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# The impact of microcredit on small firms in Brazil: A potential to promote investment, growth and inclusion<sup>☆</sup>

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## Abstract

Over the past decades, microfinance has become a pillar of economic development policies. However, despite the great popularity of micro-credit programs, the results of empirical studies are mixed. Thus, more research is needed to help us understand how effective microfinance is in achieving poverty reduction, economic development, and financial inclusion. This paper contributes to the literature by relying on a unique dataset from one of the biggest Fintech companies in Brazil to study the impact of microcredit on small firms' outcomes. Using a difference-in-difference approach, we find that access to credit increases monthly revenues and profits by nearly 4.5%. We show that the effects are stronger for women-led businesses and less experienced entrepreneurs. In addition, we find that credit renewal strengthens the benefits of credit access. We discuss several policy implications from our results. In particular, the permanent availability of credit – as opposed to one-time/short-term interventions – has greater potential to generate virtuous cycles of ever more reinvestment and growth, indicating larger gains from relaxing borrowing constraints in the long run.

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## 1. Introduction

The failure of the formal and informal financial sectors to provide affordable credit to poor individuals and small businesses is often viewed as one of the main factors reinforcing the vicious circle of economic and social structures that ultimately cause poverty. Consequently, over the past decades, microfinance has become a pillar of economic development policies. The great popularity of micro-credit programs has stimulated a large body of literature evaluating the impact of these programs to identify ways to improve their effectiveness and sustainability. However, the results of empirical studies are mixed. On the one hand, some recent papers such as [Banerjee et al. \(2019\)](#) and [Korosteleva and Stepien-Baig \(2020\)](#) find positive effects from credit access on entrepreneurship and poverty alleviation. On the other hand, there is an increasing number of studies that find no positive impact of microcredit at all. However, many of these studies face statistical issues that limit their results. [Dahal and Fiala \(2020\)](#), for instance, review eight microfinance studies that use randomized control trials and find that they are underpowered to detect any sizable effects.<sup>1</sup>

Thus, more research is needed to help us understand how effective microfinance is in achieving its poverty reduction objectives, economic development, and financial inclusion. In this paper, we contribute to this literature by relying on a unique dataset from a private microcredit company focused on the Northeastern region of Brazil to evaluate how access to credit affects microentrepreneurs' outcomes. By studying the impact of microfinance on small firms, we can identify the best practices in microfinance and replicate them to improve its effectiveness. Brazil is an interest case since several microcredit programs were developed in the country and it was one of the first countries in the world to experiment such programs. Moreover, Brazilian government adopted a series of measures to encourage the participation of the private sector in microcredit concession, including the creation of a profit-making legal entity, SCM, (Microentrepreneur Credit Society) with microcredit granting purposes; the allowance for banks to use up to 2% of its compulsory deposit to fund microcredit; and the creation of PNMPO (National Program of Oriented Productive Microcredit), aimed to boost employment and income generation by providing resources for oriented productive microcredit and technical support for microcredit institutions.<sup>2</sup>

Despite such programs and initiatives, credit in Brazil is still scarce, especially for small companies. According to [Alves and Soares \(2020\)](#), Brazil had more than 10,5 million small companies (with at most five workers) in 2013, most of them informal. Among these companies, 94% did not rely on credit within the three previous months. Thus, understanding the consequences of microcredit in Brazil is very important in terms of public policy and can provide an important contribution to the literature on microfinance.

The dataset used in this paper is from Avante, a digital lending platform that provides capital loans to small businesses. Avante is one of the biggest Fintech companies in Brazil with about 56.1 thousand borrowers in the period from September 2016 to May 2019, which is the period of our analysis. Fintechs have played an increasingly important role in microfinance programs in developing countries like Brazil. The main advantage of Fintech companies compared to more traditional microfinance lending models is that they leverage technology to offer more

<sup>1</sup> See [Roodman \(2012\)](#), [Dahal and Fiala \(2020\)](#) and [Banerjee et al. \(2015\)](#), for instance.

<sup>2</sup> For further details see [Carvalho \(2021\)](#), [BNDES \(2019\)](#) and [Barone et al. \(2002\)](#).

accessible, efficient, and customized lending solutions, reaching a wider range of borrowers in underserved areas.

To evaluate the consequences of microcredit on entrepreneurs, we use a difference-in-differences approach that compares the changes in outcomes such as revenues and profits of recipients of credit (treatment group) and non-recipients of credit (control group). Control groups are built using propensity score matching techniques to match beneficiaries of micro-credit programs with non-beneficiaries with similar characteristics. We also control for individual, time, region and industry fixed-effects and heteroskedastic robust standard errors.

We find sizeable effects of access to microcredit. On average, revenues and profits for entrepreneurs who succeeded in their credit requests were nearly 4.5% higher than for those who failed. We also consider the effects for different subgroups by separating entrepreneurs by gender, experience, size of the loan, type of allocation of resources, and size of the business. We find that the impact of credit access on revenues and profits was higher for women-led businesses and less experienced entrepreneurs, which is consistent with the idea that these groups are more likely to face tighter credit restrictions. In addition, self-employed entrepreneurs experienced substantially higher gains from credit access than those with one or more employees.

While the richness of our dataset allows us to achieve a significant degree of comparability between treatment and control groups based on several observable characteristics, it is still possible that having obtained credit or not may mean relevant differences *ex-ante*. Thus, as a robustness exercise, we restrict our sample to individuals who were successful in their credit application. We then compare those who received credit only once with those who received it many times. We find that the increase in profits and revenues after credit access is much higher for entrepreneurs with renewal granted. This result indicates that the continuation of the microcredit program has additional benefits for entrepreneurs beyond a one-time/short-term impact.

