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Can microcredit impact the activity of small and medium enterprises? New evidence from a Regression Discontinuity Design in Panama

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Can microcredit impact the activity of small and medium enterprises? New evidence from a Regression Discontinuity Design in Panama*

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Abstract

In this paper, we conduct an impact analysis of microcredit on entrepreneurial activity using a new data-set collected among 740 entrepreneurs located in Panama. Our focus is on a new type of microfinance institution which grants loans to enterprises falling in what we call the financial missing middle, i.e., enterprises which are too big for traditional microcredit but not big enough for commercial banks. We collected an unbalanced panel of data on enterprise's business and credit history. Using our partner's rules of credit attribution, we build a regression discontinuity design to evaluate the effect of loan's obtainment on the activity of financed enterprises. Our results show a limited impact of access to credit on firm's revenues despite a significant impact on investment in equipment and immobilization. The magnitude of the positive effect is higher on micro-enterprises while auto-enterprises are negatively impacted by microcredit as is usually documented in the literature. We emphasize that the cost of credit is one of the major determinants of the limited impact of microcredit on entrepreneurial activity.

JEL codes : D22, G21, L26, O12, O16
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1. Introduction

Evaluating microcredit's impact on its beneficiaries has been a major topic of interest for both development researchers and policymakers over the past two decades (Banerjee, 2013; Fouillet and al., 2013) as it was seen as a useful tool for poverty reduction. Unfortunately, the literature converges toward a conclusion arguing that microcredit has no or at the best a very limited impact on its users. The most recent evidence is provided by the compilation of six randomized control trial studies in a special issue of the American Economic Journal: Applied Economics in January 2015 (Banerjee et al., 2015). Indeed, all six experiments conducted in different countries over four continents, found no significant impact of microfinance institutions (MFIs) on their client's welfare.

One common trend that these studies share with all other microcredit's impact evaluations, since Pitt and Khandker (1998)'s seminal contribution is their focus on the so-called traditional MFIs (generally small loans, gender oriented, group-based lending). Indeed, microcredit primary objective is to provide access to financial services for people who are excluded from the market by commercial banks. By offering funds for the creation and/or extension of an income generating activity, MFIs seeks to pull their clients out of poverty. Thus, most of the literature on microcredit's impact evaluation uses measures of clients economic and social welfare as dependent variables. By doing so, these studies ignore an important mechanism of microcredit: resources obtained through MFIs are mainly intended to finance business activities that generate enough revenues to repay the loan. Consumption or other sources of welfare improvement are indeed secondary measures of microcredit's impact because only the surplus left after loan repayment should be allocated to the growth of these variables. Also, it is standard in the literature to use a difference-in-difference approach to evaluate the effect of microcredit on its beneficiaries. This methodology is regularly criticized (Hulme, 2000) for various reasons: sample bias selection (Morduch, 1999, 2000), the construction of the control group (Karlan, 2001), the external validity of such case studies.

The objective of the present paper is twofold. First, we present a model of microcredit's impact evaluation based on a partnership with a new type of MFI in Panama which focuses on a new range of clients: enterprises trapped in what we call the missing middle of financial markets. This segment regroups all enterprises with financial needs exceeding the funding capacity of traditional MFIs while remaining too small to interest commercial banks. Second, we build a new model of microcredit's impact analysis using a regression discontinuity (RD) approach based on our partner MFI's credit attribution rules. Our estimation is performed on a sample of micro, small and medium enterprises (MSME) that are representative of the potential clientele of our partner MFI. We collected the data in July 2014 during a field investigation covering the four main provinces of Panama in terms of economic activity and population. Our sample includes both clients of our partner MFI and others financial institutions such as traditional MFI, commercial banks or direct competitors of our partner. Some entrepreneurs with no access to financial services constitute a control group for evaluating the effect of loan obtainment on entrepreneurial activity.

Our paper fall within a pretty recent trend in the literature on microcredit's impact evaluation which focuses on variables measuring business activity. It can be related to previous papers from Cotler and Woodruff (2008) in Mexico and Banerjee et al. (2010) in India. But these studies are also focused on traditional MFIs that are known for targeting enterprises operating on a scale that is too small to generate macroeconomics effects on employment or growth. We choose to focus on enterprises that are usually unserved by financial institutions because their needs exceed the funding capacity of traditional MFI's while their characteristics do not fulfill the eligibility criterion of commercial banks. Yet, these enterprises compose the majority of developing countries entrepreneurial base. Our partner MFI has the objective to develop a dynamic private sector able to create jobs and promote economic growth. Thus, its targets this type of enterprises by offering loans ranging from 1 000$ to 50 000$ with maturity dates going from 12 to 80 months. But, given the interest rates situated between 20 and 35% per year, these loans are still considered as microcredit despite the amount and the maturity that are significantly higher than what is seen with traditional MFIs.

Another contribution of our paper is the use of a methodology that exploits the existence of a discontinuity in the distribution of entrepreneurs generated by the application of a loan eligibility criterion. Indeed, like all financial institutions, our partner MFI is concerned by his loans repayment rates and thus only attributes credit to entrepreneurs that may generate enough revenues to cover their loan and interest repayment. In practice, for each applicant, the MFI calculates the debt-to-income ratio by dividing the sum of all his revenues[*] with the monthly amount due for the repayment of the loan he is applying for. The discontinuity into the distribution of entrepreneurs is created by the existence of a threshold value for that debt-to-income ratio below which the MFI considers that an applicant is not eligible for the required loan. To build our empirical model of RD design, we follow the recommendations of Lee and Lemieux (2010) to ensure that the existence of this discontinuity is exogenous from the entrepreneur's point of view. As the value of the threshold is only known to the MFI, we formulate the hypothesis that an entrepreneur cannot manipulate his information to self-select on either side of the threshold. We test empirically for evidence of self-selection by using the test developed by McCrary (2008) to verify the continuity of our assignment variable (the value of the debt-to-income ratio) around the threshold value. We estimate our empirical model with the new methodology developed by Calonico et al. (2014a, b) that produces RD estimates and associated confidence intervals that both are robust to the bandwidth choice. By doing so, they correct the propensity of previous RD estimations techniques to over-reject the null hypothesis of no treatment effect. Our analysis is centered on the average loan granted by our partner MFI in 2014. At 6 000$, this amount is significantly higher than what is studied in

[*] Which are enterprise's profits plus all other activities revenues net from all household expenses and other loans repayment fees.

the existing microcredit's impact evaluation literature. Our results show a positive and significant effect of loan obtainment on the level of investment measured both by equipment (working capital) or long term fixed assets (immobilization). There is also a positive effect on the amount of revenue generated by the entrepreneurial activity although its magnitude is smaller and more variable than what is obtained on the two measures of investment. These effects appear to be conditioned by the rigor with which the eligibility rule is determined across different financial institutions as shown by three alternate RD setups: sharp RD (strict application of the rule), Fuzzy I RD (treatment group include all eligible entrepreneurs) and Fuzzy II RD (treatment group comprise ineligible entrepreneurs whom got a loan nonetheless). By progressively introducing eligible non-financed and non-eligible financed entrepreneurs into the treatment group, we seek to investigate the role of credit costs on the evaluation of microcredit's impact. Indeed, the eligibility rule being dependent on the credit attribution conditions (amount, duration, interest rate), going from sharp to fuzzy design correspond to a relaxation of the rule and thus to a reduction of credit costs. It appears that our partner MFI’s rule is too restrictive for a 6 000$ loan because the inclusion of non-eligible financed entrepreneurs raises the magnitude of estimated effects from loan obtainment. Decomposing these results by enterprise's size shows that the positive effects of loan obtainment are concentrated on microenterprises while auto-enterprises (no employee other than the owner) are negatively affected as is documented in the literature. To test the robustness of our results to the choice of loan amount, we replicate the analysis on two other loan sizes: the average loan in our sample (13 688$) and the highest loan that is frequently granted by our partner (30 000$).

The rest of the paper is organized as follows. A first section introduces some facts about our partner MFI and its position in the Panamanian financial sector before presenting the structure of the data used in this paper. In section 3, we present the details of our identification strategy using the threshold generated by our partner MFI's credit eligibility criterion to build our RD model. Section 4 starts with the tests assessing the validity of our empirical methodology before reviewing the main results investigating the effects of the 6 000$ loan amount on entrepreneurial activity in Panama. Finally, before conclusion, section 5 presents the results of robustness checks.

2. Data and descriptive statistics

Our data-set was collected during a field study in July 2014 with the collaboration of a new type of MFI established in Panama since 2010. At that date, the MFI had a portfolio of 2 500 clients worth of 14 millions of US dollars in gross loans. A particular feature of this MFI is its focus on the enterprises of the missing middle of financial markets i.e. enterprises that are too big for traditional MFIs but not large enough for commercial bank's standards. Offered loans go from 1 000 to 50 000$ with associated maturity dates between 12 and 80 months and interest rates of 20 to 35% per year. With an average loan of approximately 6 000$, our partner is very different from traditional MFI usually studied in the literature on microcredit's impact evaluation. It is an important actor on the Panamanian microfinance market that is constituted among others by 11 traditional MFIs and 5 commercial banks operating with microfinance licenses. Graphic 1 in appendix A presents the average loan granted by some financial institutions[*] included in our study sample.

We notice that commercial banks (Banco General and Nacional) usually offers loan amounts that are higher than those of our partner while traditional MFI's (Microserfin and Azteca) are on a smaller segment of the market. It also seems that our partner has two direct competitors on its enterprise's financial missing middle segment (Banco Delta and Continental). Despite the large number of financial institutions of different types offering credit on the Panamanian

[*] Our sample contains clients of approximately 50 different financial institutions. Graphic 1 presents the two most important commercial banks and traditional MFIs alongside with the two competitors of our partner in the financial missing middle.

market, approximately one-third of the 543 000 MSME accounted for throughout the country are unserved according to a report published in 2010 by the Panamanian Microfinance Network called REDPAMIF. Hence, we designed our survey so our sample is representative of the population of MSME in Panama with this particular feature pointed out by the REDPAMIF. Moreover, these firms represent the population of potential clients for MFIs targeting the missing middle. Starting with our partner business plan, we identified the profile of the MSME that are likely to be its client and planned a random data collection among those enterprises (for more details on our survey design, refer to Diallo and Goyette (2016)). We conducted 740 interviews on a representative set of MSME located across the country and collected data on their activity and credit history. Overall, our sample is composed of 255 entrepreneurs with an outstanding loan for their activity and 485 entrepreneurs with no access to financial services. Among the latter, there are 225 entrepreneurs that declared they did not want to apply for a credit or did not need more capital. That leaves us with 260 entrepreneurs who are credit constrained, meaning they need to borrow for investment but doesn’t have access to financial services. The proportion of 35% of credit constrained MSME in our sample is very close to the 33% identified in the REDPAMIF report in 2010. Also, our investigation covers the four main provinces (Panama, Chiriquí, Coclé and Veraguas) which account for more than 90% of the economic activity in Panama and where 7 of the 9 branches of our partner MFI are located. Figure 2 presents the map of Panama with the geographical coverage of our data collection.

