the program on the value of the loan portfolio is similar when the dummy variable for FND funding is included.

As a second robustness check, we limit the sample to the 29 treatment group credit unions that did not obtain an FND loan by 2012. Here, we re-do each matching procedure after dropping the other 36 credit unions in the full treatment group. Panel C of table 15 shows the results in this reduced sample. The size of the effects is comparable to those in panel A of table 15, but the effect on the loan portfolio is not statistically significant, possibly because the sample is much smaller, implying less power to detect effects.

Finally, we examine the effect of the program on credit unions' loans from members, banks or other institutions. We find a strong effect of the program on these loans (panel A of table 16).[14] Unfortunately, the data do not allow us to disaggregate loans from members, banks or other institutions by funding source. However, the effects in panel B and panel C of table 16 suggest that the source of increased borrowing is not only FND. The effect of the program on credit unions' loans remains positive and significant when we control for having received an FND loan (panel B of table 16) and we still find a positive and significant effect in the sample of credit unions that did not obtain an FND loan by 2012 (panel C of table 16). We thus conclude that the program had a standalone effect on outreach and did not simply operate through increased borrowing from FND.

[13] We only have the year in which a credit union first obtained a loan from FND, but we do not have information on whether they had a loan in each consecutive year or on loan amounts.
[14] Since loans from members, banks or other institutions are zero for credit unions that close, we do not need to make assumptions about the values for closed credit unions here.

6. Conclusion

This paper studies the impact of a program that provides grants for technical assistance on the lending interest rates and outreach of credit unions that finance borrowers in rural Mexico. We find that the program lowered credit unions' lending interest rates by up to 2.6 percentage points, compared to a pre-program rate of 17.8 percent. The program led to an increase in the value of credit unions' loan portfolio by about 50 percent. A robustness check using paid-in capital as a proxy for number of members also suggests that the program increased credit unions' outreach.

Digging into the mechanisms behind the drop in interest rates, we find that the program lowered operating costs, suggesting that the technical assistance allowed credit unions to streamline their operations. We also find weak evidence of decreased NPL ratios, indicating that the program helped credit unions learn how to better screen and monitor borrowers. The increased efficiency and lower NPL ratio are reflected in higher ROA, but credit unions passed at least some of these gains on to borrowers in the form of lower lending interest rates.

All in all, our findings indicate that limited technical capacity constrains credit unions from financing more borrowers in rural areas and that technical assistance can help overcome this constraint. In the case of FND, providing grants for technical assistance seems to have worked well in helping them achieve their goal of expanding access to credit in rural areas.

References

Anderson, Stephen, Rajesh Chandy, and Bilal Zia. Forthcoming. "Pathways to Profits: Identifying Separate Channels of Small Firm Growth through Business Training." *Management Science*.

Austin Peter C. 2011. "Optimal Caliper Widths for Propensity-Score Matching When Estimating Differences in Means and Differences in Proportions in Observational Studies." *Pharmaceutical Statistics* 10: 150–61.

Austin Peter C. 2014. "A Comparison of 12 Algorithms for Matching on the Propensity Score." *Statistics in Medicine* 33(6): 1057–69.

Beck, T.,2007. "Efficiency in financial intermediation: Theory and empirical measurement" In Microfinance and Public Policy (pp. 111-125). Palgrave Macmillan, London.

Beck, T. and Hesse, H. 2009. "Why are interest spreads so high in Uganda?" *Journal of Development Economics* 88(2): 192-204.

Berger, Allen N., and Lamont K. Black. 2011. "Bank size, lending technologies, and small business finance." *Journal of Banking & Finance* 35(3): 724-35.

Besley, Timothy. 1995. "Savings, credit and insurance". In Behrman, Jere and Srinivasan, T N, (eds.) *Handbook of Development Economics, Volume 3*. Handbooks in economics; v. 9. North Holland, Amsterdam. ISBN 0-444884815

Bloom, Nicholas, Benn Eifert, Aprajit Mahajan, David McKenzie, and John Roberts. 2013. "Does Management Matter? Evidence from India." *Quarterly Journal of Economics* 128 (February): 1–51.

Brock, P.L. and Suarez, L.R., 2000. Understanding the behavior of bank spreads in Latin America. Journal of development Economics, 63(1), pp.113-134.

Bruhn, Miriam, Dean Karlan, and Antoinette Schoar. 2018. "The Impact of Consulting Services on Small and Medium Enterprises: Evidence from a Randomized Trial in Mexico." *Journal of Political Economy* 26(2).

Bruhn, Miriam, and David McKenzie. 2009. "In Pursuit of Balance: Randomization in Practice in Development Field Experiments." *American Economic Journal: Applied Economics* 1(4): 200–32.

Campos, Francisco, Aidan Coville, Ana Fernandes, Markus Goldstein, and David McKenzie. 2014. "Learning from the experiments that never happened: Lessons from trying to conduct randomized evaluations of matching grant programs in Africa." *Journal of the Japanese and International Economies* 33: 4-24.

CNBV. 2017. Reporte Nacional de Inclusion Financiera.

Dehejia, Rajeev H., and Sadek Wahba. 2002. "Propensity Score Matching Methods for Nonexperimental Causal Studies." *Review of Economics and Statistics* 84(1): 151–61.

