Multilevel latent class modeling to segment the microfinance market

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LONGITUDINAL ANALYSIS OF MICROFINANCE BORROWERS IN BRAZIL: A DYNAMIC MARKET SEGMENTATION

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ABSTRACT

The impact of microfinance in alleviating poverty is still undefined. A dynamic modeling approach is used to group clients of a microcredit program in Latin America in homogeneous segments and follow them over time. Five segments are identified, based on variables related to the business, the owners and their families, and the operations performed within the program. Results show that borrowers do not improve. Many of them remain in the same segment, some even move to a segment with worse conditions, however, mission drift does not occur. It also emerged that the program cannot reach a win-win situation with borrowers.

Keywords: microfinance; latent class Markov models; dynamic market segmentation; longitudinal research; Brazil.

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1. INTRODUCTION

Microfinance concerns the provision of various small-scale services, such as credit, savings, insurance, training, mortgages, transfer services and retirement plans (Khavul, 2010; Bateman & Chang, 2012; Garikipati, 2017). The main reason why these services are offered on a small scale is because of the target clients (Garikipati, 2017): microfinance is provided for those who live in the poverty zone and are excluded from formal banking systems (Mersland & Strøm, 2010). The goal of microfinance is to offer these services in order to provide economic support for clients in poor conditions, the goal being to alleviate poverty through entrepreneurship (Khavul, 2010; Bateman & Chang, 2012; Newman et al., 2014; Chliova et al., 2015; Cull & Morduch, 2017).

Microfinance should achieve the dual objective of social outreach and financial sustainability (Hermes et al., 2011). It should improve borrowers' social welfare and, at the same time, enable microfinance institutions (MFIs) to make a profit (Cull & Morduch, 2017). When both these outcomes are achieved, this is defined as a win-win situation (Morduch, 1999). The issue of financial viability is so important, however, that it raises some questions concerning whether MFIs (which are sustainable through subsidies) should be maintained, and whether MFIs that are earning a lot of money from the poor are behaving correctly (Bateman & Chang, 2012).

However, some researchers argue that the outcome of microfinance schemes can vary: in some cases, clients are effectively helped and fare better, while in others their living conditions further deteriorate (Banerjee et al., 2015a; Banerjee et al., 2015b; Chen et al., 2017). Random field experiments in India have shown that after 15 to 18 months of borrowing, most businesses supported by microfinance remain very small and profit-free (Banerjee et al., 2015b). Beyond the microfinance outcome, we must emphasize the urgent need to take a closer look at the clients involved in long term relationships and the mechanisms employed in microfinance programs (Chen et al., 2017).

Many researchers in the field have mentioned the need to monitor microfinance clients over time (Newman et al., 2014; Dutta & Banerjee, 2017; Garikipati, 2017), but few studies have involved into a longitudinal analysis. There is nothing in the recent literature on how the situation of microfinance clients evolved over time, judging from their business data and sociodemographic variables. Longitudinal research on microfinance would help to clarify its impact on borrowers' social welfare, revealing changes in their personal and business conditions, and pointing to the need to offer them new products (Shapiro, 2015; Souza et al., 2019). It is also important to recognize the influence of the dynamic context in which these clients live (Ahlin et al., 2011; Chliova et al., 2015; Chen et al., 2017). Shahriar and Garg (2017) have shown that a win-win situation can be achieved in long-term relationships, while in the short term there is a greater chance of one side making a loss. The effects of this pursuit of a win-win relationship led some microfinance institutions to deviate from the main objective and move on to looking for more lucrative clients - an action known as mission drift (Mersland & Strøm, 2010; Xu et al., 2016; Ghosh & Guha, 2017).