The data-set contains information on the entrepreneur socioeconomic characteristics, his entrepreneurial activity and his access to financial services whether it is for personal or professional use. By asking information on credit and loans at different dates, we build an unbalanced panel data on enterprise's business and credit history. The data structure allows us to perform the necessary cross-verifications for implementing a RD design according to Lee and Lemieux (2010):

- Ensuring the comparability of the financed and non-financed enterprises prior to loan obtainment with the data at the enterprise's creation date;
- Calculating the debt-to-generated income ratio in 2009 in order to evaluate the eligibility to the treatment according to our partner MFI rules right before the start of its operations;
- Assessing the impact of loan obtainment up to 4 years after the treatment by estimating the difference in the measures of entrepreneurial activity between the treatment and control groups in 2014.

Before discussing all the model specifications and estimation results, we first present in table 1 some descriptive statistics on different measures of entrepreneurial activity. These statistics permit us to outline the profile of the average enterprise in our sample which operates mainly into four sectors: retail (36%), services (24%), manufacturing (9.5%) and housing/food services (9%). This sectoral distribution is similar to what is observed in the Panamanian economy in its entirety. With an annual revenue of 120 864$ and 2.6 employees, the average enterprise of our sample fall in the range of micro-enterprises accordingly to the World Bank classification. Indeed, the last Panamanian World Bank Enterprises Survey (WBES) which focus on medium and large enterprises were conducted in 2010 and surveyed firms that have in average 149 000 000$ in sales and 25.7 employees. Also enterprises in our sample are younger than those of the WBES with an average of 10 years of activity compared to 16 in the WBES.

Self-employment is very common in our sample as two third of the entrepreneurs declare their business as being their only activity. For the financial access, approximately one third of the enterprises in our sample possesses a loan for their business. We recall that 35% of the entrepreneurs in our sample were credit constrained because they did not have access to financial services while they needed capital to invest in their business. The rest of the sample respond that they did not need more capital to operate their enterprise. We use these differences to build our empirical model presented in the next section.

3. The model

To evaluate the impact of loan obtainment on entrepreneurial activity, we build an empirical model that can be described by the following general equation:

$$Y_i = \alpha + \beta T_i + X_i + \varepsilon_i \quad (1)$$

Where *Yi* is our variable of interest, which successively indicates for each entrepreneur *i*, different measures of entrepreneurial activity (see table 1): annual value of revenues, costs of exploitation, fixed assets and equipments, number of employees and monthly cost of wages. X_i is the set of control variables later identified in subsection 3.2. Variable *Ti* indicates the treatment (loan obtainment) and is evaluated in 2009, the last year prior to the beginning of our partner's activity in Panama. Its dichotomic value (0 or 1) is determined by the entrepreneur's capacity to obtain a loan following the eligibility criterion set by our partner MFI. This criterion compares, for each applicant entrepreneur, the debt-to-generated income ratio (or more shortly the debt coverage ratio which we note DC_i) with a threshold value *s* for each loan size. Mathematically, treatment is allocated accordingly to the following equation:

$$T_i = \begin{cases} 0 \ if \ DC_i < s \\ 1 \ if \ DC_i \geq s \end{cases} \quad (2)$$

For each entrepreneur, the value of DC_i is calculated by dividing all his revenues net from all his expenses by the monthly repayment associated with the loan he is applying for. This monthly repayment itself is defined into the MFI's confidential credit policy by a special formula that combines loan's amount, duration and the associated interest rate. *s* is the threshold value for DC_i below which an entrepreneur *i* is considered non-eligible for a specific loan. Different values for *s* are defined for each loan size into the confidential credit policy of our partner MFI thus creating an exogenous discontinuity in the distribution of entrepreneurs. Next subsection explains in more details the setting of the eligibility criterion and why we can use it to design the RD model for our empirical approach.

3.1. Identification

Our model is built on the existence of a discontinuity in the entrepreneur's distribution around a specific value for the debt coverage ratio. For our approach to be valid, this threshold value needs to be exogenous from the entrepreneur's point of view, meaning he cannot manipulate directly his DC_i value in order to place himself on one side or the other of the threshold. To verify this, we first present theoretically the multi-stage process through which our partner MFI grants his loans and later we show some empirical evidence for the exogeneity of the threshold in subsection 4.1.1.

Like all MFIs in the world, our partner has credit officers who actively look for new clients on the field and act as loans seller. They have at their disposal a methodological guide for identifying potential clients and filling a loan application. The credit officer collects all the relevant data on the potential client before submitting the application to his branch manager (our partner currently has 9 branches in Panama). The manager performs a preliminary check to ensure that the application contains all the required information and then hands it to the credit analyst (at the MFI headquarters) whose job is twofold. First he compares the information collected by the credit officers with those contained in the MFI client’s database covering all the sectors of the economy. The analyst can even perform a surprise visit to the potential client in order to verify the existence of the business and his performances. Second, he ensures that credit conditions proposed by the credit officer respect the MFI's confidential credit policy (amount, maturity, interest rate, collateral). Then, he calculates the DC_i value and compares it to a specific threshold also defined into the confidential credit policy. For example, an entrepreneur is eligible for a 30 000$ loan if his debt-coverage ratio is at least 1.25, meaning his monthly generated revenues represents a minimum of 1.25 times the monthly payment due for that loan.

It's only when these steps are completed that the loan application is finally introduced to the credit committee who has the final word on all applications. For our partner MFI, approximately 50% of the applications filled by the credit officers pass the verification process and are submitted to the credit committee. Once the committee approves the application, before loan disbursement, all the documents and possessions presented as collateral by the applicant as guarantees have to be reviewed and validated by the legal department. Any inconsistency in that step can also lead to the rejection of the application. During the whole process, the potential client has the possibility to withdraw his application, especially if the conditions offered by the credit officer happen to be modified.

But apart from his first contact with the credit officer or exceptionally with the credit analyst in case of a field verification, the applicant has no other interaction with any of the MFI's decision-maker. Plus, credit officers do not have the instructions contained into the confidential credit policy and thus cannot share them with the applicant to influence the information collected into the loan application form. Only the credit analyst is qualified to perform the ratio calculation and decides whether he submits or not an application to the credit committee which decide to grant or not the credit. Thus, loan obtainment is considered as random from entrepreneur's point of view since the applicant cannot directly influence the decisions of the credit analyst and the credit committee. We consider that the rule defining loan's eligibility is exogenous meaning entrepreneurs cannot self-select on one side or the other of the threshold. We verify this by performing an empirical test with the procedure proposed by McCrary (2008) in subsection 4.1.1.

Thus, the treatment group is constituted of all eligible entrepreneurs according to the criterion defined in our partner MFI's confidential credit policy. For the purpose of our study, we negotiated an access to that document and apply this rule to all entrepreneurs in our sample. Given the high number of possible loan amounts, we have to set some particular loan sizes where we will evaluate the impact of loan obtainment on entrepreneurial activity (β parameter's value). We consider the average loan size granted by our partner in 2014 for the core of our analysis. This 6 000$ amount appears to be relevant in regards of the features of both our sample and our partner MFI but also to some characteristics of the enterprises studied here. Indeed, given the revenues generated by these enterprises (see table 1) and their monthly profit of approximately 6 000$, they seem to be able to afford the repayment fees due for a 6 000$ loan. Plus, one specific of the Latin American microcredit sector is its commercial focus, meaning the amount of the average loan is higher there than in the other regions of the world (Weiss and Montgomery, 2005). To test the sensitivity of our main results to the loan amount, we reproduce the analysis on the average loan size in our sample (13 688$) and the highest loan amount that is frequently granted by our partner MFI (30 000$). Threshold values for DC_i are 1.25, 3.81 and 6.25 respectively for 30 000$, 13 689$ and 6 000$.

3.2. Comparison of treatment and control groups prior to treatment

As recommended by Lee and Lemieux (2010), we perform a test comparing our treatment and control groups prior to treatment date to ensure that both groups were similar then. For each of our measures of entrepreneurial activity, we thus compare the two groups situated on either side of the threshold. But we notice that some entrepreneurs in our database have missing observations for the variables required in the calculation of *DC*. As we cannot evaluate their eligibility for a loan, we are forced to exclude them from our analysis and check for any potential bias induced in our estimation. The first test to verify whether excluded observations are any different from those included in our analysis is a simple comparison of the means into the two subgroups, taking into account that they have different variance. The second one runs a regression of a dummy equal to one for excluded observations on measures of entrepreneurial activity and test the significance level of the associated coefficient. We control for the presence of multiple investigators during our data collection and include clusters at the district level to control for geographical disparities. Table 2 presents the results of these exclusion tests with the first line of the column "observations" indicating the number of included observations while the second is the number of excluded ones for each variable. From that table, we notice that despite the exclusion of some observations, our sample size (ranging from 375 to 419 depending on the considered variable) is still large enough to reach the minimum number required to ensure that it is representative of our population of interest (336 observations). Also we observe that only the variable number of employees seems to be affected by the exclusion of some observations because the excluded enterprises possess approximately 1.2 more employees than the included ones. This means that our estimation of the impact of access to microcredit on the number of employees may be subject to an upward bias, requiring some level of cautiousness in its interpretation. With that in mind, we now turn our attention to the comparison of our measures of entrepreneurial activity between treatment and control groups for the included observations.

Table 3 presents the results of this mean equality test with the first line of the column "observations" indicating the number of non-financed enterprises while the second line is the number of financed enterprises. The test is performed prior to any treatment meaning that our interest variables are considered in their value at the starting date of each enterprise. It shows that only the measure of annual exploitation costs at the beginning of operation exhibits a significant difference according to enterprise's financing status. This variable can be influenced by some structural factors like the sector of activity or other unobservable factors (e.g. managerial habits or ability) that might also affect our other measures of entrepreneurial activity. We thus choose to include it as a control variable rather than taking it as an interest variable. Beside this difference on the measure of exploitation costs, there are also other variables that can be correlated to an entrepreneur's access to credit while influencing his establishment's performance. In table 4, we compare the main characteristics of the entrepreneur and his firm which can affect the result of his activity among the two groups of enterprises defined on the basis of their access to financial services. From these numbers, we observe that on average, financed enterprises have an operating duration that is 3.21 years longer than non-financed ones. Also they are owned by older entrepreneurs (1.79 years) who have had access to financial services for a longer duration whether it is for personal or professional use. Finally, we can point out that there is a significant difference in the variable identifying the sector of activity, meaning some sectors have more access to financial services than others[*]. We thus include these five variables (entrepreneur's age and personal use of financial services, firm's age, sector of activity and professional use of financial services) as controls (X_i) in our empirical model in addition to the measure of exploitation costs.