Demirguc-Kunt, Asli, Leora Klapper, Dorothe Singer, and Peter Van Oudheusden. 2015. "The Global Findex Database 2014: Measuring Financial Inclusion around the World." World Bank Policy Research Working Paper No. 7255.

Dercon, Stefan. 2002. "Income risk, coping strategies, and safety nets." *The World Bank Research Observer* 17(2): 41–166.

Dupas, Pascaline and John Robinson. 2013. "Savings constraints and microenterprise development: Evidence from a field experiment in Kenya." *American Economic Journal: Applied Economics* 5(1): 163–92.

Fafchamps, Marcel. 2003. "Rural poverty, risk and development." Edward Elgar Publishing.

Ghate, Prabhu. 1992. "Informal finance: some findings from Asia." Oxford University Press.

Jacoby, Hannan G. and Emmanuel Skoufias. 1997. "Risk, financial markets, and human capital in a developing country." *The Review of Economic Studies* 64(3): 311–35.

Kazianga, Harounan. and Christopher Udry. 2006. "Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso." *Journal of Development economics* 79(2): 413–46.

Martinez Peria, M.S. and Mody, A. 2004. "How foreign participation and market concentration impact bank spreads: evidence from Latin America." *Journal of Money, Credit and Banking* 511-537.

Maudos, J. and Solís, L. 2009. "The determinants of net interest income in the Mexican banking system: An integrated model." *Journal of Banking & Finance* 33(10): 1920-1931.

Morduch, Jonathan. 1999. "Between the state and the market: Can informal insurance patch the safety net?" *The World Bank Research Observer* 14(2): 187–207.

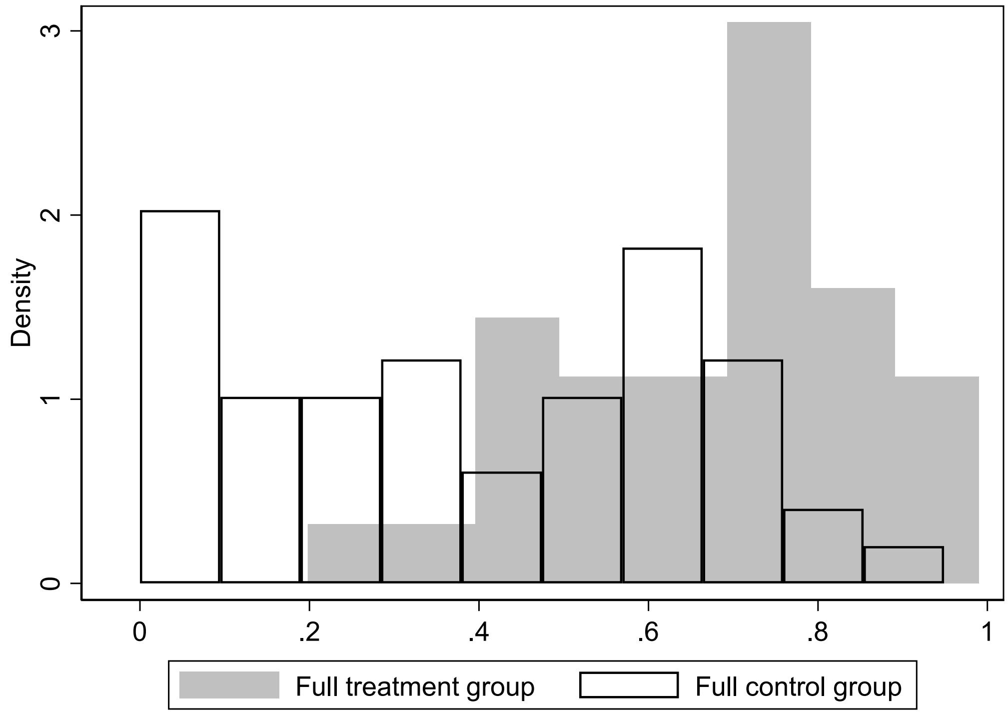
Moretto, Louise and Barbara Scola. 2017. "Development Finance Institutions and Financial Inclusion: From Institution-Building to Market Development." CGAP Focus Note. March 2017.

Onchan, Tongroj. 1992. "Informal rural finance in Thailand." Informal Finance in Low-Income Countries, ed. by DW Adams, and D. Fitchett. Westview Press, Boulder, CO.

Udry, Christopher. 1990. "Credit markets in Northern Nigeria: Credit as insurance in a rural economy." *The World Bank Economic Review* 4(3): 251–69.