To achieve this gap in the results on long-term relationships, this paper aims to analyze the migration of distinct groups of clients from a microfinance program, checking the social and financial efficiency and looking for eventual mission drift with an application to a microfinance program in Brazil (CrediAmigo). To reach this scope, we adopt a dynamic market segmentation to identify homogeneous clusters of borrowers and monitor their progress over time. Our findings enable us to identify the profiles of these clusters of borrowers, and establish whether or not their socio-economic conditions improve while they are involved in the program. We do not intend to perform impact evaluation since we do not dispose of outcomes from an experiment. Our purpose is to conduct an exploratory and longitudinal study about a microfinance institution to understand the migration of the borrowers over time.

Finally, this paper aims to give a theoretical contribution to the field of microfinance, providing new information through a longitudinal study from which it emerges that microfinance has a high potential for social action, but does not achieve social efficiency, not reaching its dual objective. In addition, our analyses seek to provide evidence on the importance of recognizing customers' profiles and the mechanisms used in microfinance (Morduch, 2000; Newman et al., 2017). Most research on this topic is conducted in Asian countries; this paper contributes to information on microfinance in Brazil, obtaining results that could be at least a starting point for research also in other Latin American countries (Van Rooyen et al., 2012). The methodological contribution consists in the application of dynamic market segmentation as a form of longitudinal analysis; the obtained results demonstrate the efficiency of this technique to detect information emerging only when identifying clusters of clients and following their behavior over time. Managers in the financial and banking sectors could benefit of the results of the analyses to define target strategies.

2. MICROFINANCE PROGRAMS

The impact of microfinance in alleviating poverty and improving borrowers' social welfare has already been demonstrated in a number of studies (Newman et al., 2014; Wulandari & Kassim, 2016). According to Newman et al. (2014), microfinance gives to the poor a chance to combat poverty, generate income, and seize business opportunities. The same authors argue that lending also has a direct effect on entrepreneurial activity, increasing financial capital, as well as having a positive impact on business results, thereby generating more psychological capital for clients.

The previously-mentioned findings highlight the fact that changes occur when a client has access to microfinance, but these changes do not necessarily always go in the same direction, and at the same pace (Banerjee et al., 2015a). Despite its stories of success, doubts have been raised about the ability of microfinance programs to create a sustainable entrepreneurship (Field et al., 2013).

There is some evidence suggesting that, although billions have been borrowed by MFIs around the world, their effects on borrowers and entrepreneurship might have been not always positive (Khavul, 2010; Bruton et al, 2015). Negative outcomes can happen because both human and financial capital are necessary to create a business, and people living in impoverished conditions may lack the education, experience and skills to develop and manage a business and cope with any future setback (Staniewski, 2016). This lack of expertise may encourage the poor to continue in subsistence activities rather than try to develop a business. In fact, one of the problems faced by MFIs is that many borrowers use the loans to satisfy immediate consumption needs instead of investing in value-added activities. This attitude can turn clients into defaulting borrowers because their having used the credit to cover other needs can lead to a situation where they are unable to raise capital to cover the loan (Chen et al., 2017). That is why Chen et al. (2017) and Seng (2018) suggest that microfinance may not always generate positive results for borrowers. Bateman and Chang (2012) are much more severe in their criticism, claiming that microfinance is a weapon of neoliberalism, a “trap for the poor”. Furthermore, another topic that deserves more attention about the microfinance is mission drift.

Mission drift occurs when microfinance institutions leave their primary objective of lifting people out of poverty and achieving social sustainability, to focus on the secondary objective of financial viability. This change in target directly impacts on how institutions select their clients, as they no longer seek to serve the poorest, as they do not bring in profits, and the participation of women decreases as men have better incomes. In sum, MFIs pass to give priority to individual loans and serve people who are above the poverty line (Mersland & Strøm, 2010; Amin et al., 2017; Ghosh & Guha, 2017).