4. Regression discontinuity results

After presenting all the details and hypothesis behind the structure of our empirical model, we now turn our attention to the estimation itself. Our impact analysis is based on the methodological approach developed by Calonico et al. (2014a, b) which has the advantage of producing both robust coefficients and confidence intervals. Actually, RD estimates are obtained by approximating the regression function underlying the data by local non parametric polynomial functions. These polynomials are weighted with kernel functions determined by the gap between each observation and the threshold defining the discontinuity. One major problem of the usual RD estimates is their sensitivity to the choice of the

[*] Most financed sectors are also the biggest sectors in the Panamanian economy: retail has 40 loans in our sample, services 25, manufacturing and transportation and storage 17 each, hospitality and food services 14.

bandwidth value used in the construction of the kernel functions. Indeed, the procedure used to determine the bandwidth value (as described by Imbens and Kalyanaraman (2012)) is based on the minimization of the Mean Squared Errors (MSE) producing small confidence intervals which over-rejects the null hypothesis of no treatment effect. To correct this issue, Calonico and al. (2014a, b) use twice the asymptotic theory: first, to correct the bias induced by the use of a large bandwidth value on the RD coefficients and second to construct the associated robust confidence intervals. More specifically, they estimate the extent of the bias stemming from the use of a large bandwidth and exploit it to re-center the t-stat associated to the RD estimates. Once they obtain new robust coefficients, they recalculate the associated errors while taking into account the supplementary variance induced by the bias approximation in the first step. Finally, they use the values of random deviations from the robust estimations to build the new asymptotic distribution that will determine the confidence intervals associated to the new estimates. The confidence intervals being themselves robust to the choice of the bandwidth value, they do not over-reject the null hypothesis. Thus, the effects estimated with the procedure of Calonico et al. (2014a, b) are more rigorous than those from the usual RD methods.

We apply this methodology in four different setups for our estimations. The first one is the intention-to-treat (ITT) effect which compares control and treatment groups on the basis of the simple eligibility criterion. Following Jacob et al. (2012), we then take into account the effective obtainment of a loan to set three other specifications. The Sharp RDD setup strictly applies the eligibility rule of our partner MFI: treatment group includes only eligible financed entrepreneurs while the control contains only non-eligible non-financed ones. But since our partner has been operating for only four years in 2014, the sharp RDD setup does not reflect the reality of the situation. That is why we choose to implement two more setups which account for the fact that some eligible entrepreneurs did not get credit (Fuzzy I RDD) while some non-eligible ones get funded anyway due to the presence of another financial institutions in the market (Fuzzy II RDD).

But before we detail the estimates produced by these different setups, we present the results of the empirical tests assessing the validity of our RD design. First the exogeneity of the credit's eligibility threshold defining the discontinuity in the entrepreneur's distribution. Second the graphical plot of the variable of interest on the assignment variable to obtain a first glimpse of the results we can expect from the estimation of our empirical model.

4.1. Preliminary results

4.1.1. Threshold exogeneity: McCrary's test

This test consists in verifying the continuity, around the threshold, of the density function of the variable defining the assignment of observations between treatment and control groups. In our case, that variable is the debt-to-generated income ratio which we shortly called the debt coverage ratio and noted *DC*. Developed by McCrary (2008), the test performs a local comparison of the values of the density function to the left and the right of the threshold determining the discontinuity in entrepreneur’s population. If there is no direct manipulation of the assignment variable by the entrepreneurs, the density function of *DC* should be continuous around the loan eligibility threshold.

We first build the density function of the assignment variable using a histogram dividing up the values of *DC* into a designated number of intervals. We ensure that no interval contains both observations from the treatment and the control groups. Then we perform a smoothing of the density function before and after the threshold with a kernel estimator. More formally, we define *f(DC)* as the density function of our assignment variable (the debt coverage ratio) and *s* as the threshold value determining eligibility for the treatment (obtaining a loan according to our partner's rule). For the 6 000$ loan size, the threshold is $s = 6.25$. We also define two other variables corresponding to the value of *f(DC)* respectively before and after the threshold:

$$f^{+} = \lim_{DC \to s^{+}} f(DC) \text{ and } f^{-} = \lim_{DC \to s^{-}} f(DC)$$

These variables enable us to construct the McCrary's test statistic as follows: $\theta = f^{+} - f^{-}$. Under the null hypothesis of no discontinuity in *f(DC)* around *s*, θ which represents the gap (in log) between the intercepts of f^{+} and f^{-}, is equal to zero. McCrary shows that under some usual non parametric hypothesis, θ follows a normal distribution and can be submitted to a standard hypothesis testing. Graph 3 shows, for the 6 000$ loan amount, the distribution of the density function *f(DC)* around the threshold s = 6.25. For the sake of clarity, we present the graph on a restricted interval but the global distribution as well as the robustness checks suggested by McCrary are available upon request. Graphs relatives to the other two loan amounts used in the robustness section are also available.

For a 6 000$ loan size, we obtain a θ = -0.0379 with an associated standard deviation of 0.0977. By dividing these two numbers we get a t-stat for McCrary's test of -0.388, which is below the value for the null hypothesis rejection at the 5% confidence level. For the 13 688$ and 30 000$ loan amounts, t-stat values are respectively 0.06 and 0.92 which are also below the rejection value of the null hypothesis. We thus conclude that there is no evidence of a significant discontinuity into the density function of our assignment variable around the loan's eligibility threshold for each of our three loan sizes of interest. Therefore, there is no evidence suggesting the existence of self-selection by entrepreneurs around the loan's eligibility threshold.

4.1.2. Graphical analysis

Lee and Lemieux (2010) recommend a graphical plot of the variable of interest on the assignment variable in order to identify the underlying regression function between the two variables and guide the choice of the functional form to use in the RD estimation. Calonico and al. (2015) supply the statistical tool to perform such a graphical representation. Graph 4 shows the repartition of our five variables of interest on equally distributed intervals of the debt-coverage ratio for the 6 000$ loan size. Each point on the graph represents the mean of the interest variable on the considered interval for the assignment variable. We made the hypothesis of an underlying linear regression as we use the same functional form in our RD estimates following Gelman and Imbens (2014) who warn against the use of high-order polynomials in the estimation of RD models because they can be misleading for the interpretation of coefficients.

These graphs allow us to formulate some expectations regarding the results we might obtain with the estimation of our empirical model. Again, to avoid overloading this paper, we only present the graphs for the 6 000$ loan amount, those for the two other loan sizes being available upon request. Sub-figures 4a, 4b and 4c exhibit a noticeable jump at the threshold for the average values of equipments, fixed assets and revenues while the average values for the number of employees (4d) and monthly wages (4e) are pretty similar on either sides of threshold. This means that the application of our partner MFI's loan eligibility criterion seems to generate a positive impact on equipments, fixed assets and revenues because the value of the intercept at the right of the threshold is clearly higher than the one at the left. The difference is much smaller for the number of employees and the monthly wage which indicates the potential absence of an impact on these two variables. Whether these gaps are significant cannot be evaluated graphically and thus we empirically assess their value and test their significance by estimating the model described by equations 1 and 2.

All results tables for the 6 000$ loan size presented in appendix C have the same structure. In column (1) we compare the mean of the variable of interest between the treatment and control groups without taking any other factor into account. From column (2) we introduce the control variables identified as relevant for the analysis in tables 3 and 4. Thus, column (2) controls for entrepreneur's characteristics (age and personal use of financial services) while column (3) adds firm's characteristics (firm's age, sector of activity and use of financial services). In column (4), we add the value of exploitation costs at the enterprise's creation date. Finally, in column (5), we control for the number of obtained loans with the hypothesis that a repeated treatment (obtaining more than one loan) could strengthen the effects of access to credit.

4.2. Main results for the 6 000$ loan amount

4.2.1. Intention to treat (ITT) effects on eligible enterprises

In this first subsection of the results, our analysis focuses on the loan eligibility criterion implemented by our partner MFI. We compare enterprises relatively to their position to the threshold defined for the debt-to-generated income ratio at 6.25. Thus, the coefficients showed in table 5 correspond to the effect of loan obtainment on the different measures of entrepreneurial activity if all eligible enterprises, according to the rule of our partner, were financed. As our variables of interest (excepted for the number of employees) are expressed in log, estimated coefficients indicate the average percentage of variation observed among the entrepreneurs of the treatment group. For the number of employees, the estimated coefficient can be directly interpreted as a variation in scale.

According to Banerjee et al. (2015) in the introductory article of the AEJ, the lack of impact of microcredit is not the result of a lack of investments from enterprises. Thus, our first focus will be on two measures of investment: the annual value of fixed assets owned by the enterprises and the annual estimated value of equipment's resale. As suggested by sub-figures 4a and 4b, loan obtainment generates a positive effect on the level of investment although the effect on fixed assets remains non-significant. Nonetheless, an entrepreneur who has access to a 6 000$ loan raises his annual average level of equipment by 0.717% which represents nearly 280$. This result is consistent with the responses provided by interviewed entrepreneurs to the question regarding the use they did with their credit. Indeed, the majority of our sample responded investment in the form of building stocks (51%) and buying or repairing equipments (30%). Only 7% of the financed entrepreneurs reported using their credit to buy real estate which might constitute a plausible explanation for the lack of significance on the fixed assets coefficient. To recap, by giving a 6 000$ credit to an entrepreneur on the basis of its eligibility rule, our partner MFI might expect an average positive effect on equipment level of approximately 0.047$ for each dollar lent.

If we turn our attention to the annual value of revenues generated by enterprises, it appears that loan obtainment might induce a positive and significant variation of 0.573%. That expected positive effect is new compared to what is found in the existing literature where microcredit fail to have a positive impact on enterprises revenues. The third line of table 5 shows that if our partner MFI could strictly apply its eligibility rule for the 6 000$ loan, the group of financed entrepreneurs could raise their annual revenues by approximately 533$. This represents nearly 5% of the Panamanian GDP per capita which was 10 700$ in 2014 using the World Development Indicators. However, loan obtainment seems to be insufficient to induce an effect on labor both in terms of number of employees or level of salary. As foreseen by graphs 4d and 4e, there is no significant impact expected from loan obtainment on labor in our sample. So, even if the coefficients of the regressions presented in the fourth and fifth lines of table 5 are positive, none of them are significant.

4.2.2. Average treatment effects on the treated with Sharp RDD setup

For this new setup, we exclude from the treatment group any entrepreneur that is considered as non-eligible according to the criterion of our partner MFI. Also, we exclude from the control group any financed entrepreneur thus obtaining the situation of a perfect experimental design based on the MFI's eligibility rule. This strict implementation of the rule corresponds to the design of a Sharp RD and its results are presented in table 6.