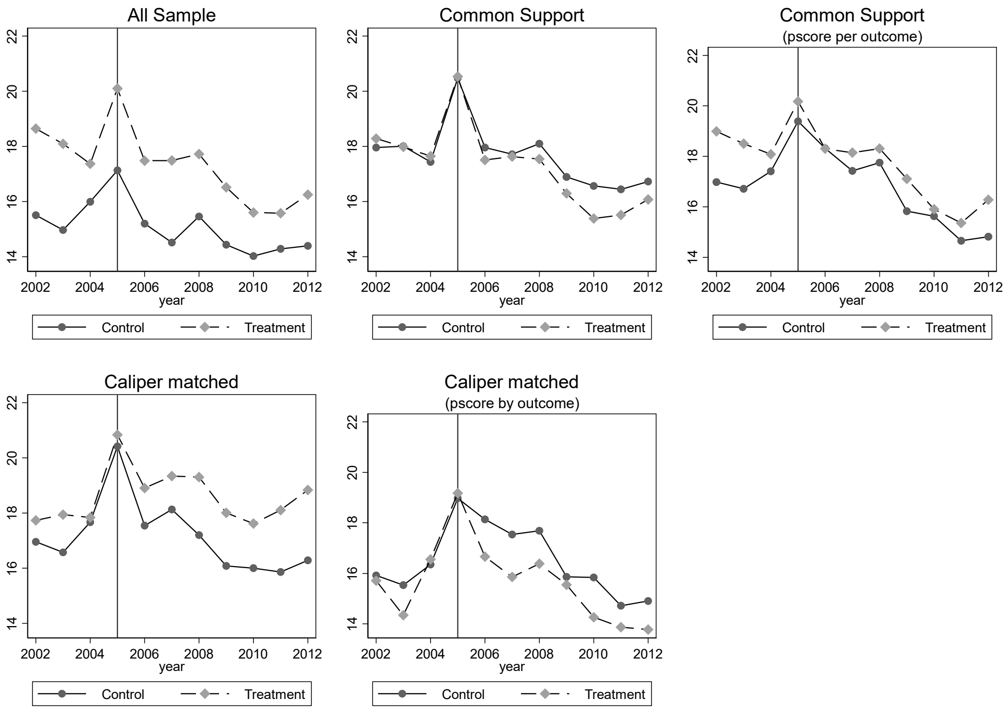
Udry, Christopher. 1994. "Risk and insurance in a rural credit market: An empirical investigation in northern Nigeria." *The Review of Economic Studies* 61(3): 495–526.

Figure 1. Propensity scores for the full treatment and control groups



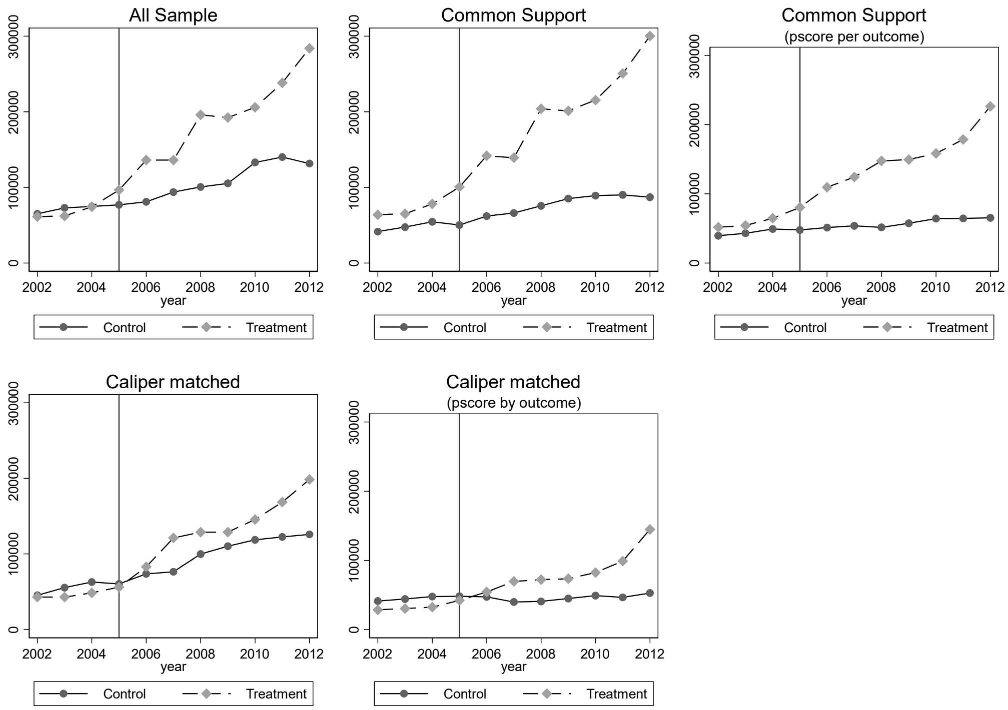
Notes: The figure plots the histogram of the propensity scores of credit unions in the treatment and control group. The scores were obtained from a probit regression of a dummy variable that equals one for credit unions in the treatment group and zero otherwise on the averages and growth rates of all outcome variables listed in table 5.

Figure 2. Lending interest rates for credit unions in the treatment and control group



Notes: The figure plots the lending interest rates of credit unions in the treatment and control groups across the three samples. For credit unions that close, lending interest rates after closing are filled in with the lending interest rates that they had in the last period before closing.

Figure 3. Total loan portfolio for credit unions in the treatment and control group



Notes: The figure plots the average total loan portfolio of credit unions in the treatment and control groups across the five samples. For credit unions that close, total loan portfolio after closing is filled in with zero.

Table 1. Number of credit unions receiving grants over time by year of first grant

	2004 Cohort	2005 Cohort	2006 Cohort	2007 Cohort	2008 Cohort	2009 Cohort	2010 Cohort	2011 Cohort	Total
2004	1	0	0	0	0	0	0	0	1
2005	1	32	0	0	0	0	0	0	33
2006	1	32	18	0	0	0	0	0	51
2007	1	28	15	7	0	0	0	0	51
2008	1	27	12	3	8	0	0	0	51
2009	1	16	6	2	5	1	0	0	31
2010	0	17	7	3	4	0	1	0	32
2011	0	14	3	4	0	0	0	1	22
2012	0	2	0	0	0	0	0	0	2

Notes: The columns classify credit unions according to the year of their first grant. The rows indicate the number of credit unions that receive grants each year.