In order to reach a win-win situation and gain a better understanding of the impact of microfinance, it is imperative to recognize the profile of MFIs' clients (Morduch, 1999; Khavul, 2010; Cull & Morduch, 2017; Garikipati, 2017). One factor that it is determinant in the efficiency of the microfinance is the target market (Gutierrez-Goiria et al., 2017). It is also essential to understand the mechanisms used by MFIs, and establish which of them achieve the best results for a given group of clients. The MFIs' mechanisms are characteristic of the products and services they offer to borrowers (Morduch, 1999; Newman et al., 2014). They may be an issue because many MFIs offer standard products and services, or copy those of other organizations, which may not fulfill their clients' specific needs (Morduch, 1999; Souza et al., 2019).

3. DYNAMIC MARKET SEGMENTATION IN THE BANKING SECTOR

The concept of market segmentation proposed by Smith (1956) aims to divide a heterogeneous market into smaller homogeneous groups in order to identify target consumers, and this enables organizations to formulate better strategies to serve target groups. To improve the results obtainable from this segmentation process, however, researchers considered using dynamic market segmentation (Wedel & Kamakura, 2000; Kamakura, 2009), which aims to explain how groups are formed and how they change, and to predict how they will change in future. Dynamic segmentation is fundamental to many markets because it is unrealistic to consider segments as stationary, given that consumers' needs and product choices change (Bassi, 2016). Dynamic segmentation is a method for dividing the market into homogeneous groups, while also acknowledging that these groups are constantly changing in composition. As consumer behavior changes, it is important to offer goods and services that adapt to these changes, and can thus continue to satisfy target consumers (Kamakura, 2009).

Given their strategic and economic importance, banks served as a research setting for a number of market segmentation studies (Kamakura, 2009; Ebbes et al., 2010; Masserini et al., 2016). The banking sector is a turbulent environment with far-reaching boundaries, in which identifying segments is considered a non-trivial problem (Ebbes et al., 2010). The main finding of a survey conducted by Masserini et al. (2016) on the service quality of banks, for example, was that each consumer reacted differently to each medium-term action taken by the management. This shows how the tendency of customers' needs to change over time may influence a financial institution's long-term performance (Masserini et al., 2016).

Previous studies applying dynamic segmentation to the context of banking institutions have shown that it raises the discriminatory and predictive power of their models (Kamakura, 2009). Dynamic market segmentation is an interesting option to consider when developing strategies, and an appropriate tool for institutions seeking to obtain better results, both for the bank and for their clients (Kamakura, 2009; Ebbes et al., 2010; Bassi, 2016).

Kamakura (2009) used dynamic market segmentation to look at how a bank's clients switched between segments over a period of 18 months, and used this information to predict how they would change over the six months thereafter. The author was able to predict bank customers churn (i.e. clients leaving the bank), and forecast which products each client would purchase in the future. Ebbes et al. (2010) used dynamic segmentation to group banks by their strategies and results obtained over the years. Their results showed which banks needed to change their strategies over time in order to satisfy their clients. Finally, Bassi (2016) segmented bank customers by the products they purchased to shed light on how their behavior changed over the years, and thus suggested strategy improvements for companies in the financial market.

Applying dynamic segmentation to microfinance programs should produce results identifying which strategies prove best for which type of client, also in terms of improving their social condition. To achieve this, we observe in the present study how clients migrate between the identified segments, and provide some insight on each segment. Using dynamic market segmentation reveals which segments produce the best returns for the MFIs, and whether the borrowers are achieving good results too, and reaching the dual goal of social and financial efficiency. Finally, our longitudinal analysis enables us to see if a mission drift occurs in the institution (i.e. if MFIs are pursuing their secondary goal of financial efficiency instead of focusing on their primary goal, which is to help people emerge from poverty) (Mersland & Strøm, 2010).