Compared to the results in table 5, we observe that the strict application of our partner rule of eligibility strengthens the effect of loan obtainment on investment while the positive effect on revenues is not significant anymore when we introduce control variables in columns (3) to (5). Indeed, the estimated coefficients shows a growth of 1.275% and 1.359% respectively on the annual value of fixed assets and equipment's resale value. These variations represent an increase of 665$ and 530$ in the annual values of these two measures of investment. But the coefficient on the annual total revenues exhibits a decline in his magnitude and loose his statistical significance. To explain this change between the two setups, we turn our attention to the variation in the number of employees because if its coefficient remains non-significant, its level almost double. This might suggest a tendency for entrepreneurs to recruit and train some extra workers following the increase of their investment levels. But as these new employees induce more salary costs and are not fully operational right away, their presence could reduce the impact of loan obtainment on the values of generated revenues.

Once again this setup is limited as it somewhat describes an ideal world where we could have implemented a perfect survey design relying on the eligibility rule defined by the credit policy of our partner MFI. But in practice, some eligible entrepreneurs refuse to participate in the experiment and some non-eligible ones finding their way into the program. We will now examine successively these two situations which are more close to the reality of our sample that contains eligible entrepreneurs who did not apply for credit and ineligibles entrepreneurs whom are clients from others financial institutions.

4.2.3. Average treatment effects on the treated with Fuzzy I RDD setup

Here we modify our treatment group to include all eligible entrepreneurs regardless of their financed status. We did so because as we stated in section 2, there was 225 entrepreneurs of our sample who declared they did not need a credit or more capital. If some of them were eligible and choose deliberately to not apply for a credit, those no-show entrepreneurs might induce a bias in our estimate by generating a self-selection mechanism into our treatment group. Thus we replicate our RD analysis and introduce these no-shows into treatment group to correct for any potential self-selection bias of our previous estimates. This Fuzzy I RDD setup is similar to an instrumental variable (IV) design where treatment is instrumented by the eligibility rule (Jacob et al., 2012).

The new set of results presented in table 7 shows that the exclusion of no-show entrepreneurs in our sample have induced a general overestimate of our coefficients, except for the revenues. Indeed, in comparison to the results of sharp RDD, the fuzzy I setup exhibits coefficients with lower magnitude on investment and labor while those on revenues are both higher and more significant. Thus, it appears that eligible entrepreneurs who did not apply for credit have higher level of revenues than those who applied for the 6 000$ since their inclusion in the treatment group raises the value and statistical significance of the average gap separating treatment and control groups. This higher level of revenues might justify, at least for some of them, why they did not apply for a credit and declare that they did not need more capital for their enterprise. Nonetheless, the drop in the estimated effect of loan obtainment on the two measures on investment confirm the assessment of Banerjee et al. (2015) that financed entrepreneurs in fact realize investment following credit obtainment. We notice that the inclusion of no-show entrepreneurs in our treatment group has reduced the gap between treatment and controls from 1.275% to 0.933% for fixed assets and 1.359% to 1.035% for equipments. These variations indicate that loan obtainment has allowed financed entrepreneurs to undertake some investment that they could not have realized otherwise.

4.2.4. Average treatment effects on the treated with Fuzzy II RDD setup

Our analysis relying on a quasi-experimental design with no perfect enforcement of the rule because of the presence of other financial institutions in the market. Indeed, not all financial institutions apply the same eligibility rule as our partner MFI to their applicants and thus our sample include entrepreneurs considered as non-eligible by our partner but who got credit at another institution. These cross-over entrepreneurs should be introduced into the treatment group in order to evaluate the average treatment effect on treated. In practice, their inclusion allows us to simulate the effect of a relaxation of the eligibility rule as they obtain credit at more favorable conditions than the eligible financed entrepreneurs. As his revenues remains unchanged, the only reason why an entrepreneur becomes a cross-over is a lowering of the threshold value for *DC*, i.e. lower monthly repayment fees. This situation corresponds to a relaxation of loan attribution conditions or more simply to a reduction of credit costs.

Results in table 8 shows that, in addition to the inclusion of no-show entrepreneurs, introducing the cross-overs into the treatment group barely affects the coefficients associated with investment. But the effect on revenues is much more noticeable as the gap between treatment and control groups goes from 0.592% to 0.897%. Given the level of the Panamanian GDP per capita at that time, that supplementary revenues of 818$ per year following loan obtainment represents a subsequent raise for an entrepreneur. On our partner MFI side, we calculate what we call the impact factor for each dollar lent by reporting the estimated effect to the amount of the granted loan. For example, the estimated raise on financed entrepreneur's annual revenues corresponds to an impact factor of 0.136$ for each dollar granted on a 6 000$ loan amount.

4.2.5. The role of credit costs

In the Sharp RDD, the treatment group were constituted by financed eligible entrepreneurs while control group comprises non-eligible non-financed entrepreneurs. For the previous Fuzzy II setup, the control group remains the same but the treatment group includes both eligible non-financed entrepreneurs (no-shows) and non-eligible financed ones (cross-overs). To evaluate the potential benefits from a relaxation of its eligibility rule on our partner MFI (client's portfolio extension and impact factor improvement), we have to adjust the Fuzzy II setup's treatment group. Indeed, the relaxation of the rule is reflected only by the inclusion of the cross-over entrepreneurs and not the no-shows as these latter are already eligible. Thus, we reproduce our analysis with a so-called Fuzzy II.b design where the no-shows are excluded from the treatment group. It is now constituted by all eligible financed entrepreneurs and cross-over ones.

Results in table 9 show that our partner MFI could benefit from a relaxation of its eligibility rule for the 6 000$ loan as all the estimated coefficients have a higher magnitude compared to the Sharp design. The impact of loan obtainment on the annual value of fixed assets goes from 665$ to 739$ which correspond to an increase in the impact factor of each lent dollar from 0.1109$ to 0.1233$. The change of impact on equipment's level is smaller and goes only from 530$ per year to 583$ which correspond to a growth of this variable's impact factor of approximately 0.009$. These results translate the fact that more favorable loan conditions can be an incentive to undertake long term investment.

But the most important change is on the labor variables as the magnitude of estimated coefficients practically doubles even if remaining statistically insignificant. The relaxation of credit attribution rules allows average financed enterprise to hire 1.696 supplementary workers. Given that the enterprises of our sample have an average of 2.61 employees, this variation represents a growth of almost 65% of the workforce associated with a positive 0.731% augmentation in the monthly costs of wages. Even if these changes in labor remains statistically insignificant, the direction of the change speaks in favor of a slackening of the conditions applied by our partner. Indeed, under our partner MFI's present conditions of loan attribution, an entrepreneur who obtains a 6 000$ loan have to repay a monthly amount of 224$. As seen before, financed entrepreneurs choose first to invest the obtained funds in fixed assets and/or equipments as those variables are always positively impacted by loan obtainment. At the same time, the average value of monthly cost of wages indicates that hiring an extra worker cost approximately 543$ per month. Thus, in order to fulfill his loan repayment fees while being able to hire that supplementary worker, a financed entrepreneur has to experience a non-negligible raise of his generated revenue. But the estimated impact of loan obtainment on total annual revenues generated by financed enterprises is only 665$ in the fuzzy 2.b design. Even if it is higher than the 407$ obtained in the sharp RDD, that variation remains small and statistically insignificant. Yet, a reduction of credit costs as analyzed in this fuzzy 2.b setup is a first step toward the improvement of microcredit's impact on entrepreneurial activity in Panama. But beyond that channel we can also ask ourselves if all enterprises surveyed in our sample are affected in the same way by loan obtainment? We investigate this question in the following subsection.

4.2.6. Heterogeneous effects by enterprise's size

The existing literature on microcredit's impact evaluation usually focuses on firms of the same type: those owned by one person who also is the unique employee. These auto-enterprises constitute the majority of our sample because self-employment is still pretty common in the segment we consider in this study. But we also have a considerable number of micro-enterprises with the number of employees going up to 38, a heterogeneity we use to investigate the differentiated effects by enterprise's size. We separate our sample in two sub-samples with auto-enterprises on one side and micro-enterprises on the other side. We reproduce the estimation of the average effects of loan obtainment on treated entrepreneurs for each of the three setups we presented earlier. We consider only the most complete specification which include all the controls variables and correspond to the column (5) of the previous results tables. Also, as we used the variable number of employees to constitute our two types of enterprises, we can no longer estimate the effects of loan obtainment on employee’s headcount.

Table 10 presents the results of these estimates with a common trend for all three setups: microcredit has negative effect on entrepreneurial activity only for auto-enterprises. That finding is consistent the existent literature as summarized by the six studies in the special issue of the AEJ. What is new is the persistent and significant positive effect of loan obtainment on either revenues and/or investment for micro-enterprises. It appears that for a 6 000$ loan, micro-enterprises experience a positive and significant impact both in terms of investment and revenues levels especially when the eligibility rule is strictly implemented. This result is robust to the inclusion of eligible entrepreneurs who did not get financed (no-shows) indicating that our result is not driven by self-selection bias. Also the inclusion of cross-over entrepreneurs (column 3: Fuzzy II RDD) reduces the positive impact of microcredit on investment level below the point of statistical significance. Nonetheless, the effect on revenues remains practically unchanged with a 0.718% growth in their annual value.

For auto-enterprises, if the strict implementation of the credit attribution rule seems to be beneficial for investment levels, loan obtainment affects negatively financed enterprise's generated revenues and wages costs. This result confirms the assessment of the existing literature that microcredit's clients indeed undertakes investment but fails to transform it in income for the entrepreneur and/or his household. We notice that the relaxation of the rule with the inclusion of cross-overs mitigate the negative effects on revenues and wage but induce some negative effects on investment levels. Even if they remain statistically insignificant, these effects provide some insights about the importance of client's screening and monitoring for MFIs that specifically target auto-enterprises.

5. Robustness checks

To test the robustness of all these results to our choice of loan size, we reproduce the RD analysis on two other amounts: the mean of the first loan obtained by the surveyed enterprises in our sample (13 688$) and the highest loan amount that is frequently granted by our partner (30 000$). We do not consider the highest amount permitted by its credit policy because our partner has not yet reached the point where it can grant 50 000$ to clients with whom a credit history is still being build following the dynamic incentives process. Indeed, it is still very rare for our partner and fellow competitors to grant loans higher than 30 000$ especially given the fact that this will place them in direct competition with commercial banks that are more efficient on that segment of the market. Thus, there are very few entrepreneurs whom benefited from this higher loan amount and this feature restricted some of the setups in our analysis leading us to present succinctly the results on the 30 000$ loan size in the appendix E. For the 13 689$ loan, according to our partner MFI's rule, an entrepreneur is eligible if his generated revenues are at least equal to 3.81 times the associated monthly repayment of 511$. We reproduce the RD analysis with sharp, fuzzy I and fuzzy II setups and presents results only for the most complete specification that includes all the controls variables. Thus, tables in appendix D are comparable to the column (5) of the main results in tables 5 to 9.