Table 2. Number of credit unions opening a credit line with FND over time by year of first grant

	2004 Cohort	2005 Cohort	2006 Cohort	2007 Cohort	2008 Cohort	2009 Cohort	2010 Cohort	2011 Cohort	Total
2002	0	1	0	0	0	0	0	0	1
2003	0	8	1	0	0	0	0	0	9
2004	1	10	0	0	0	0	0	0	11
2005	0	1	2	0	0	0	0	0	3
2006	0	3	3	0	0	0	0	0	6
2007	0	1	0	0	0	0	0	0	1
2008	0	1	0	1	1	0	0	0	3
2009	0	1	0	0	1	0	0	0	2
2010	0	0	0	1	0	0	0	0	1
No credit line from FND	0	6	12	5	6	1	1	1	32
Total	1	32	18	7	8	1	1	1	69

Notes: The columns classify credit unions according to the year of their first grant. The rows indicate the number of credit unions that opened a credit line with FND each year.

Table 3. Number of grants over time by type of grant

	# of CUs with FND grant	# of grants	# of Technical Assistance	# Equipment	# Capitalization
	(1)	(2)	(3)	(4)	(5)
2004	1	1	1	0	0
2005	33	48	22	1	25
2006	51	102	73	12	17
2007	51	97	59	11	27
2008	51	102	57	24	21
2009	31	56	37	7	12
2010	32	55	42	6	7
2011	22	38	28	3	7
2012	2	2	1	1	0
Total grants		501	320	65	116

Notes: Columns 1 and 2 show the number of credit unions and grants provided per year. Columns 3 to 5 classify grants according to the type of program, i.e. technical assistance, purchase of equipment or capitalization. Capitalization includes credit guarantees and interest rate subsidies.

Table 4. Summary statistics for the pre-program years (2002-2004)

	Mean	Median	Std Dev
Lending interest rate (%)	16.91	16.52	7.50
Operating cost ratio (%)	8.18	6.71	5.46
NPL ratio (%)	18.98	4.43	29.68
Funding interest rate (%)	7.31	7.65	4.18
ROA (%)	-1.48	0.27	7.10
Loan portfolio (000s Mexican pesos)	68,241	25,011	139,743
Loans from members, banks or other institutions (000s Mexican pesos)	69,362	17,232	204,903

Notes: The table presents summary statistics for all 124 credit unions in our sample during the pre-program years of 2002-2004.

Table 5. Comparison of pre-program means across treated and control credit unions

	Full treatment group	Full sample		Common support		Common support (pscore by outcome)		Caliper matched		Caliper matched (pscore by outcome)	
	Mean	Normalized difference in means	*p-value*	Normalized difference in means	*p-value*	Normalized difference in means	*p-value*	Normalized difference in means	*p-value*	Normalized difference in means	*p-value*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Lending interest rate	18.030	0.342	0.002	0.027	0.832	0.254	0.079	0.134	0.401	-0.077	0.667
Operating cost ratio	7.635	-0.214	0.047	-0.163	0.181	-0.157	0.183	0.168	0.287	0.213	0.142
NPL ratio	10.168	-0.657	0.000	-0.098	0.424	-0.212	0.084	0.141	0.374	-0.004	0.977
Funding interest rate	8.390	0.572	0.000	0.369	0.004	0.540	0.000	-0.068	0.666	-0.100	0.511
ROA	-0.819	0.199	0.065	0.061	0.636	0.273	0.023	-0.073	0.648	-0.076	0.616
Loan portfolio	65,945	-0.034	0.744	0.273	0.038	0.197	0.104	-0.134	0.396	-0.247	0.094
Loans from members, banks or other institutions	62,526	-0.070	0.507	0.305	0.022	0.099	0.409	-0.118	0.456	-0.048	0.740

Notes: Column 1 shows pre-program means of credit unions in the treatment group. Columns 2 to 11 show normalized differences and corresponding p-values in the different samples. The normalized differences are calculated as $(\bar{x}_T - \bar{x}_C)/\sqrt{(\overline{s_T^2} + \overline{s_C^2})/2}$ where $\overline{x_j}$ and $\overline{s_j}$ are the sample mean and variance of the outcome for treated credit unions (j=T) and the comparison subsample from the control group (j=C) respectively (Imbens and Rubin, 2015).

Table 6. p-values of parallel trends coefficients between treated and control credit unions in the pre-program years

	Full sample	Common support	Common support (pscore by outcome)	Caliper matched	Caliper matched (pscore by outcome)
	(1)	(2)	(3)	(4)	(5)
Lending interest rate	0.317	0.931	0.293	0.679	0.819
Operating cost ratio	0.852	0.165	0.747	0.235	0.518
NPL ratio	0.044	0.842	0.931	0.509	0.319
Funding interest rate	0.020	0.085	0.118	0.651	0.831
ROA	0.652	0.906	0.900	0.864	0.519
Loan portfolio	0.726	0.896	0.610	0.169	0.676
Loans from members, banks or other institutions	0.625	0.815	0.957	0.249	0.652

Notes: The table reports the p-values for the coefficient γ of the regression $y_{it} = \alpha+\beta * Trend_t+\gamma Treatment_i * Trend_t+\varepsilon_{it}$, where α is the constant term and y_{it} corresponds to the outcome of interest (in rows) for credit union i and quarter t. $Trend_t$ is a linear time trend for the pre-program years and $Treatment_i$ is equal to 1 for credit unions in the treatment group and 0 for credit unions in the control group. ε_{it} is an error term, clustered at the credit union level. Columns 1 to 5 present the p-values for γ across the different samples.