This paper contributes to a large literature studying the effects of microcredit on entrepreneurship and poverty alleviation. [Banerjee et al. \(2019\)](#) finds evidence that credit access to talented but low-wealth entrepreneurs can help them to escape the poverty trap in India. [Korosteleva and Stepien-Baig \(2020\)](#) show how entrepreneurship can contribute to poverty alleviation in transition economies, especially for women. [Berrone et al. \(2014\)](#) and [Thapa \(2015\)](#) study entrepreneurs and firms' characteristics that are associated with better performance in Argentina and Nepal, respectively. [Thanh et al. \(2019\)](#) find positive effects of microcredit in rural areas in Vietnam.

Regarding to Brazil, [Neri and Giovanini \(2005\)](#) find a significant correlation between credit access and formality indicators, asset ownership and participation in cooperatives. [Monzoni Neto \(2006\)](#) identifies significant effects of the microcredit program *São Paulo Confia* over firms' sales, margin, profits and income. [Aroca and Hewings \(2009\)](#) find a positive impact on individuals' income from microcredit programs in Brazil administered by banks. [Gonzalez et al. \(2014\)](#) identifies nearly 10% growth in the average revenues of women participating in a program of solidarity group lending of Banco Real, a commercial Brazilian bank. Finally, [Goldszmidt et al. \(2021\)](#) relies on data from BNDES, the largest government bank in Brazil, and finds no significant impact of microcredit on entrepreneurs in the long run, except for the poorest municipalities in the northeast of the country.

This paper also relates to the literature examining the aggregate consequences of microcredit on poverty and welfare. [Maksudova \(2010\)](#) shows the Granger causality from microfinance to economic growth using Microfinance Information Exchange (MIX) data. [Buera et al. \(2012\)](#),

Mahjabeen (2008) and Raihan, Osmani, and Khalily (2017) rely on general equilibrium models to evaluate the macro-impact of microfinance targeted to small business. Our work complements this literature since these papers draw upon micro evaluations of real-world microfinance programs to discipline and validate their models.

We also complement the literature relying on field experiments. de Mel et al. (2008) identified about 400 non-employer entrepreneurs in urban areas of Sri Lanka and gave them one-time grants either in kind (inventories or equipment) or in cash. While they find sizeable impacts on investment, their point estimates of the follow up work in de Mel et al. (2012) shows stability of the impacts over time, rather than leading to virtuous cycles of ever more re-investment and growth indicating that the gains from relaxing borrowing constraints are limited. They also find limited effects on female entrepreneurs. McKenzie and Woodruff (2008) carry out a similar study for Mexico and find further support to these findings.

Despite being studied for a long time and considered an important topic for public policy, especially for developing and poor economies, the efficacy of microcredit is still debated. Empirical evidence about the benefits of microfinance is still limited, primarily due to small data samples or other limitations that hinder the results in terms of external validation.<sup>3</sup> This paper contributes to this discussion with a robust quasi-experimental procedure relying on a unique dataset from Brazil. We add to the previous literature by focusing on the effects of a non-governmental organizations' microfinance program on entrepreneurs' outcomes. We also study the continuation of the microcredit program beyond its one-time/short-term impact, finding evidence that the permanent availability of the microcredit option to poor households has increasing long run impacts.

The paper is organized as follows. Section 2 and 3 describes the data and the empirical strategy. Section 4 presents our results. In section 5, we discuss our conclusions and policy implications.

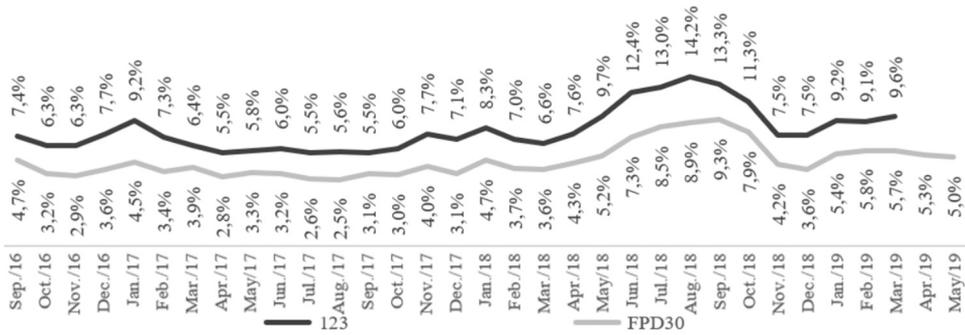
## 2. Data

This paper relies on data from Avante, which is a digital lending platform that provides capital loans to small businesses. Avante is one of the biggest non-profitable private microcredit companies in Brazil with about 56.1 thousand borrowers in the period from September 2016 to May 2019, which is the period of our analysis.<sup>4</sup> Avante operates mostly in Ceará, Pernambuco, Maranhão and Paraíba, all states in the northeast of the country. In the period under study, most of the clients were self-employed (70%), women (64%) and had more than one contract with Avante (76%). The loans granted by the company were between 350 and 80,000 Brazilian Reais (USD 74 – USD 17,020), ranging from 1700 Reais for new borrowers to 3200 Reais for clients with credit renewal granted, on average, and were offered as unsecured individual microcredit with no collateral. The average interest rate was 3.9% per month (58.3% per year) with an average term of 6 months.