If our partner MFI's eligibility conditions were strictly applied to grant credit to all eligible individuals, first row of table 11 shows that we might expect a positive and significant impact of loan obtainment on financed entrepreneur's investment and revenues levels. The magnitude of the ITT effects is similar to what were observed with 6 000$ except that this time the coefficient on fixed assets is also significant. This change indicates that this higher loan amount with lower interest rate and longer duration seems more favorable for entrepreneurs to undertake longer and more costly investments. But on the down side, it also seems to reduce the expected effect of loan obtainment on labor whether in terms of number of employees or monthly wages costs.

Taking into account the effective obtainment of a loan confirms the previous insight provided by the ITT estimates. The sharp RD setup where treatment and control groups are built on the strict implementation of eligibility rule shows positive and significant effects on investment with magnitudes that are pretty similar to those on the 6 000$ loan amount. We notice an important reduction in the positive effect on revenues and the appearance of a negative coefficient on the monthly cost of wages. This phenomenon can stem from two different sources: the cost of credit and/or some level of substitution of the production factors. Indeed, the monthly repayment due for this intermediate loan size is more important than before and financed entrepreneurs needs more revenues to fulfill their obligations. As they undertake more long term investment that takes times to yield returns, they have to find alternative sources of cash in the short term to repay their credit fees. The most straightforward source is a reduction in the cost of employee’s salary especially if the obtained loan allows entrepreneurs to buy capital that can be substituted to workers. That interpretation is sustained by the results of the fuzzy 2.b setup where we introduce cross-over entrepreneurs in the treatment group thus simulating the effect of credit costs reduction. Compared to the sharp RD, the negative effect on wages are mitigated while positive effects on revenues and investment are reinforced.

For fuzzy I and II setups, obtained results are also close to those obtained with the 6 000$ loan amount with positive and significant effects on investment and revenues. In the fuzzy I RDD, the inclusion of no-show entrepreneurs in the treatment groups induces a drop in the coefficient estimated in the sharp design. The gap is higher to what was observed with the 6 000$ loan which is not surprising as entrepreneur's choice to not apply for a loan can be reinforced by the cost of credit which gets higher with the loan amount. Still, our partner MFI could benefit from a relaxation of his credit attribution's rule since the inclusion of cross-overs entrepreneurs in the treatment group (fuzzy II) strengthens the effects of loan obtainment on our five measures of entrepreneurial activity.

Once again, positive effects of loan obtainment are concentrated on micro-enterprises while auto-enterprises are negatively impacted as shown by table 12. The extent of the drop in investment is more important than what was obtained with the 6 000$ loan size. Nonetheless, auto-enterprises might draw some benefits from a reduction of the credit costs on this intermediate loan size as the negative impact of loan obtainment on revenues and wages disappear when we go from the sharp to fuzzy setups. The magnitude of the negative effect estimated on the two measures of investment is also reduced.

6. Summary and concluding remarks

This paper provides a model for microcredit's impact evaluation based on a regression discontinuity design. Using a new database collected on a representative sample of Panamanian micro, small and medium enterprises (MSME) that might be potential clients for a non-traditional MFI, we evaluate the effects of loan obtainment on different measures of entrepreneurial activity. Indeed, rather than studying a MFI similar to those documented in the literature, we partnered with an institution which specifically targets enterprises trapped in what we called the financial missing middle. These enterprises are too big to benefit from the products and services of traditional MFIs because their financial needs exceed the loan range offered by these institutions. On the other hand, their size, financial needs and/or collateral capacity are well below the standards of commercial banks. According to our Panamanian sample, these enterprises have an average annual revenue of 120 864$ and a mean of 2.6 employees per establishment, numbers that place them in the segment of micro-enterprises.

Our partner MFI offers its services with a loan range between 1 000 and 50 000$, maturity dates going from 12 to 80 months and interest rates situated between 20 and 35% per year. To select its clients, its applies an eligibility criterion based on the calculation of a debt-to-income ratio for each loan applicant. It’s the setting of applicant's eligibility to a particular threshold value for that ratio that creates a discontinuity in the distribution of entrepreneurs. These threshold values being defined in our partner MFI's confidential credit policy, we exploit the discontinuity induced by the existence of this eligibility criterion to build our empirical RD approach. We selected three particular loan sizes to evaluate the effect of loan obtainment on entrepreneurial activity: the average loan of our partner (6 000$), the average loan in our sample (13 688$) and the highest loan that is currently granted by our partner (30 000$).

Results show that depending on the considered loan size, estimated impacts are different reflecting financed entrepreneur's behavioral response to credit costs. Indeed, higher loan sizes (30 000 and 13 689$) exhibit positive effects on the level of equipments and fixed assets while a 6 000$ loan seems more effective on revenues and even somehow on the number of employees. For the first two loan amounts, enterprise's annual revenues slightly decrease despite the growth in investment which lead us to investigate the role of credit costs. Using the credit policy of our partner MFI, we calculate the cost of credit according to loan characteristics (amount, duration, interest rate). We observe that given the debt burden, financed enterprises choose between short term investment which directly affects revenues and long term investment which impacts equipment and/or immobilization. In both cases, loan obtainment is generally insufficient to induce a significant change on employment because of the important repayment fees. Indeed, under the present conditions applied by our partner MFI, a 6 000$ loan amount requires a monthly repayment of 224$. In the meantime, the estimated impact of this loan obtainment on annual revenues ranges from 407$ (sharp RDD) to 818$ (Fuzzy II RDD). In comparison to the value of the Panamanian GDP per capita in 2014, these variations represent a significant raise in financed entrepreneur's revenues. But at the same time, as a supplementary worker costs 543$ per month, it is easy to understand why microcredit did not generate a significant impact on employment level. Decomposing these results by enterprise's size shows that positive effect of microcredit on entrepreneurial activity is concentrated on microenterprises. Also, as it is usually documented in the literature on microcredit's impact evaluation, loan obtainment has a negative impact on auto-enterprises.

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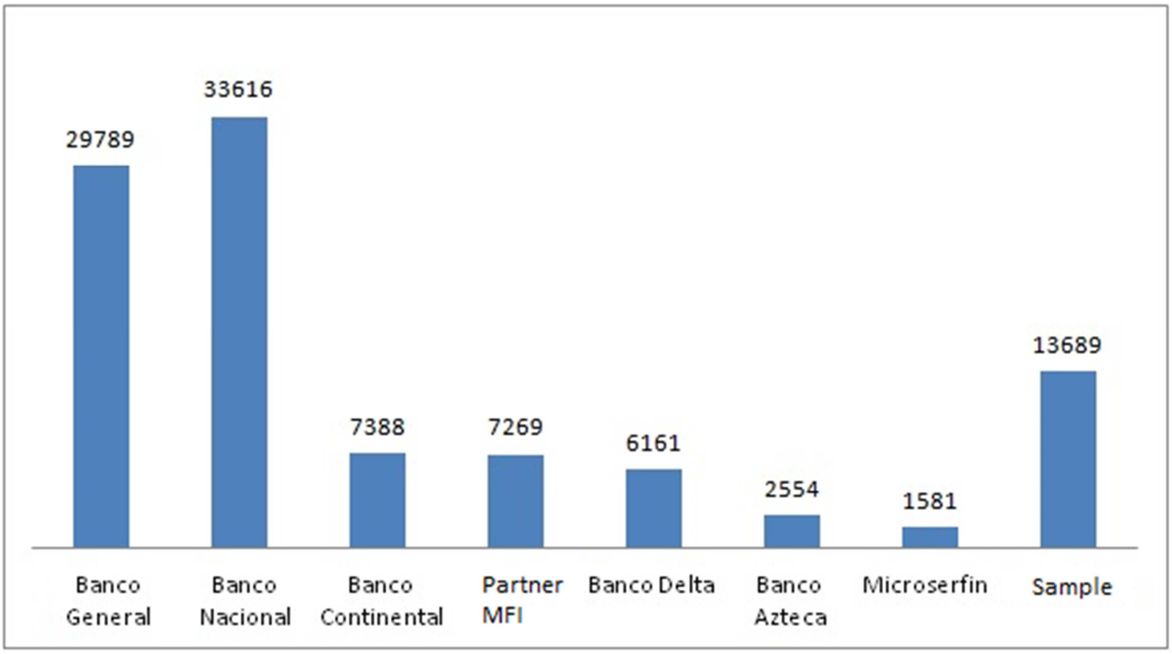
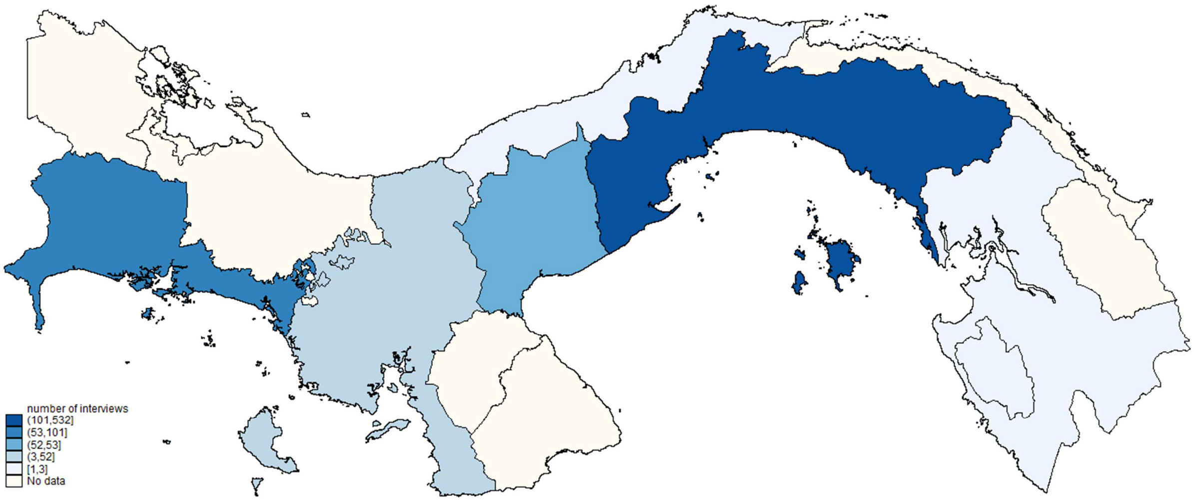
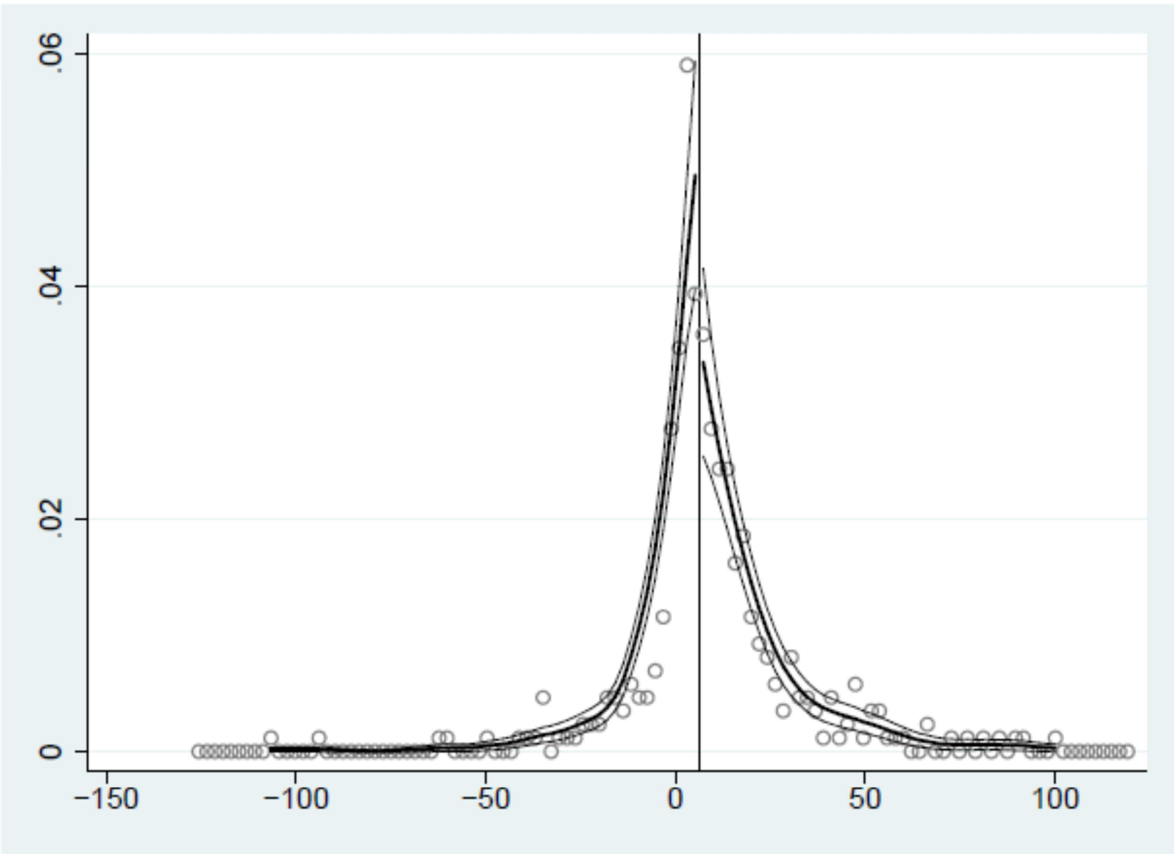
Appendix A: Graphics