Table 7. Comparison of means between early and late adopters three years before program

	Early adopters	Full sample late adopters		Common support		Common support (pscore by outcome)		Caliper matched		Caliper matched (pscore by outcome)	
	Mean	Normalized difference in means	*p-value*	Normalized difference in means	*p-value*	Normalized difference in means	*p-value*	Normalized difference in means	*p-value*	Normalized difference in means	*p-value*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Lending interest rate	17.782	-0.178	0.236	-0.381	0.016	0.058	0.726	-0.707	0.003	-0.317	0.232
Operating cost ratio	7.668	0.051	0.731	0.094	0.545	-0.011	0.945	0.376	0.094	0.038	0.862
NPL ratio	8.479	0.011	0.941	0.025	0.873	0.104	0.525	-0.101	0.672	-0.351	0.110
Funding interest rate	8.246	-0.081	0.588	-0.188	0.229	-0.083	0.609	-1.344	0.000	-0.067	0.758
ROA	-0.911	-0.162	0.284	-0.204	0.194	-0.087	0.611	-0.161	0.502	-0.030	0.896
Loan portfolio	77,437	-0.045	0.766	-0.055	0.729	-0.165	0.329	-0.464	0.082	-0.112	0.622
Loans from members, banks or other institutions	76,892	-0.044	0.771	-0.065	0.681	0.178	0.275	-0.451	0.091	-0.476	0.059

Notes: Column 1 shows the pre-program outcome means of early adopters, defined as treated credit unions that obtained grants for the first time in 2005. Columns 2 to 11 of the table show the normalized differences and corresponding p-values between early adopters and late adopters in the different samples. The normalized differences are calculated as $(\bar{x}_T - \bar{x}_C)/\sqrt{(\overline{s_T^2} + \overline{s_C^2})/2}$ where $\overline{x_j}$ and $\overline{s_j}$ are the sample mean and variance of the outcome for early-treated credit unions (j=T) and the comparison subsample from the group treated after 2005 (j=C) respectively (Imbens and Rubin, 2015).

Table 8. p-values of parallel trends coefficients between early and late adopters three years before program

	Full sample	Common support	Common support (pscore by outcome)	Caliper matched	Caliper matched (pscore by outcome)
	(1)	(2)	(3)	(4)	(5)
Lending interest rate	0.295	0.554	0.129	0.372	0.590
Operating cost ratio	0.204	0.211	0.290	0.721	0.873
NPL ratio	0.482	0.370	0.159	0.667	0.973
Funding interest rate	0.002	0.001	0.039	0.343	0.731
ROA	0.334	0.181	0.227	0.156	0.102
Loan portfolio	0.241	0.249	0.250	0.280	0.587
Loans from members, banks or other institutions	0.251	0.267	0.474	0.285	0.176

Notes: The table reports the p-values for the coefficient γ of the regression $y_{it} = \alpha+\beta*Trend_t+\gamma Treatment_i*Trend_t+\varepsilon_{it}$, where α is the constant term and y_{it} corresponds to the outcome of interest (in rows) for credit union i and quarter t. $Trend_t$ is a linear time trend for the three years before each credit union started the program and $Treatment_i$ is equal to 1 for treated credit unions that participated in the program by 2005 and 0 for treated credit unions that participated in years after. ε_{it} is an error term, clustered at the credit union level. Columns 1 to 5 present the p-values for γ across the different samples.

Table 9. Impact of grants on probability of survival

	Full sample	Common support	Caliper matched
	(1)	(2)	(3)
Treatment dummy	0.21***	0.12***	0.10**
	[0.041]	[0.039]	[0.045]
Constant	1.00***	1.00***	1.00***
	[0.016]	[0.014]	[0.019]
Observations	1,364	1,056	638
R-squared	0.56	0.476	0.478
# of treated credit unions	65	60	29
# of control credit unions	59	36	29

Notes: This table eports the results of the regression $y_{it} = \alpha_i + \beta_t + \gamma Treatment_{it} + \varepsilon_{it}$, where y_{it} is an indicator variable that equals 1 if credit union *i* is still operating in year *t* and 0 if the credit union closed. α_i is a credit union fixed effect, and β_t is a year fixed effect. The variable $Treatment_{it}$ is equal to 1 for a given credit union i in the year t where it received the first benefit through the program and for all years thereafter. It is equal to 0 for all years before the credit union received the first benefit through the program. ε_{it} is an error term, clustered at the credit union level. Columns 1 to 3 present the regression results across the different samples.