4. THE DATABASE

Data were obtained from the database of the CrediAmigo program. Our sample refers to 250,118 operations and 12,737 clients, covering the period from January 2003 to December 2016. The original database included 43 variables, but some (e.g. date of birth and age) were subsequently removed because they were redundant. Other variables were not useful for our purposes because almost all of the sample units gave the same answer (e.g. purpose of the loan), so such variables obviously could not distinguish segments. After cleansing the dataset for the above-mentioned reasons, 30 variables remained: 14 were used as indicators (to identify segments), and 16 as covariates (to describe segments). Table 1 contains descriptive statistics (means and standard deviations for continuous variables, probability distributions for categorical variables) of the 30 variables used in the analysis. The variables in Table 1 refer to the businesses, the owners and their families, and to the microfinance operation performed as part of the CrediAmigo program. Furthermore, a variable of operation cost by Microfinance Information Exchange (MIX) was used to calculate the profit for the bank.

<<INSERT TABLE 1 HERE>>

Some records (i.e., operations) had to be removed from the dataset due to missing values or obvious errors. Since the study was conducted longitudinally, if some of a client's operations were removed, then all the related information was omitted too. We thus had a final dataset of 12,306 clients performing a total of 217,280 operations. Table 2 contains some descriptive information by year: the number of operations and clients, profit of the business in first year of borrowing, the program profit in the first year and in total, the percentage of women and of joint liability groups. Comparing the rows of Table 2 shows how the characteristics of the program varied over the observational period. For example, the percentage of women participating as constantly increased. The number of operations and clients increased till 2011, then stabilized.

<<INSERT TABLE 2 HERE>>

Some variables need more explanation. ‘Administrative control’, for example, describes the level of administrative control that entrepreneurs have over their business: ‘no control’ means entrepreneurs have no tools for controlling their business; ‘precarious’ describes entrepreneurs who have a notebook to keep track of some administrative operations; ‘adequate’ is used when entrepreneurs have a cashbook; and ‘satisfactory’ when they have access to advanced administrative management tools.

The ‘total assets’ variable includes all of a borrower’s assets, while ‘current assets’ are the assets the borrower has in cash at the bank, credit from third parties, and stocks. The ‘type of activity’ variable concerns how the business is conducted, while the ‘place of business’ concerns the entrepreneur’s relationship with the place where the business is conducted (on the street, or at a site rented or purchased by the entrepreneur). ‘Additional earnings’ indicates how much money a borrower earns from sources other than the business in question. ‘Solidarity group’ indicates whether or not borrowers belong to a joint liability group.

Table 3 outlines the characteristics of the financial products offered by the program. It is important to note that CrediAmigo offers both individual and group lending schemes. The majority of the operations involve group lending and the joint liability groups modality (Khavul, 2010).

<<INSERT TABLE 3 HERE>>

5. LATENT CLASS MARKOV MODELS

The method used to obtain the dynamic segmentation of CrediAmigo clients is a latent class Markov (LCM) model. This approach has the potential to segment customers into homogeneous groups and to estimate the probabilities of transition between segments over time (Bassi, 2016; Bassi, 2017). Latent Gold 5.1 software was used (Vermunt & Magidson, 2013).

Let us consider the simplest formulation of a LCM model (Wiggins, 1973), which assumes that true unobservable transitions follow a first-order Markov chain. As in all standard latent class model specifications, local independence of the indicators is assumed, i.e., indicators are conditionally independent, given the latent variables[1].

Let X_{it} denote a segment belonging to time *t* for a generic sample unit *i*, *i=1,..,n*. Y_{ijt} is an observed categorical variable related to item *j, j=1,..., J* for unit *i* at time *t*. $P(X_{i1}=k_1)$ is the probability of the initial state of the latent Markov chain. $P(X_{it}=k_t / X_{it-1}=k_{t-1})$ is the probability of transition between state k_{t-1} and state k_t from time *t-1* to *t*, with *t*=2,...,*T*, where *T* represents the total number of consecutive, equally-spaced time-points over which a unit is observed. Then let $P(Y_{ijt}=h_t / X_{it}=k_t)$ be the probability of unit *i* giving the answer h_t at time *t*, given that unit *i* at time *t* belongs to segment k_t; this is also called the model measurement component.