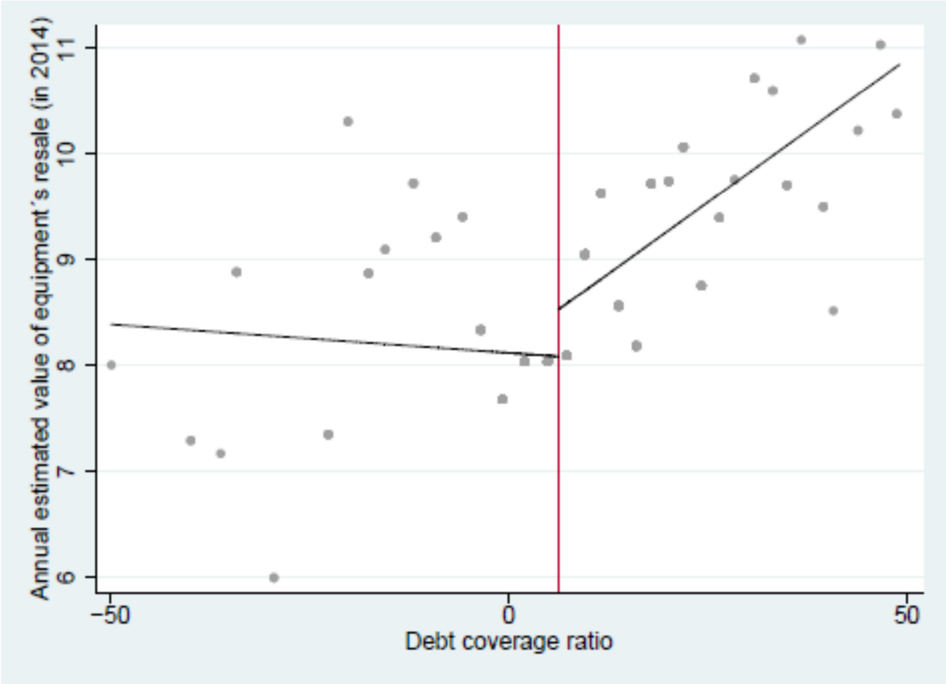
Graph 1: Average loan size (in US dollars) granted by financial institutions in Panama

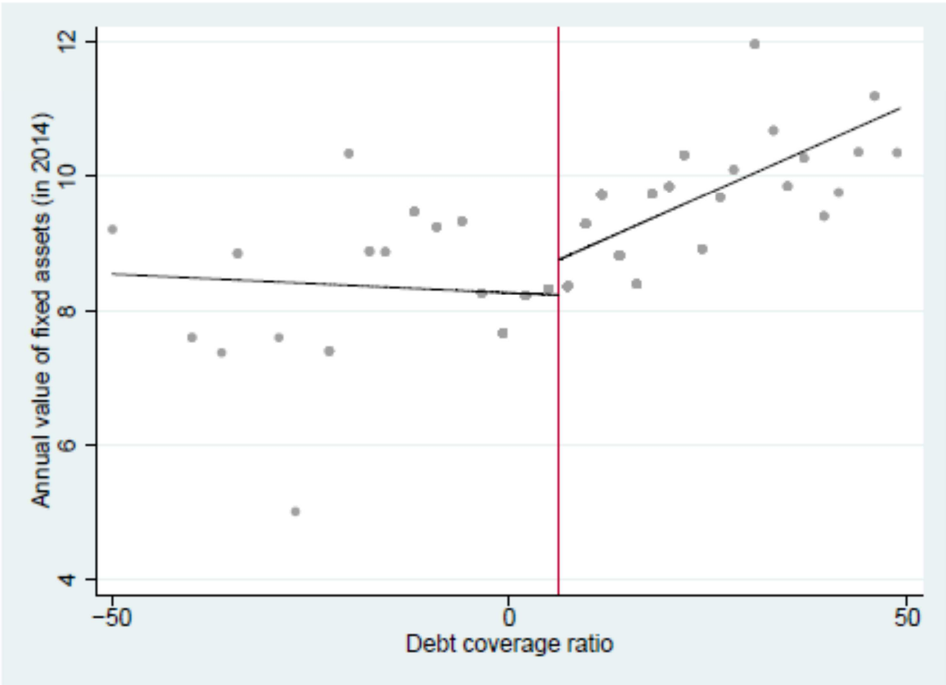


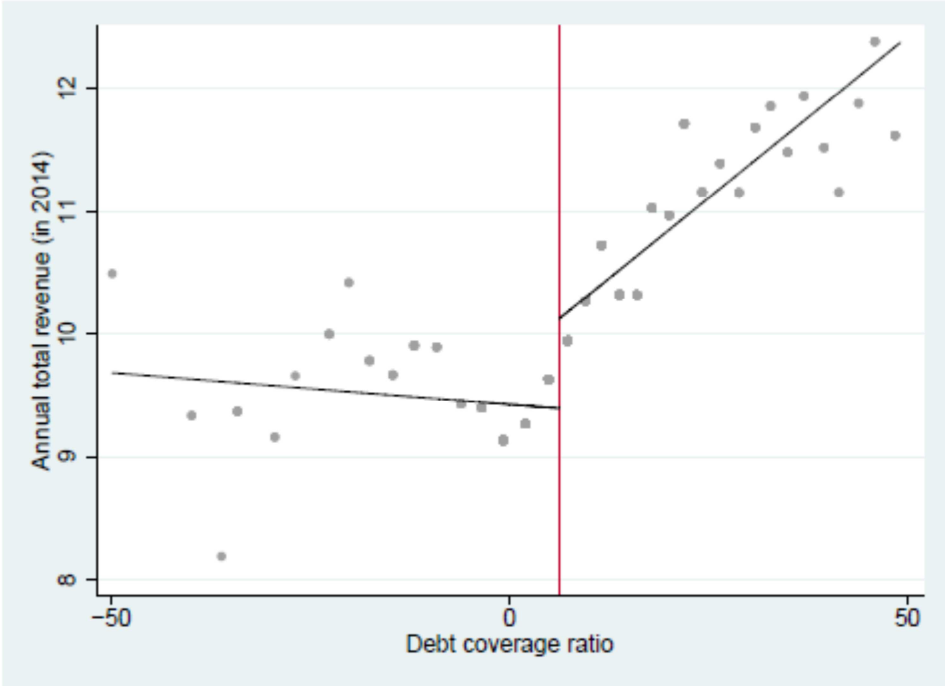
Graph 2: Survey geographical localization