Table 10. Impact of grants on lending interest rate

	Full sample	Common support	Common support (pscore by outcome)	Caliper matched	Caliper matched (pscore by outcome)
	(1)	(2)	(3)	(4)	(5)
Panel A: Lower bound- Assume closed credit unions have same lending interest rate as in last observed year					
Treatment dummy	-1.06	-0.8	-0.77	0.9	-0.71
	[1.169]	[1.280]	[0.988]	[1.335]	[1.047]
Constant	16.87***	17.83***	18.38***	16.83***	15.89***
	[0.624]	[0.585]	[0.666]	[0.656]	[0.715]
R-squared	0.581	0.526	0.599	0.594	0.633
Panel B: Upper bound- Assume closed credit unions have highest lending interest rate observed for the same credit union					
Treatment dummy	-3.74***	-2.58**	-2.20**	-0.4	-1.33
	[1.126]	[1.253]	[0.910]	[1.345]	[1.206]
Constant	16.99***	17.90***	18.37***	16.97***	15.89***
	[0.606]	[0.557]	[0.638]	[0.609]	[0.703]
Observations	1,199	956	785	572	440
R-squared	0.572	0.555	0.639	0.59	0.617
# of treated credit unions	59	56	51	26	21
# of control credit unions	49	31	24	24	21

Notes: Panel A reports the results of the regression $y_{it} = \alpha_i+\beta_t+\gamma Treatment_{it}+\varepsilon_{it}$, where y_{it} is the lending interest rate of credit union *i* in year *t*. α_i is a credit union fixed effect, and β_t is a year fixed effect. The variable $Treatment_{it}$ is equal to 1 for a given credit union i in the year t where it received the first benefit through the program and for all years thereafter. It is equal to 0 for all years before the credit union received the first benefit through the program. ε_{it} is an error term, clustered at the credit union level. Columns 1 to 5 present the regression results across the different samples. For credit unions that close, lending interest rates after closing are filled in with values based on the two different assumptions presented in Panels A and B.

Table 11. Impact of grants on operating cost ratio

	Full sample	Common support	Common support (pscore by outcome)	Caliper matched	Caliper matched (pscore by outcome)
	(1)	(2)	(3)	(4)	(5)
Panel A: Lower bound- Assume closed credit unions have same operating cost ratio as in last observed year					
Treatment dummy	-1.13*	-0.68	-0.77	-0.52	-0.64
	[0.589]	[0.666]	[0.651]	[0.912]	[0.723]
Constant	8.36***	7.81***	8.02***	8.31***	7.44***
	[0.402]	[0.411]	[0.447]	[0.638]	[0.563]
R-squared	0.771	0.703	0.773	0.681	0.665
Panel B: Upper bound- Assume closed credit unions have highest operating cost ratio observed for the same credit union					
Treatment dummy	-2.22***	-1.33*	-1.48**	-1.24	-1.52*
	[0.651]	[0.734]	[0.724]	[1.037]	[0.814]
Constant	8.42***	7.80***	8.01***	8.30***	7.44***
	[0.397]	[0.424]	[0.465]	[0.669]	[0.591]
Observations	1,243	966	970	576	670
R-squared	0.768	0.703	0.757	0.666	0.649
# of treated credit unions	61	57	53	26	32
# of control credit unions	53	33	40	26	32

Notes: The table reports the results of the regression $y_{it} = \alpha_i+\beta_t+\gamma Treatment_{it}+\varepsilon_{it}$, where y_{it} is the NPL ratio of credit union *i* in year *t*. α_i is a credit union fixed effect, and β_t is a year fixed effect. The variable $Treatment_{it}$ is equal to 1 for a given credit union i in the year t where it received the first benefit through the program and for all years thereafter. It is equal to 0 for all years before the credit union received the first benefit through the program. ε_{it} is an error term, clustered at the credit union level. Columns 1 to 5 present the regression results across the different samples. For credit unions that close, their operating cost ratios after closing are filled in with values based on the three different assumptions presented in Panels A and B.

Table 12. Impact of grants on NPL ratio

	Full sample	Common support	Common support (pscore by outcome)	Caliper matched	Caliper matched (pscore by outcome)
	(1)	(2)	(3)	(4)	(5)
Panel A: Lower bound- Assume closed credit unions have same NPL ratio as in last observed year					
Treatment dummy	-0.26	-2.31	-0.76	-1.29	-0.68
	[3.682]	[3.205]	[3.330]	[3.230]	[3.742]
Constant	21.78***	11.27***	12.05***	9.56***	13.03***
	[2.151]	[1.811]	[1.932]	[1.972]	[2.202]
R-squared	0.736	0.466	0.517	0.432	0.55
Panel B: Upper bound- Assume closed credit unions have highest NPL ratio observed for the same credit union					
Treatment dummy	-2.69	-5.68*	-4.37	-3.97	-4.77
	[3.772]	[3.311]	[3.438]	[3.700]	[3.884]
Constant	21.76***	11.26***	12.08***	9.52***	13.07***
	[2.155]	[1.803]	[1.926]	[2.090]	[2.189]
Observations	1,248	964	854	576	611
R-squared	0.734	0.53	0.567	0.474	0.601
# of treated credit unions	62	57	51	26	29
# of control credit unions	54	33	31	26	29

Notes: The table reports the results of the regression $y_{it} = \alpha_i + \beta_t + \gamma Treatment_{it} + \varepsilon_{it}$, where y_{it} is the lending interest rate of credit union *i* in year *t*. α_i is a credit union fixed effect, and β_t is a year fixed effect. The variable $Treatment_{it}$ is equal to 1 for a given credit union i in the year t where it received the first benefit through the program and for all years thereafter. It is equal to 0 for all years before the credit union received the first benefit through the program. ε_{it} is an error term, clustered at the credit union level. Columns 1 to 5 present the regression results across the different samples. For credit unions that close, their NPL ratios after closing are filled in with values based on the three different assumptions presented in Panels A and B.