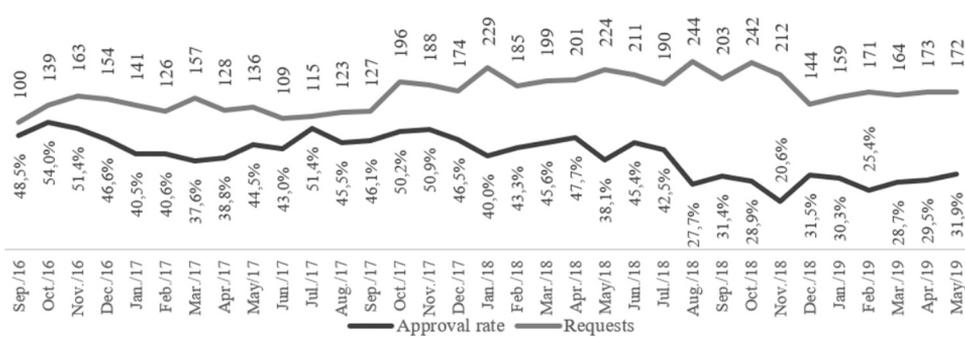
The company's process for underwriting credit is based on a network of agents present in more than 100 cities where the company operates. These agents are responsible for screening the micro-entrepreneurs through a process in which they visit and interview them, registering all the information with an App developed by the company. This App contains geolocation which

<sup>3</sup> See, for instance, Bédécarrats et al. (2019); Bédécarrats et al. (2020) and Dahal and Fiala (2020).

<sup>4</sup> The access to this database was granted under a non-disclosure agreement.



**Fig. 1.** Delinquency behaviour (123 and FPD30 indexes). FPD30 index is the balance of contracts with at least 30 days of outstanding payment of their first installment over the balance of all contracts signed that month. 123 index is the balance of contracts where the client failed to pay at least one of the 3 first installments over the balance of all contracts signed that month.



**Fig. 2.** Number of requests and rate of credit approval per month. Requests are normalized to 100 in the beginning of the sample, September 2016.

is used on algorithms to protect the company against fraud.<sup>5</sup> The delinquency rate of Avante, measured by the rate of First Payment Default within 30 days (FPD30) and the Delinquency Percentage within the 3 First Installments (123), were below 10%, as shown in Figure 1.

The credit grant approval rate depends not only on the credit rate defined with information from agents, but also varies with the date of the request, as shown in Figure 2 below. In some periods the credit is more restricted, with approval rate varying between 20% and 25%. In other periods the credit is much more flexible, and the approval rate reaches more than 50% of the requests. Moreover, apparently there is no correlation between credit approval and the size of the loans.

<sup>5</sup> The information provided by the entrepreneurs is reported by the agents without external back checks. However, the agent responsible for the interview has authority to block a concession if in doubt of any information given. Furthermore, agents are paid according not only to their productivity (e.g. quantity/volume of credit concessions), but also to the quality of their portfolio (e.g. level of delinquency of the agent’s clients and recovered credit volume). Hence, they have incentives to keep data as reliable as possible.

**Table 1**  
Number of records.

Description	n
Initial records in base	240,097
(a) Records with negotiation history	(31,328)
(b) Incorrectly filled records	(93,537)
(c) Records without score	(3771)
Valid Records	111,461)
(d) “Contaminated records”	(23,665)
(e) Records with only one observation	(41,866)
(f) Records with no <i>matching</i>	(10,792)
<b>Total Records</b>	<b>35,138</b>

Overall, we have 240,097 records configuring 231,716 credit proposals evaluated by the company from September 2016 to May 2019. These proposals represent 208,769 credit requested by 92,545 micro-entrepreneurs from 521 Brazilian cities.<sup>6</sup> We have information on more than 53 variables, including date, entrepreneurs’ and businesses’ characteristics, and information about the credit request.<sup>7</sup>

In order to conduce our study, it was made necessary a cleaning of the records, discarding (a) all information of credit proposal if not the very last analyzed by the company (e.g. history of request negotiation); (b) records that were incorrectly filled and, therefore, were reported as invalid (e.g. invalid micro-entrepreneurs’ revenues); (c) records with missing information for decisive credit score; (d) records for which client’s first observation is not the first interaction with the company (e.g. contaminated records); (e) all records containing only one interaction (e.g. records with only one observation); and (f) records without appropriate comparison group (e.g. records without matching). [Table 1](#) presents a summary of our cleaning procedure.

The final sample includes information on 35,138 credit requests from 13,779 individuals. 34% of these requesters were men. These contracts were allocated across 224 cities, mainly from 4 States in the Northeast of Brazil. Ceará was the state with the largest number of credit requests in the period (49.8%), followed by Maranhão (29.9%), Pernambuco (9.7%) and Paraíba (4.6%). A small portion (6%) of contracts is found distributed in 17 cities from other states of the country. [Figure 3](#) presents graphically this distribution across gender and regions.

The average revenue from businesses varies between 5868.39 Reais in the control and 6066.23 Reais in the treated sample.<sup>8</sup> 69.4% of the entrepreneurs reported not being employers, 21.9% reported to employ only 1 worker and 8.7% to have two employees. [Figure 4](#) shows the distribution of credit requests at the 10th, 25th, 50th, 75th, and 90th percentile of revenues from the solicitants.

<sup>6</sup> The same credit request may have undergone more than one proposal negotiation (in the case of changes in value conditions or payment terms, for instance) and the same client might have more than one credit request throughout his relationship with the company.

<sup>7</sup> This data set is very reach. We have several financial variables that we can use to evaluate the effects from credit access, including the revenues and the profits from the businesses, and several other variables that can be used as control or to construct subgroups, for instance, requested value, number of instalments, credit request motive, previews credit experience and gender of the entrepreneur.