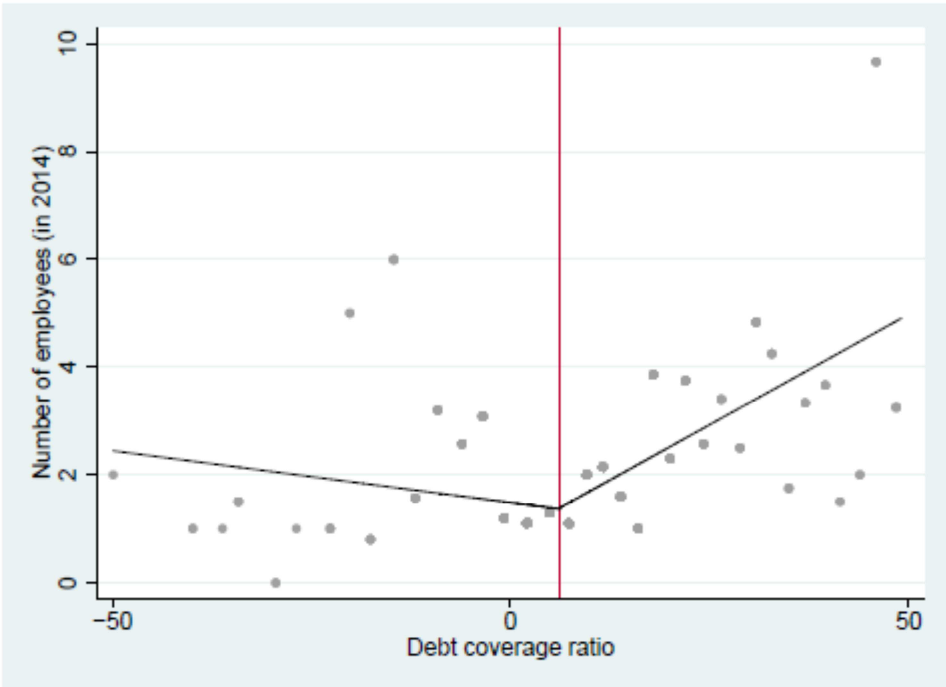


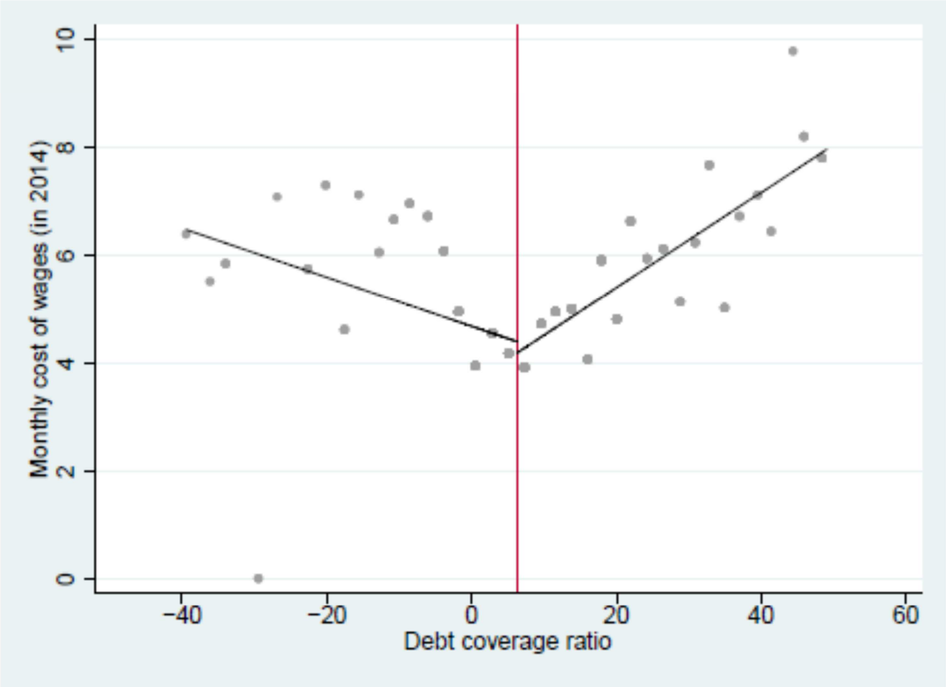
Graph 3: Distribution of the assignment variable for the 6 000$ loan size


Annual estimated value of equipment´s resale (in 2014)
6
7
8
9
10
11
−50
0
50
Debt coverage ratio


Annual value of fixed assets (in 2014)
4
6
8
10
12
−50
0
50
Debt coverage ratio


Annual total revenue (in 2014)
8
9
10
11
12
−50
0
50
Debt coverage ratio


Number of employees (in 2014)
0
2
4
6
8
10
−50
0
50
Debt coverage ratio



Graph 4 (4-a to 4-e): Linear regression of interest variables on intervals of DC

Appendix B: Preliminary analysis results tables

Variable (in 2014)	Obs	Mean	Std dev	Min	Max
Annual total revenue	674	120 863.9	797 040.6	240	17 000 000
Annual costs of exploitation	636	45 149.87	305 953.6	0	7 000 000
Annual value of fixed assets	649	49 468.39	329 473.6	0	8 000 000
Annual estimated value of equipment’s resale	614	38 192.2	218 633	0	5 000 000
Number of employees	737	2.61	3.97	0	38

Monthly cost of wages	667	1 418.58	3 743.46	0	60 000

All the number, except for the variables number of employees, are expressed in US dollars

Table 1: Profile of the average enterprise

Dependent variable (in 2014)	Observations	Mean equality test	Regression with an exclusion dummy
Annual total revenue	416 258	-72 600.61 [-0.990]	59 415.39 [0.77]
Annual costs of exploitation	417 219	17 044.91 [0.887]	-21 963.88 [-0.83]
Number of employees	419 318	-1.263*** [-4.045]	1.184** [3.20]
Monthly cost of wages	407 260	-590.35* [-1.734]	537.98 [1.41]
Annual value of fixed assets	393 256	6 866.65 [0.307]	-16 042.26 [-0.50]
Annual estimated value of equipment's resale	375 239	2 080.65 [0.133]	907.33 [0.05]

t-stat in square brackets.
Levels of statistical significance: * for 10%, ** for 5% and *** for 1%

Table 2:Test for the exclusion of some observations

Variable (at the beginning of operations)	Observations	Mean's equality test
Annual total revenue	278 126	-80 494.36 [-1.011]
Annual costs of exploitation	287 124	17 049.65* [1.501]
Number of employees	288 129	-0.0804 [-0.435]
Monthly cost of wages	276 116	57.094 [0.528]
Annual value of fixed assets	251 120	-3 603.51 [-1.004]
Annual estimated value of equipment's resale	214 111	-2 638.64 [-0.758]

t-stat in square brackets. Levels of statistical significance: * for 10%, ** for 5% and *** for 1%

Table 3:Comparison of treatment and control groups prior to the treatment

Control variable	Non financed	Financed	Difference
Sex	1.464 (0.029)	1.426 (0.044)	0.0373 [0.708]
Age	44.862 (0.761)	46.653 (1.017)	-1.791* [-1.410]
Entrepreneur's total number of schooling years	12.409 (0.277)	12.642 (0.449)	-0.233 [-0.440]
Personal use of financial services	0.472 (0.029)	0.775 (0.037)	-0.303*** [-6.420]
Enterprise's age	10.014 (0.678)	13.225 (0.759)	-3.211*** [-3.154]
Enterprise's type	1.386 (0.047)	1.372 (0.078)	0.014 [0.155]
Sector of activity	11.034 (0.307)	11.930 (0.493)	-0.895* [-1.541]
Professional use of financial services	0.139 (0.021)	0.659 (0.042)	-0.519*** [-11.01]

Std dev in parenthesis. t-stat in square brackets.
Levels of statistical significance: * for 10%, ** for 5% and *** for 1%

Table 4:Comparison between financed and non-financed entrepreneurs and enterprises

Appendix C: Results tables for the 6 000$ loan amount

Dependent variable	(1)	(2)	(3)	(4)	(5)
Annual value of fixed assets (in log)	0.384 [0.458]	0.446 [0.430]	0.622 [0.380]	0.612 [0.381]	0.626 [0.385]
Annual estimated value of equipment's resale (in log)	0.449 [0.494]	0.525 [0.460]	**0.711*** [0.412]	**0.712*** [0.412]	**0.717*** [0.416]
Annual total revenue (in log)	0.256 [0.202]	0.298 [0.193]	**0.577***** [0.181]	**0.571***** [0.181]	**0.573***** [0.182]
Number of employees	0.203 [0.423]	0.157 [0.415]	0.506 [0.423]	0.490 [0.417]	0.494 [0.407]

Monthly cost of wages (in log)	0.487	0.445	0.532	0.525	0.533
	[0.911]	[0.867]	[0.850]	[0.849]	[0.845]
Entrepreneur's controls (EC)	No	Yes	Yes	Yes	Yes
Firm's controls (FC)	No	No	Yes	Yes	Yes
Exploitation costs	No	No	No	Yes	Yes
Number of loans	No	No	No	No	Yes

Robust std errors in square brackets. Levels of statistical significance: * for 10%, ** for 5% and *** for 1%
EC: age, personal use of financial services. FC: age, sector, use of financial services. Number of included observations: 311

Table 5: Intention to treat effects of microcredit on entrepreneurial activity

Dependent variable	(1)	(2)	(3)	(4)	(5)
Annual value of fixed assets (in log)	**2.038*****	**1.608****	**1.078****	**1.068****	**1.275*****
	[0.655]	[0.635]	[0.496]	[0.497]	[0.488]
Annual estimated value of equipment's resale (in log)	**2.218*****	**1.894*****	**1.262****	**1.242****	**1.359****
	[0.710]	[0.664]	[0.547]	[0.548]	[0.544]
Annual total revenue (in log)	**0.880*****	**0.663****	0.366	0.397	0.438
	[0.282]	[0.308]	[0.349]	[0.341]	[0.369]
Number of employees	1.088	0.693	-0.036	0.059	0.972
	[0.729]	[0.741]	[0.693]	[0.680]	[0.701]
Monthly cost of wages (in log)	0.911	0.362	-0.226	-0.221	0.346
	[1.279]	[1.384]	[1.295]	[1.286]	[1.322]
Entrepreneur's controls (EC)	No	Yes	Yes	Yes	Yes
Firm's controls (FC)	No	No	Yes	Yes	Yes
Exploitation costs	No	No	No	Yes	Yes
Number of loans	No	No	No	No	Yes

Robust std errors in square brackets. Levels of statistical significance: * for 10%, ** for 5% and *** for 1%
EC: age, personal use of financial services. FC: age, sector, use of financial services. Number of included observations: 167

Table 6: Average treatment on the treated of microcredit on entrepreneurial activity, Sharp RDD

Dependent variable	(1)	(2)	(3)	(4)	(5)
Annual value of fixed assets (in log)	**1.128****	**1.110****	**0.877***	**0.865***	**0.933****
	[0.495]	[0.484]	[0.461]	[0.462]	[0.466]
Annual estimated value of equipment's resale (in log)	**1.249****	**1.258****	**1.005***	**0.998***	**1.035****
	[0.560]	[0.531]	[0.524]	[0.525]	[0.528]
Annual total revenue (in log)	**0.473****	**0.553*****	**0.554*****	**0.546*****	**0.592*****
	[0.186]	[0.203]	[0.205]	[0.206]	[0.207]
Number of employees	0.441	0.341	0.080	0.129	0.430
	[0.457]	[0.438]	[0.432]	[0.432]	[0.442]
Monthly cost of wages (in log)	0.576	0.501	0.132	0.138	0.318
	[1.092]	[1.049]	[1.034]	[1.031]	[1.036]
Entrepreneur's controls (EC)	No	Yes	Yes	Yes	Yes
Firm's controls (FC)	No	No	Yes	Yes	Yes
Exploitation costs	No	No	No	Yes	Yes
Number of loans	No	No	No	No	Yes