Table 13. Impact of grants on funding interest rate

	Full sample	Common support	Common support (pscore by outcome)	Caliper matched	Caliper matched (pscore by outcome)
	(1)	(2)	(3)	(4)	(5)
Panel A: Lower bound- Assume closed credit unions have same funding interest rate as in last observed year					
Treatment dummy	-0.24	-0.18	0.18	0.65	1.25*
	[0.508]	[0.570]	[0.554]	[0.682]	[0.680]
Constant	7.81***	8.53***	7.75***	7.40***	7.49***
	[0.335]	[0.370]	[0.371]	[0.506]	[0.447]
R-squared	0.612	0.552	0.608	0.513	0.635
Panel B: Upper bound- Assume closed credit unions have highest funding interest rate observed for the same credit union					
Treatment dummy	-1.40***	-1.18**	-0.98**	-0.24	0.18
	[0.477]	[0.473]	[0.488]	[0.612]	[0.625]
Constant	7.83***	8.51***	7.74***	7.37***	7.50***
	[0.304]	[0.342]	[0.332]	[0.460]	[0.396]
Observations	1,248	968	1,007	577	616
R-squared	0.593	0.521	0.562	0.472	0.58
# of treated credit unions	60	56	53	25	29
# of control credit unions	54	33	43	26	29

Notes: The table reports the results of the regression $y_{it} = \alpha_i + \beta_t + \gamma Treatment_{it} + \varepsilon_{it}$, where y_{it} is the ROA of credit union *i* in year *t*. α_i is a credit union fixed effect, and β_t is a year fixed effect. The variable $Treatment_{it}$ is equal to 1 for a given credit union i in the year t where it received the first benefit through the program and for all years thereafter. It is equal to 0 for all years before the credit union received the first benefit through the program. ε_{it} is an error term, clustered at the credit union level. Columns 1 to 5 present the regression results across the different samples. For credit unions that close, their funding interest rates after closing are filled in with values based on the three different assumptions presented in Panels A and B.

Table 14. Impact of grants on ROA

	Full sample	Common support	Common support (pscore by outcome)	Caliper matched	Caliper matched (pscore by outcome)
	(1)	(2)	(3)	(4)	(5)
Panel A: Lower bound- Assume closed credit unions have same ROA as in last observed year					
Treatment dummy	0.67	1.04	-0.17	0.27	1.62
	[0.902]	[1.009]	[0.997]	[1.105]	[1.253]
Constant	-1.60**	-0.39	-1.11	-0.53	-0.06
	[0.708]	[0.464]	[0.755]	[0.531]	[0.655]
R-squared	0.382	0.369	0.322	0.386	0.337
Panel B: Upper bound- Assume closed credit unions have lowest ROA observed for the same credit union					
Treatment dummy	4.05***	2.68**	2.98**	2.1	4.58***
	[1.311]	[1.338]	[1.455]	[1.574]	[1.677]
Constant	-1.63**	-0.38	-1.12	-0.52	-0.04
	[0.729]	[0.634]	[0.723]	[0.915]	[0.914]
Observations	1,240	964	922	573	606
R-squared	0.518	0.402	0.467	0.416	0.428
# of treated credit unions	60	57	51	26	29
# of control credit unions	51	31	37	24	29

Notes: The table reports the results of the regression $y_{it} = \alpha_i+\beta_t+\gamma Treatment_{it}+\varepsilon_{it}$, where y_{it} is the operating cost ratio of credit union *i* in year *t*. α_i is a credit union fixed effect, and β_t is a year fixed effect. The variable $Treatment_{it}$ is equal to 1 for a given credit union i in the year t where it received the first benefit through the program and for all years thereafter. It is equal to 0 for all years before the credit union received the first benefit through the program. ε_{it} is an error term, clustered at the credit union level. Columns 1 to 5 present the regression results across the different samples. For credit unions that close, their ROA indicators after closing are filled in with values based on the three different assumptions presented in Panels A and B.