For a generic sample unit *i*, a LCM model is defined as:

$$P(\mathbf{Y_{i1}},\ldots,\mathbf{Y_{iT}})=\sum_{k_1}^{K}\ldots\sum_{k_T}^{K}P(X_{i1}=k_1)\prod_{t=2}^{T}P(X_{it}=k_t \mid X_{it-1}=k_{t-1})\prod_{j=1}^{J}\prod_{t=1}^{T}P(Y_{ijt}=h_t \mid X_{it}=k_t) \tag{1}$$

where:

$\mathbf{Y}_{it}$, is the vector containing the values of the observed variables, or indicators, at time *t* for unit *I*; and

k_t varies over *K* latent states and h_t over a set of *H* categories.

[1] In the LCM model with one indicator per latent variable, the assumption of local independence coincides with the Independent Classification Error (ICE) condition.

In a LCM model with concomitant variables, latent state membership and latent transitions are expressed as functions of covariates with known distribution (Dayton & MacReady, 1988): $P(X_{i1} = k_1 / \mathbf{Z}_{i1} = \mathbf{z}_1)$, where $\mathbf{z}_1$ is a vector containing the values of covariates for unit i at time *1* estimates effects of covariates on the initial state and $P(X_{it} = k_t / X_{it-1}, \mathbf{Z}_{it} = \mathbf{z}_t)$, where $\mathbf{z}_t$ is a vector containing the values of covariates for household i at time t, estimates effects of covariates on latent transitions.

On the basis of the above-defined components, the complete model for unit i is given by:

$$P(\mathbf{Y}_i = \mathbf{y} \mid \mathbf{Z}_i = \mathbf{z}) = \sum_{k_1}^{K} \ldots \sum_{k_T}^{K} P(X_{i1} = k_1 \mid \mathbf{Z}_{i1} = \mathbf{z}_1) \prod_{t=2}^{T} P(X_{it} = k_t \mid X_{it-1} = k_{t-1}, \mathbf{Z}_{it} = \mathbf{z}_t) \prod_{j=1}^{J} \prod_{t=1}^{T} P(Y_{ijt} = h_t \mid X_{it} = k_t)$$

where:

$\mathbf{Y_i}$ is the vector containing the values of the observed variables for unit i at the measurement times T;

$\mathbf{Z_i}$, is the vector containing the values of the covariates for unit i at the measurement times T.

If the indicators are continuous variables, the LCM model is written as follows:

$$f(\mathbf{y}_i \mid \mathbf{Z}_i, \boldsymbol{\theta}) = \sum_{k_1=1}^{K} \ldots \sum_{k_T=1}^{K} P(X_{i1} = k_1 \mid \mathbf{Z}_{i1}) \prod_{t=2}^{T} P(X_{it} = k_t \mid X_{it-1} = k_{t-1}, \mathbf{Z}_{it}) \prod_{j=1}^{J} \prod_{t=1}^{T} f_k(y_{ij} \mid X, \mathbf{Z}_{ijt} \boldsymbol{\theta}_k)$$

where: $f(y_{ij}|X,\mathbf{Z}_{ijt}, \theta_k)$ is the probability density of each observed variable that depends on the cluster and on individual covariates; and θ_k denotes the unknown parameters of the specific density k.

Conditional probabilities are typically parameterized and restricted by means of logistic regression models. Parameters are estimated via maximum likelihood using the E-M algorithm (Dempster et al., 1977).

6. RESULTS

As shown in Table 4, the LCM model revealing the best fit to the data has six latent states, and its BIC value is the lowest among the LCM models compared. When we look at the standard R-squared, however, the best model is the one with five states. Given the size of the latent states shown in Table 5, we opted to rely on the results of the five-state model since the sixth state has a negligible dimension of 2.86%. Such a small group cannot be considered a market segment for the simple fact that it does not satisfy the property of numerical consistency. The model with six latent states also shows the highest percentage of classification errors.