Robust std errors in square brackets. Levels of statistical significance: * for 10%, ** for 5% and *** for 1%
EC: age, personal use of financial services. FC: age, sector, use of financial services. Number of included observations: 275

Table 7: Average treatment on the treated of microcredit on entrepreneurial activity, Fuzzy I RDD

Dependent variable	(1)	(2)	(3)	(4)	(5)
Annual value of fixed assets (in log)	0.577	0.668	**0.938***	**0.923***	**0.942***
	[0.651]	[0.611]	[0.553]	[0.556]	[0.556]
Annual estimated value of equipment's resale (in log)	0.672	0.786	**1.071***	**1.071***	**1.080***
	[0.702]	[0.650]	[0.597]	[0.598]	[0.601]
Annual total revenue (in log)	0.409	0.466	**0.884*****	**0.875*****	**0.879*****
	[0.302]	[0.287]	[0.294]	[0.295]	[0.293]
Number of employees	0.309	0.238	0.791	0.766	0.751
	[0.633]	[0.623]	[0.681]	[0.670]	[0.621]

Monthly cost of wages (in log)	0.729	0.662	0.794	0.783	0.793
	[1.333]	[1.267]	[1.257]	[1.255]	[1.242]
Entrepreneur's controls (EC)	No	Yes	Yes	Yes	Yes
Firm's controls (FC)	No	No	Yes	Yes	Yes
Exploitation costs	No	No	No	Yes	Yes
Number of loans	No	No	No	No	Yes

Robust std errors in square brackets. Levels of statistical significance: * for 10%, ** for 5% and *** for 1%
EC: age, personal use of financial services. FC: age, sector, use of financial services. Number of included observations: 311

Table 8: Average treatment on the treated of microcredit on entrepreneurial activity, Fuzzy II RDD

Dependent variable	(1)	(2)	(3)	(4)	(5)
Annual value of fixed assets (in log)	**1.902****	**1.452***	**1.201***	**1.188***	**1.418****
	[0.902]	[0.857]	[0.637]	[0.639]	[0.624]
Annual estimated value of equipment's resale (in log)	**1.982****	**1.688***	**1.386****	**1.368****	**1.495****
	[0.967]	[0.900]	[0.681]	[0.682]	[0.674]
Annual total revenue (in log)	**0.949****	0.692	0.593	0.586	0.715
	[0.425]	[0.442]	[0.578]	[0.581]	[0.584]
Number of employees	1.302	0.711	0.713	0.734	1.696
	[1.074]	[1.110]	[1.080]	[1.050]	[1.088]
Monthly cost of wages (in log)	1.038	0.247	0.112	0.108	0.731
	[1.717]	[1.864]	[1.754]	[1.741]	[1.738]
Entrepreneur's controls (EC)	No	Yes	Yes	Yes	Yes
Firm's controls (FC)	No	No	Yes	Yes	Yes
Exploitation costs	No	No	No	Yes	Yes
Number of loans	No	No	No	No	Yes

Robust std errors in square brackets. Levels of statistical significance: * for 10%, ** for 5% and *** for 1%
EC: age, personal use of financial services. FC: age, sector, use of financial services. Number of included observations: 202

Table 9: Simulation of a reduction of credit costs

Specification	Sharp RDD		Fuzzy I		Fuzzy II	
Dependent variable	Auto	Micro	Auto	Micro	Auto	Micro
Annual value of fixed assets (in log)	1.985	**1.175****	-0.968	**0.704***	-0.959	0.466
	[2.775]	[0.493]	[1.173]	[0.380]	[1.130]	[0.399]
Annual estimated value of equipment's resale (in log)	3.139	**1.594*****	-0.079	**1.215****	-0.152	0.570
	[2.247]	[0.479]	[1.228]	[0.535]	[1.142]	[0.473]
Annual total revenue (in log)	-0.729	**0.777****	-0.417	**0.791*****	-0.387	**0.718*****
	[0.491]	[0.368]	[0.408]	[0.228]	[0.405]	[0.222]
Monthly cost of wages (in log)	-2.622	0.402	-0.773	0.308	-0.790	0.204
	[1.623]	[0.319]	[1.844]	[0.218]	[2.158]	[0.199]

Robust std errors in square brackets. Levels of statistical significance: * for 10%, ** for 5% and *** for 1%

Table 10: Heterogeneous effects of microcredit by enterprise size (1)

Appendix D: Results tables for the 13 689$ loan amount

Dependent variable	ITT	Sharp	Fuzzy I	Fuzzy II	Fuzzy II.b
Annual value of fixed assets (in log)	**0.709***	**1.393*****	**0.904****	**0.966****	**1.658*****
	[0.369]	[0.517]	[0.461]	[0.488]	[0.587]
Annual estimated value of equipment's resale (in log)	**0.700***	**1.360****	**0.935***	**0.948***	**1.512****
	[0.412]	[0.577]	[0.527]	[0.537]	[0.640]
Annual total revenue (in log)	**0.553*****	0.266	**0.593*****	**0.788*****	0.332
	[0.183]	[0.280]	[0.192]	[0.279]	[0.378]
Number of employees	0.088	0.258	0.086	0.126	0.273
	[0.399]	[0.495]	[0.418]	[0.563]	[0.674]

Monthly cost of wages (in log)	0.478	-0.477	0.380	0.688	-0.289
	[0.858]	[1.374]	[1.015]	[1.199]	[1.647]
Observations	311	175	284	311	202

Robust std errors in square brackets. Levels of statistical significance: * for 10%, ** for 5% and *** for 1%

Table 11: Effects of microcredit on entrepreneurial activity for the intermediate size loan

Specification	Sharp RDD		Fuzzy I		Fuzzy II	
Dependent variable	Auto	Micro	Auto	Micro	Auto	Micro
Annual value of fixed assets (in log)	-5.038	**1.021****	-1.762	0.741	-1.383	0.367
	[1.449]	[0.495]	[1.413]	[0.458]	[1.045]	[0.407]
Annual estimated value of equipment's resale (in log)	NEO	**1.176*****	-0.929	**1.135****	-0.955	0.494
		[0.449]	[1.485]	[0.541]	[1.075]	[0.507]
Annual total revenue (in log)	NEO	0.682	-0.099	**0.650*****	0.084	**0.657*****
		[0.481]	[0.448]	[0.219]	[0.425]	[0.215]
Monthly cost of wages (in log)	-2.542	0.431	0.698	0.240	0.533	0.128
	[3.841]	[0.354]	[1.625]	[0.218]	[1.532]	[0.197]

Robust std errors in square brackets. Levels of statistical significance: * for 10%, ** for 5% and *** for 1%. NEO: not enough observations to perform the RD analysis

Table 12: Heterogeneous effects of microcredit by enterprise size (2)

Appendix E: Results for the 30 000$ loan amount

As said before, there are very few entrepreneurs who benefited from this higher loan amount and this feature even restricted some of our analysis as shown by table 14 where there are not enough observations on auto-enterprises to run the sharp RD setup. Nonetheless we were able to perform our main analysis without further restrictions and if the usual ITT results suggest a positive expected impact, the rigor with which the eligibility rule is implemented exhibits all his importance for this highest loan amount.

We notice from table 13 above that the strict application of eligibility rule considered in the sharp RD permits the limitation of the negative effect generated by loan obtainment on revenues and labor. Indeed, if the relaxation of the rule started with the fuzzy I and II setup seems to produce positive effects, we have to investigate further than these first sight results. Thus, we observe that the positive and statistically significant coefficient that appears on the revenues is obtained at the cost of a drastic drop in the effects on investment levels. However, if on the short term, according to the sharp RD results, financed entrepreneurs have to withdraw cash-flows from the labor factor to allocate them to the monthly repayment of 1 120$, higher levels of investment in fixed assets and equipments will yield higher returns in the long term. Thus, contrary to what was observed with the previous two loan sizes, our partner MFI does not benefit from a relaxation of its eligibility rule on the 30 000$ loan amount as shown by the results of the fuzzy 2.b setup which exhibits smaller effects than sharp RD. If that general conclusion holds for auto-enterprises which experience pretty similar negative impacts on both setups as shown by table 14, it seems that micro-enterprises suffers from the tightness of the rule. In fact, the inclusion of no-shows and cross-overs entrepreneurs permits the appearance of some positive and statistically significant coefficients for this type of enterprises. Nonetheless, the observed variations remain modest as this higher loan amount is more costly and enterprises with somewhat small size might experience some troubles absorbing this sudden inow of capital which represents one-third of their average annual revenues.

Dependent variable	ITT	Sharp	Fuzzy I	Fuzzy II	Fuzzy II.b
Annual value of fixed assets (in log)	**0.759****	**1.589****	**0.951****	**0.819****	**1.288****
	[0.348]	[0.673]	[0.464]	[0.374]	[0.593]
Annual estimated value of equipment's resale (in log)	**0.802****	**1.766****	**1.069****	**0.858****	**1.063***
	[0.347]	[0.735]	[0.528]	[0.372]	[0.611]
Annual total revenue (in log)	**0.609*****	-0.0814	**0.580*****	**0.658*****	-0.113

	[0.166]	[0.379]	[0.203]	[0.181]	[0.318]
Number of employees	0.053	--0.116	0.189	0.057	-0.544
	[0.330]	[0.565]	[0.401]	[0.352]	[0.552]
Monthly cost of wages (in log)	0.442	-1.203	0.327	0.473	-1.081
	[0.787]	[2.035]	[1.046]	[0.832]	[1.721]
Observations	311	187	295	311	202

Robust std errors in square brackets. Levels of statistical significance: * for 10%, ** for 5% and *** for 1%

Table 13: Effects of microcredit on entrepreneurial activity for the high size loan

Specification	Sharp RDD		Fuzzy I		Fuzzy II	
Dependent variable	Auto	Micro	Auto	Micro	Auto	Micro
Annual value of fixed assets (in log)	NEO	0.553	-0.901	0.716	-0.883	0.475
		[0.573]	[1.140]	[0.520]	[1.142]	[0.383]
Annual estimated value of equipment's resale (in log)	NEO	0.157	-0.098	**1.064***	-0.096	0.596
		[0.570]	[1.219]	[0.593]	[1.219]	[0.376]
Annual total revenue (in log)	NEO	0.125	-0.301	**0.656*****	-0.294	**0.600*****
		[0.702]	[0.384]	[0.250]	[0.385]	[0.206]
Monthly cost of wages (in log)	NEO	0.217	-0.809	0.354	-0.831	0.325
		[0.398]	[1.809]	[0.239]	[1.815]	[0.216]

Robust std errors in square brackets. Levels of statistical significance: * for 10%, ** for 5% and *** for 1%. NEO: not enough observations to perform the RD analysis

Table 14: Heterogeneous effects of microcredit by enterprise size (3)