<sup>8</sup> Further details on the sample construction are presented in the next sections.

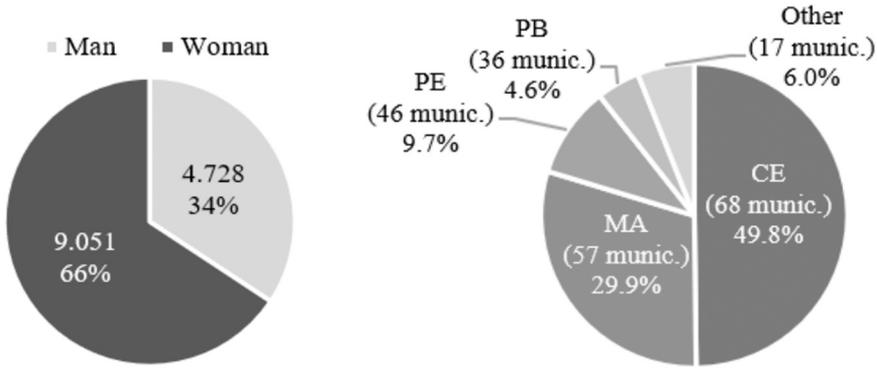


Fig. 3. Distribution of entrepreneurs in the sample. On the left: distribution by gender. On the right: geographic distribution.

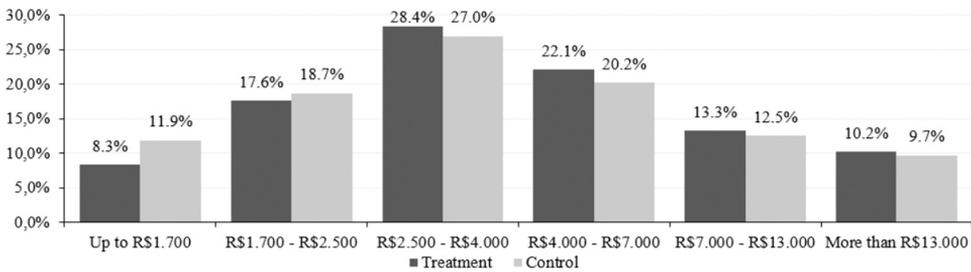


Fig. 4. Distribution of requests per revenues of solicitants. Revenues in Brazilian.

### 3. Empirical strategy

Since the data is not experimental, obtaining an ideal control group to isolate the impact from access to credit (treatment) is not trivial. As pointed out by Rosenbaum and Rubin (1983) one strategy to deal with this challenge is to use propensity score matching techniques. According to the authors, the propensity score is defined as the conditional probability of assignment to a particular treatment given a vector of observed covariates. Therefore, the balancing of the scores may be applied to allow direct comparisons between the treatment and control groups.

In this paper, we aim to compare the changes in revenues and profits of those who got credit and those that did not. Hence, our treatment group is composed of the entrepreneurs that had their credit request granted and had at least another interaction with Avante. In turn, our control group is composed of those that did not receive credit, but also had further interactions with the company. Figure 5 summarizes our treatment and control definition.

Since we are only considering individuals who have at least two contacts with the company, a potential caveat of this paper arrives from the fact that we are not able to consider the results that would be observed on the revenues of entrepreneurs that following access to credit, or declined request, had no further interaction with the company. The absence of this information might cause some bias over the selection, underestimating the effects for both treatment and

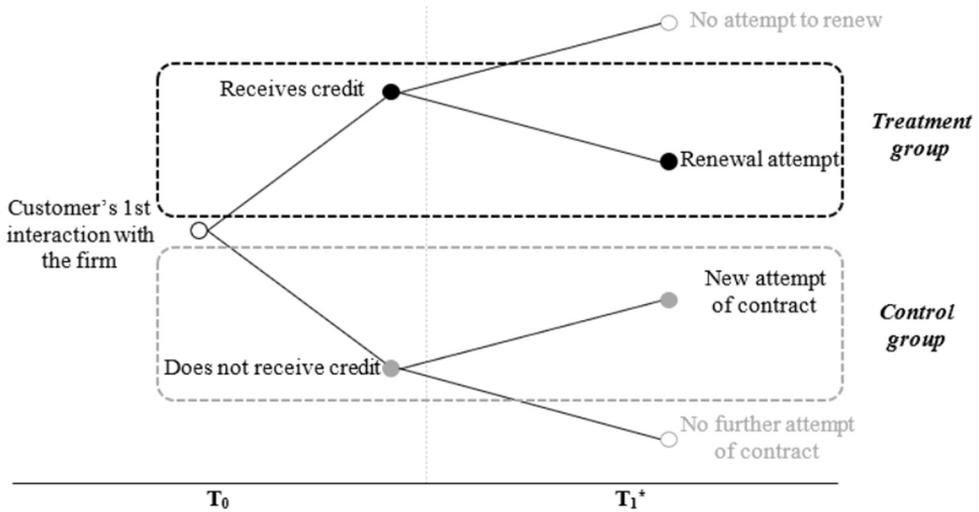


Fig. 5. Treatment and control groups. Average  $(T_1 - T_0) = 180$  days. Median  $(T_1 - T_0) = 171$  days.

control groups.<sup>9</sup> We try to minimize this problem by considering an alternative definition of treatment and control groups based on credit renewal.

In order to ensure the comparability of the control and treatment groups, we rely on the assumption of the propensity score matching that entails that there must not be any non-observable characteristics affecting participation in the treatment. In our case, the credit decision is taken based on observable information available on the database along with the evaluator’s judgment about the credit score, which is a discreet grade from ‘A’ to ‘F’, being ‘A’ the lowest probability of delinquency and ‘F’ the highest. To the applied data there are credit concessions both approved and declined within all scores, which makes the comparison between the groups easier.