<<INSERT TABLE 4 HERE>>

<<INSERT TABLE 5 HERE>>

Table 6 illustrates the profiles of the five latent states in terms of the means (for continuous variables) and conditional probabilities (for categorical variables) of the 14 variables used as indicators in the LCM model, and found statistically significant in identifying the latent states. The 20 covariates are treated as inactive in the model estimation step, so they are only used for descriptive purposes. These 16 covariates all have statically different values across the five latent states.

<<INSERT TABLE 6 HERE>>

Latent state 1 is the second-largest segment, including almost 28% of all the operations. The level of the activity of the businesses associated with the operations in this latent state is simple accumulation, and all types of administrative control are adopted. These businesses have no expenses for employees, nor for taxes or duties. Most of the other economic variables characterizing their activity, i.e. payments for materials, transport, water and light, and total and current assets, are in line with the average level of the sample as a whole. Other expenses for the family, and other costs, and the total amount paid are slightly higher than the average.

The distributions of the covariates in the five latent states identify the cluster of businesses in terms of the nature of the final operations conducted within the CrediAmigo program, and the socio-economic status of the owners of the business and their families. For the covariates, cluster 1 has 86.5% of operations involving a joint liability group, a lower percentage than in other latent states. The main products within the CrediAmigo program are the Giro Popular Solidário and the Capital de Giro Solidário. The typical joint liability group in this cluster consists of four borrowers who have around five installments to pay on their loans. The entrepreneurs work from home in the retail sector. The age of the business and the owners' characteristics (gender, age, marital status, education) are all very near the mean values for the sample. This latent state thus identifies a sort of central, or typical cluster of businesses. This cluster is profitable for the bank, since it earns on average 10 US$ per operation.

Latent state 2 is the largest (with 47% of operations) and concerns the cluster where almost 45% of businesses associated with the operations are classified as precarious because of their lack of administrative control, and the simple accumulation or subsistence level of the activity. In this cluster 2, the microcredit operations involve owners of small businesses with a total operational cost around five times lower than the mean for the sample. The other variables - relating to the operational costs (payments for employees, transport, water and light, payment for taxes and duties, other costs), and to current and total assets - also have much lower values than the mean for the sample, and the other expenses for family are the lowest. Looking at the distribution of the covariates, we can see that this cluster consists of almost 97% of operations conducted in a joint liability group, and the main product is the Giro Popular Solidário. The joint liability group includes an average number of four clients and they have five installments to pay on the loan. This cluster generates the worst profit, even though the owners declare others sources of income. The borrowers are the youngest and include the highest percentage of females, people who are single and/or poorly-educated, and working in the retail sector as street vendors. Probably due to the entrepreneurs' young age, these businesses have been in the program for the shortest amount of time. For the bank, this group generates a loss of an average of 25 US$ per operation. So this largest segment of operations achieves the worst economic results.

Latent state 3 comprises 10.47% of the sample of operations. Administrative control is adequate or satisfactory, the level of the activity is extended accumulation or small business. Expenses and assets amount to twice the average for the sample. The joint liability group usually consists of three people, and 17.3% of the borrowers take out individual loans. The principal product is the Capital de Giro Solidário. The borrowers in this group have six installments to pay on their loan. They generally run their business from a trading point or from home. While there are no differences in gender or marital status, the level of education is higher than in the other clusters. This is a profitable cluster for the bank, that earns 66 US$ per operation.