Table 15. Impact of grants on total loan portfolio

	Full sample	Common support	Common support (pscore by outcome)	Caliper matched	Caliper matched (pscore by outcome)
	(1)	(2)	(3)	(4)	(5)
Panel A: Main specification					
Treatment dummy	65,574.23*	73,356.21**	65,963.94**	48,202.67	35,163.52*
	[38,957.154]	[34,244.390]	[32,154.173]	[55,756.606]	[18,303.887]
Constant	60,060.58***	52,592.26***	47,880.12***	42,272.59*	36,098.90***
	[18,119.354]	[19,547.730]	[13,708.330]	[23,109.068]	[9,839.847]
Observations	1,225	958	981	574	641
R-squared	0.78	0.715	0.68	0.707	0.515
# of treated credit unions	62	57	54	26	31
# of control credit unions	54	33	41	26	31
Panel B: Controlling for FND loans					
treat_all	69,614.68	80,036.11*	66,896.58	60,509.41	31,451.38*
	[47,102.527]	[45,007.339]	[40,845.715]	[65,158.755]	[17,307.377]
dum_fndloan	-12,923.26	-21,597.03	-3,167.42	-62,801.26	14,669.08
	[44,422.792]	[48,761.600]	[41,450.247]	[57,864.328]	[12,347.561]
Constant	60,228.21***	52,934.39***	47,890.73***	43,299.83*	36,089.52***
	[17,811.809]	[19,084.405]	[13,640.861]	[22,159.427]	[9,707.361]
Observations	1,225	958	981	574	641
R-squared	0.78	0.715	0.68	0.709	0.515
# of treated credit unions	62	57	54	26	31
# of control credit unions	54	33	41	26	31
Panel C: Only credit unions without FND loans					
Treatment dummy	53,637.89	70,088.03	72,851.60	86,419.98	101,367.90
	[58,546.539]	[56,326.324]	[55,168.629]	[77,004.427]	[68,021.750]
Constant	58,246.65***	45,781.23**	39,652.53**	47,558.35	37,619.94
	[20,044.307]	[19,978.620]	[17,177.803]	[31,833.592]	[25,585.777]
Observations	855	616	685	381	415
R-squared	0.806	0.707	0.714	0.707	0.718
# of treated credit unions	28	26	27	18	20
# of control credit unions	54	33	40	19	20

Notes: Panel A reports the results of the regression $y_{it} = \alpha_i+\beta_t+\gamma Treatment_{it}+\varepsilon_{it}$, where y_{it} is the total loan portfolio of credit union *i* in year *t*. α_i is a credit union fixed effect, and β_t is a year fixed effect. The variable $Treatment_{it}$ is equal to 1 for a given credit union i in the year t where it received the first benefit through the program and for all years thereafter. It is equal to 0 for all years before the credit union received the first benefit through the program. ε_{it} is an error term, clustered at the credit union level. Columns 1 to 5 present the regression results across the different samples. Panel B includes in the regression an indicator variable that equals 1 in the first year where a credit union obtained a loan from FND and in all following years, and 0 in all years before a credit union obtained a loan from FND (or for all years for credit unions that did not obtained a loan from FND by 2012). Panel C restricts the sample to credit unions that did not obtain an FND loan by 2012.

Table 16. Impact of grants on loans from members, banks or other institutions

	Full sample	Common support	Common support (pscore by outcome)	Caliper matched	Caliper matched (pscore by outcome)
	(1)	(2)	(3)	(4)	(5)
Panel A: Main specification					
Treatment dummy	94,390.32**	100,029.07**	57,875.12***	84,829.96	36,648.84**
	[45,387.336]	[44,374.747]	[20,885.581]	[76,883.932]	[15,114.512]
Constant	57,866.23***	45,971.07**	40,500.83***	33,708.71	25,354.69***
	[20,607.185]	[22,711.001]	[10,368.408]	[29,114.043]	[5,260.540]
Observations	1,254	969	987	578	667
R-squared	0.815	0.709	0.645	0.687	0.717
# of treated credit unions	62	57	52	26	32
# of control credit unions	54	33	42	26	32
Panel B: Controlling for FND loans					
treat_all	102,205.96*	110,664.79*	48,464.45**	101,126.63	39,038.11**
	[57,839.341]	[59,302.763]	[21,181.375]	[90,946.386]	[17,295.535]
dum_fndloan	-24,932.66	-34,295.62	30,349.39	-82,957.40	-10,350.62
	[54,758.217]	[60,261.664]	[24,437.260]	[80,571.119]	[15,928.211]
Constant	58,124.19***	46,455.88**	40,452.97***	35,025.56	25,349.37***
	[20,309.924]	[22,212.799]	[10,200.710]	[27,885.473]	[5,250.251]
Observations	1,254	969	987	578	667
R-squared	0.815	0.709	0.647	0.689	0.717
# of treated credit unions	62	57	52	26	32
# of control credit unions	54	33	42	26	32
Panel C: Only credit unions without FND loans					
Treatment dummy	88,093.99	102,113.54	34,363.11	122,839.62	31,668.22*
	[76,700.243]	[78,639.631]	[20,989.871]	[106,767.834]	[17,779.024]
Constant	58,192.20**	40,590.08	34,458.41***	41,649.80	29,199.85***
	[23,252.811]	[24,619.102]	[8,637.507]	[40,276.509]	[6,592.394]
Observations	884	628	701	383	482
R-squared	0.845	0.686	0.688	0.688	0.71
# of treated credit unions	28	26	26	18	23
# of control credit unions	54	33	41	19	23

Notes: Panel A reports the results of the regression $y_{it} = \alpha_i+\beta_t+\gamma Treatment_{it}+\varepsilon_{it}$, where y_{it} is the amount of loans from members, banks or other institutions obtained by credit union *i* in year *t*. α_i is a credit union fixed effect, and β_t is a year fixed effect. The variable $Treatment_{it}$ is equal to 1 for a given credit union i in the year t where it received the first benefit through the program and for all years thereafter. It is equal to 0 for all years before the credit union received the first benefit through the program. ε_{it} is an error term, clustered at the credit union level. Columns 1 to 5 present the regression results across the different samples. Panel B includes in the regression an indicator variable that equals 1 in the first year where a credit union obtained a loan from FND and in all following years, and 0 in all years before a credit union obtained a loan from FND (or for all years for credit unions that did not obtained a loan from FND by 2012). Panel C restricts the sample to credit unions that did not obtain an FND loan by 2012.