In this study, we use the Mahalanobis-Metric Matching based on Rubin (1980) and Zhao (2004). To balance comparisons between treatment and control groups we select characteristics of entrepreneurs that might be predictive of treatment such as credit score, the date of the credit request, the state where the business is based and revenues. This procedure ensures comparability between the samples prior to the treatment. After the matching, we have 29,283 records of 11,260 entrepreneurs in the control and 5883 records of 2519 entrepreneurs in the treatment samples. Table 2 presents the quality of the match.

The t-statistics before and after matching show bias reduction effect to the balancing of covariates. The table also displays sample balancing tests as well as bias results. After the matching, 10,792 records were discarded from 3792 entrepreneurs that revealed zero score in the sample reposition indicator, i.e., records that were impossible to find correspondence to comparison samples. With an average bias reduction from 27.1 to 0.3 and median bias from 19.1 to 0.2, the comparability between the entrepreneurs’ samples is quite reasonable, mitigating eventual problems of endogeneity and selection bias.

<sup>9</sup> For the control group it might be the case that only the most resilient entrepreneurs try once again to apply for credit. Some entrepreneurs could also close their business. On the other hand, for the treatment group it might be the case that after taking the loan, the best entrepreneurs have no need of third-party resources anymore.

**Table 2**  
Average mean test and balancing of covariates.

Covariates	Before matching			After matching		
	Treatment	Control	<i>t-stat</i>	Treatment	Control	<i>t-stat</i>
<i>UF</i>	8.67	9.73	-21.20 ***	8.70	8.71	-0.23
<i>Time</i>	16.69	15.59	6.37 ***	11.84	11.85	-0.13
<i>Revenue</i>	5650.60	5802.50	-2.14 **	5397.90	5362.40	0.55
<i>Score</i>	3.32	4.30	-46.00 ***	3.02	3.02	-0.00
PS R <sup>2</sup>			0.08			0.00
LR χ <sup>2</sup>			2572.08			0.35
Average bias			27.10			0.30
Median bias			19.10			0.20
No. entrepreneurs	11,260	6311		11,260	2519	
No. observations	29,283	16,647		29,283	5883	

### 3.1. Estimation of treatment effect

Once the matching was done, data of individuals in distinct periods was collected in order to estimate the Average Treatment Effect on Treated (ATT). Our general specification is the following:

$$Y_{ic} = \alpha + \beta T_i + X_c + e_{ic}$$

where Y stands for either monthly revenues or profits of an individual i in the group c. In line with Correia (2016) we control for: (i) credit concession date (proxy to seasonality), (ii) business category (industry), (iii) interaction between date and state (proxy to regional seasonality effect) and (iv) interaction between date and business category (proxy to industry-specific seasonality). The estimate standard-errors are grouped at the individual level i, as unit of randomization.

## 4. Results

In order to access the implications of microcredit on entrepreneurs we compare the changes in revenues and profits between treatment and control groups.

### 4.1. Main model

We begin with our main specification that only separate entrepreneurs in treatment and control groups. Table 3 shows the results from 5 different specifications using the log revenue as the dependent variable. In each of these specifications we control for individual fixed effects, but change the other controls used.

We can see that in all cases considered the treatment variable is statistically significant, which suggests that credit increases revenues. In particular, our main specification (5) shows that, on average, the revenues increase was almost 5% higher for entrepreneurs with credit granted. We also find positive and statistically significant effects from credit access. In particular, our main specification indicates that profits are 4.58% for entrepreneurs with credit access.

**Table 3**  
Impact of credit access on revenue.

Outcome: <i>log revenue</i>	Model				
	(1)	(2)	(3)	(4)	(5)
<i>constant</i>	8.3193 *** (0.0008)	8.3230 *** (0.0024)	8.3218 *** (0.0023)	8.3218 *** (0.0023)	8.3205 *** (0.0022)
<i>treatment</i>	0.0550 *** (0.0030)	0.0418 *** (0.0087)	0.04622 *** (0.0083)	0.04225 *** (0.0083)	0.0472 *** (0.0080)
Individual FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes	Yes
<i>time • UF</i> FE	No	No	Yes	No	Yes
<i>time • industry</i> FE	No	No	No	Yes	Yes
R <sup>2</sup>	0.9357	0.9369	0.9391	0.9387	0.9408
R <sup>2</sup> Adjusted	0.9430	0.8961	0.8986	0.8974	0.8999
No. Observations	35,126	35,126	35,076	35,008	34,958
No. Individuals	13,767	13,767	13,746	13,724	13,703

**Table 4**  
Impact of credit access on profit.

Outcome: <i>log revenue</i>	Model				
	(1)	(2)	(3)	(4)	(5)
<i>constant</i>	8.1633 *** (0.0009)	8.1676 *** (0.0028)	8.1664 *** (0.0027)	8.1671 *** (0.0027)	8.1658 *** (0.0026)
<i>treatment</i>	0.0567 *** (0.0033)	0.0410 *** (0.0104)	0.0455 *** (0.0099)	0.0411 *** (0.0098)	0.0458 *** (0.0094)
Individual FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes	Yes
<i>time • UF</i> FE	No	No	Yes	No	Yes
<i>time • industry</i> FE	No	No	No	Yes	Yes
R <sup>2</sup>	0.9231	0.9243	0.9266	0.9271	0.9293
R <sup>2</sup> Adjusted	0.8735	0.8753	0.8779	0.8781	0.8806
No. Observations	35,126	35,126	35,076	35,008	34,958
No. Individuals	13,767	13,767	13,746	13,724	13,703

**Table 5**  
Impact of credit renewal on revenues and profits.

	Revenues (1)		Profits (2)	
	<i>No credit renewal</i>	<i>Credit renewal</i>	<i>No credit renewal</i>	<i>Credit renewal</i>
<i>constant</i>	8.3323 *** (0.0004)	8.3276 *** (0.0024)	8.1415 *** (0.0009)	8.1732 *** (0.0029)
<i>treatment</i>	0.0225 *** (0.0116)	0.0532 *** (0.0071)	0.0124 *** (0.0139)	0.0541 *** (0.0087)
R <sup>2</sup> Adjusted	0.8919	0.8925	0.8780	0.8707
Observations	6572	27,644	10,813	27,644

## 4.2. Credit renewal

As discussed earlier in the paper, our choice of treatment and control group based on credit access is not without charge since credit access may be behind significant non-observable differences between entrepreneurs. Hence, we consider an alternative definition of treatment and control groups based on credit renewal. More specifically, we compare the changes in revenues and profits between entrepreneurs that receive credit only once with those with two or more concessions. Our results suggest significant increases in revenues and profits from credit renewal. In particular, the revenue increase for entrepreneurs receiving credit renewal is at least twice as high as those that did not. For profits, the difference is even higher and indicates that credit renewal matters more than credit access.

On the one hand, this result suggests that we have important differences between firms that got credit and those that did not, even after controlling for them. On the other hand, it also indicates that a continuation of microcredit may have additional benefits for entrepreneurs that goes beyond a one-time/short-term impact, as found in other papers.

## 4.3. Additional results (subgroups)

As briefly discussed in the introduction, some papers find that some entrepreneurs' characteristics are important determinants for microcredit efficacy. Hence, based on the main model and following the same regression specifications, we consider additional results composed by database samples based on several characteristics from entrepreneurs and business. [Figure 6](#) summarizes the main results. The first column plots the results for revenues and the second for profits. The dashes indicate one standard deviation. Most part of results are inside the standard-error band from the main model. Therefore, although such results indicate a distinction between groups, it is not possible to confirm if they are statistically divergent from the average global results.

### 4.3.1. Gender effect

It is not uncommon that microcredit programs are directed to female entrepreneurs "under the belief that they have less access to credit, lower outside options in the labor market, and therefore the highest returns to private entrepreneurship". (KABOSKI; TOWNSEND, 2012, p. 102). Hence, in [Table 6](#) we report results separated by gender, first for revenues and then for profits.

We find a statistically significant and higher impact from credit access on revenues and profits for female entrepreneurs (5.21% and 4.99% respectively) compared to male entrepreneurs (4.41% for both cases). Our results are in line with the [Pitt and Khandker \(1998\)](#) for instance, which also finds a higher impact of credit access to women in Bangladesh.

### 4.3.2. Experience

Experience is also pointed out by the literature as an important determinant for the efficacy of microcredit.<sup>10</sup> In order to complement this literature, we analyze the implications of experience over revenues in the presence of credit access. [Table 7](#) presents our results. Each column analyzes a different group of entrepreneurs in terms of their experience. In line with the

<sup>10</sup> [Fatimah-Salwa et al. \(2013\)](#), for instance, review some literature for Malaysia.

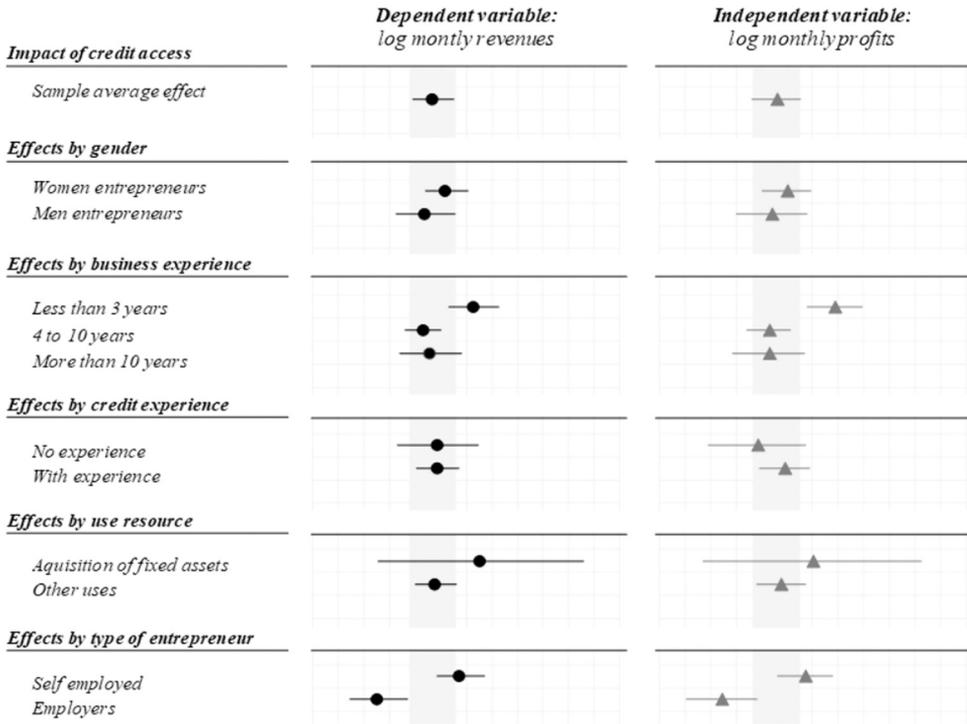


Fig. 6. Summary of additional results (subgroups). The dashes represent one standard deviation.

Table 6  
Credit access effects - by gender.

Outcome	Revenues (1)		Profits (2)	
	Women	Man	Women	Man
constant	8.2311 *** (0.0023)	8.4851 *** (0.0031)	8.1052 *** (0.0027)	8.2784 *** (0.0037)
treatment	0.0521 *** (0.0083)	0.0441 *** (0.0114)	0.0499 *** (0.0096)	0.0441 *** (0.0138)
Individual FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
time • UF FE	Yes	Yes	Yes	Yes
time • industry FE	Yes	Yes	Yes	Yes
R <sup>2</sup>	0.9353	0.9502	0.9237	0.9415
R <sup>2</sup> Adjusted	0.8905	0.9116	0.8709	0.8962
No. Observations	23,011	11,788	23,011	11,788

literature, we can see that revenues are higher with experience. However, even though for all of them there are positive effects from credit access, the benefits are not strictly increasing on experience. The ones that benefit the most are the least experienced ones (less than 3 years) with returns of around 6.3%. The benefits from credit access to the most experienced entrepreneurs is

**Table 7**

Credit access and revenues - effects by business experience.

Outcome	Revenues (1)		
	< 3 years	4–10 years	> 10 years
<i>constant</i>	8.1385 * ** (0.0025)	8.3130 * ** (0.0020)	8.4522 * ** (0.0032)
<i>treatment</i>	0.0628 * ** (0.0096)	0.0432 * ** (0.0070)	0.0460 * ** (0.0119)
Individual FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
<i>time • UF</i> FE	Yes	Yes	Yes
<i>time • industry</i> FE	Yes	Yes	Yes
R <sup>2</sup>	0.9434	0.9526	0.9435
R <sup>2</sup> Adjusted	0.8981	0.9166	0.9008
No. Observations	8893	12,710	12,401

**Table 8**

Credit access and profits - effects by business experience.

Outcome	Profits (2)		
	< 3 years	4–10 years	> 10 years
<i>constant</i>	7.9997 * ** (0.0029)	8.1725 * ** (0.0025)	8.2752 * ** (0.0037)
<i>treatment</i>	0.0686 * ** (0.0108)	0.0429 * ** (0.0085)	0.0428 * ** (0.0139)
Individual FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
<i>time • UF</i> FE	Yes	Yes	Yes
<i>time • industry</i> FE	Yes	Yes	Yes
R <sup>2</sup>	0.9355	0.9425	0.9334
R <sup>2</sup> Adjusted	0.8838	0.8989	0.8832
No. Observations	8893	12,710	12,401

only slightly higher than for those with intermediary levels of experience (4–10 years).<sup>11</sup> Our findings are quite similar for profits. The results are provided in [Table 8](#).

We also analyze if credit experience matters for profits and revenues, the results are presented in [Table 9](#). The first two columns present the results for revenues, the last two for profits. According to the results there was no difference on the impact of credit access over revenues for entrepreneurs with and without previous experience with credit. In both cases, the growth from credit access was 4.88%. On the other hand, the profit growth for entrepreneurs with no previous credit experience was 3.84% against 4.91% for those with previous experience.

<sup>11</sup> A possible explanation is that experienced entrepreneurs started from a higher average base before the treatment.

**Table 9**

Credit access - effects by credit experience.

Outcome	Revenues (1)		Profits (2)	
	<i>no exper.</i>	<i>with exper.</i>	<i>no exper.</i>	<i>with exper.</i>
<i>constant</i>	8.2663 *** (0.0037)	8.3239 *** (0.0023)	8.0503 *** (0.0045)	8.1739 *** (0.0027)
<i>treatment</i>	0.0488 ** (0.0158)	0.0488 *** (0.0083)	0.0384 ** (0.0191)	0.0491 *** (0.0098)
Individual FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
<i>time • UF</i> FE	Yes	Yes	Yes	Yes
<i>time • industry</i> FE	Yes	Yes	Yes	Yes
R <sup>2</sup>	0.9716	0.9415	0.9613	0.9307
R <sup>2</sup> Adjusted	0.9385	0.9009	0.9161	0.8825
No. Observations	2226	32,051	2226	32,051

#### 4.3.3. Type of investment

Another feature that might be important to understand the effects of microcredit is the type of investment or the purpose of the loan. Moser and Felton (2009) discuss the growing importance of assets as a complementary measure to family revenues and consumption in emergent markets. In her study of almost 30 years in Guayaquil in Ecuador, Moser (2010) shows that accumulation of assets makes communities more resilient to economic shocks and it is a sustainable mechanism to combat poverty.

In line with this evidence, Table 10 reports the effects of credit access over revenues (first two columns) and profits (columns 3 and 4) for entrepreneurs who claim to use loans to acquire fixed assets (e.g. machines, equipment, or even electrical appliances to productivity purposes), and for those who claim to apply it to other ends (e.g. working capital, debt liquidation, subsistence, among others). For both revenues and profits, the results suggest higher growth for entrepreneurs who reported to use the capital for the acquisition of fixed assets. However, due to

**Table 10**

Credit access and profits - effects by type of resource.

Outcome	Revenues (1)		Profits (2)	
	<i>Fixed assets</i>	<i>Other uses</i>	<i>Fixed assets</i>	<i>Other uses</i>
<i>constant</i>	8.5710 *** (0.0099)	8.3170 *** (0.0022)	8.2757 *** (0.0105)	8.1668 *** (0.0026)
<i>treatment</i>	0.0657 (0.0402)	0.0480 *** (0.0081)	0.0599 (0.0427)	0.0476 *** (0.0096)
Individual FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
<i>time • UF</i> FE	Yes	Yes	Yes	Yes
<i>time • industry</i> FE	Yes	Yes	Yes	Yes
R <sup>2</sup>	0.9287	0.9414	0.8932	0.9308
R <sup>2</sup> Adjusted	0.7068	0.9010	0.5606	0.8830
No. Observations	622	33,824	622	33,824

**Table 11**  
Credit access- effects by type of entrepreneur.

Outcome	Revenues (1)		Profits (2)	
	<i>Self-employed</i>	<i>Employers</i>	<i>Self-employed</i>	<i>Employers</i>
<i>constant</i>	8.2164 * ** (0.0025)	8.5468 * ** (0.0032)	8.0820 * ** (0.0030)	8.3497 * ** (0.0039)
<i>treatment</i>	0.0577 * ** (0.0093)	0.0255 * * (0.0114)	0.0571 * ** (0.0108)	0.0244 * (0.0138)
Individual FE	Sim	Sim	Sim	Sim
Time FE	Sim	Sim	Sim	Sim
<i>time • UF</i> FE	Sim	Sim	Sim	Sim
<i>time • industry</i> FE	Sim	Sim	Sim	Sim
R <sup>2</sup>	0.9314	0.9578	0.9237	0.9450
R <sup>2</sup> Adjusted	0.8826	0.9245	0.8695	0.9017
No. Observations	23,375	10,666	23,375	10,666

the small number of individuals, the effects for fixed assets are not statistically significant. Moreover, the average revenues and profits are higher for entrepreneurs investing in fixed assets.

#### 4.4. Employers and self-employed

Another feature that we can analyze in our data is whether credit access affects differently self-employed entrepreneurs. [Tarozzi et al. \(2015\)](#), for instance, identify a significant growth on revenues of self-employed entrepreneurs in Ethiopia (however, subjected to a broad variation due to standard-error). Other studies in that vein include [Crépon et al. \(2015\)](#) in Marrocos and [Augsburg et al. \(2015\)](#) in Bosnia Herzegovina.<sup>12</sup>

In order to contribute to this literature, we consider separately the effects of microcredit to self-employed and for entrepreneurs with one or more employee.<sup>13</sup> The results suggest considerable higher growth of revenues and profits for self-employed entrepreneurs compared to employers. However, business with employers have higher average revenues and profits, which might suggest that employers have a slightly better structured business or a better capability of multiplication than self-employed (more shifts to deal with customers, for instance).

## 5. Conclusions and policy implications

Microfinance is a strategy that aims to provide financial services such as small loans to low-income individuals who are often excluded from traditional banking systems. In this paper, we

<sup>12</sup> [Crépon et al. \(2015\)](#) finds significant results to growth on assets investments to self-employment activities (1454 MAD - 1 dollar  $\approx$  9.5 MAD) and on these activities profits (2.011 MAD, or 22.2% growth over the average of the sample). In turn, [Augsburg et al. \(2015\)](#) finds that individuals with access to microcredit have a 6% higher chance of obtaining revenues from self-employment activities.

<sup>13</sup> We have 9191 self-employed individuals, that is, entrepreneurs claiming to be the sole worker in the business and 4257 employers, individuals claiming to have 1 or more employees. No entrepreneur reported having more than 2 employees in addition to himself.

perform an impact evaluation of a private Brazilian microcredit firm, which operates in four states in the country's northeast region. Relying on a quasi-experimental approach, we find sizable effects of credit access on revenues and profits. The results are larger for women-led businesses, less experienced entrepreneurs, and self-employed. Moreover, credit renewal strengthens the benefits of credit access.

Our findings have several important policy implications. First, our results support the view that policymakers can rely on microfinance programs as a policy tool to help local small businesses to grow and become more profitable, expanding employment and income generation. Since our sample is composed of informal entrepreneurs with little or no credit history, an important implication of microfinance programs is to reduce dependence on informal lenders who charge high-interest rates, providing an alternative source of financing that is more affordable and accessible. In addition, by taking out and repaying microloans, these policies help informal entrepreneurs to build a credit history, allowing them to access larger loans and other financial services in the future.

Second, the fact that the positive impacts of credit are much larger for entrepreneurs with renewal granted implies that the continuation of the microcredit program has additional benefits for entrepreneurs beyond a one-time/short-term impact. This is important in terms of policy design since microfinance policies that ensure the permanent availability of credit have more potential to generate virtuous cycles of ever more reinvestment and growth, indicating that the gains from relaxing borrowing constraints may be even greater in the long run.

Third, our findings indicate that microfinance can be a policy tool to promote women empowerment by increasing their economic opportunities and social status. Thus, policymakers can support microfinance programs that target women to promote gender equality by providing incentives, funding, and regulatory frameworks that encourage their growth.

Forth, since we rely on data from one of the largest Fintechs in Brazil, our results also support the view that Fintechs can play a key role in expanding microfinance programs. By leveraging technology to streamline the lending process, fintech can offer faster and more accurate loan approvals, reducing the time and effort required for borrowers to apply for and receive loans. Policymakers should induce the growth of the Fintech sector through an adequate regulatory framework so that these institutions can be financially sustainable, allowing them to continue providing financial services to low-income individuals over the long term without relying on subsidies to operate. By stimulating the expansion of Fintechs, policymakers can help microfinance programs to reach more borrowers in underserved areas, promoting development more efficiently.

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