Latent state 4 is the smallest (5.77%), and this cluster has the best type of administrative control and of the level of the activity. It also has the highest level of spending for materials and other costs for the business and the family. Borrowers in this group have more assets and pay the highest price to the bank. The joint liability groups are formed of three people and 19% of the borrowers take out individual loans (the highest percentage of all five segments). The principal product is the Capital de Giro Solidário. Borrowers from this group have six installments to pay on the loan. Most of them run their business from a trading point. This is the group with the highest proportion of businesses in the service sector. As for the owners' features, there are no significant differences in age or in marital status, but the level of education is higher than in the other segments, and the percentage of men is higher than in the sample as a whole. Following the considerations in the paper by D'espallier et al., (2013) we conclude that the low percentage of women in this segments is due to the fact that female borrowers receive less credit from MFIs. Thus, they cannot reach this specific subgroup. Borrowers in cluster 4 have been in the program for more than 10 years and the business has been established for more than 13 years. This is the most profitable group for the bank, which earns around 78 US$ per operation.

Latent state 5 resembles segment 2 as regards administrative control and level of the activity. Although cluster 5 only accounts for 9.26% of the operations, many of the variables analyzed come very close to the mean values (as in segment 2). Some of the features of the operations in this segment, that distinguish them from the remainder of the sample, concern the fact that they were conducted early in the period of observation, and they include the largest percentage of street vendors. The bank makes a loss in this segment, albeit lower in magnitude than in the case of cluster 2 (14 US$ per operation).

Looking at the profiles of the five latent states, we can rank the segments based on the conditions of the businesses to which the operations refer. Latent state 4 is the best segment, followed by segments 3, 1, 5 and 2. The ranking remains the same when we look at the profit for the bank, confirming that businesses in better conditions guarantee more profitable operations within the CrediAmigo program. Unfortunately, the ranking is reversed if we look at the size of the segments, i.e. the most profitable operations are conducted by the smallest segment, while the businesses with the worst economic conditions form the largest segment.

The segments in Table 6 are estimated as the initial states of the latent chain of the LCM model. Table 7 contains the estimated transition probabilities across these five states, which represent how clients move over time across the five segments identified. The measurement part of the estimated model, i.e., the conditional probabilities between the indicators and the latent states, are assumed constant over time in order to ensure that the profiles of the segments do not change. The other assumption on the model is that the Markov chain is stationary. The probabilities in Table 7 show that most operations belong to the same segment during the period of observation. In other words, the conditions of the businesses and owners do not change over time in a large proportion of cases. This proportion differs for the five segments, however, and is higher for segment 2, for instance, which takes bottom place in the ranking of the businesses' economic conditions.

<<INSERT TABLE 7 HERE>>

The probabilities outside the main diagonal in Table 7 indicate the percentage of clients performing multiple operations in the reference period who do not transit from one segment to another, while the figures outside the main diagonal indicate the percentage of clients who do change segment. Since the Markov chain is assumed to be stationary, these probabilities are averaged over the reference period. All departures from segment 2 indicate a movement towards a segment associated with better economic conditions, whereas all departures from segment 4 indicate a worsening situation; movements from segment 3 to segments 1, 5 and 2, from segment 1 to 5 and 2 and from segment 5 to 2 indicate shifts towards worse settings. All such movements towards a segment associated with worse conditions indicate the undesirable outcome of the CrediAmigo program failing to improve its clients' business. This applies, for example, to the non-negligible percentages of clients shifting from segment 1 to segments 5 and 2. Some clients move to a segment associated with better business conditions, however; this is the case of all exits from state 2 (14.83%); of movements from state 5 to 1, 3 and 4 (23.17%), from 1 to 3 and 4 (7.27%), and from 3 to 4 (8.55%). While the conditional probabilities in Table 7 are gross flows, indicating the percentages of changes within each segment, Table 8 shows the absolute values of these changes. It is important to look at these latter figures as well as to examine the efficacy of the program over time. Overall, only 2,992 owners of businesses (24.31% of the sample, figures in bold in Table 8) moved to better economic conditions while participating in the program.

<<INSERT TABLE 8 HERE>>

7. DISCUSSION

This study focuses on the principal Brazilian microfinance program - CrediAmigo. It is important to emphasize that the aim was not to measure the social impact of the program, but to examine the probability of an improvement in the social and economic outreach of certain segments of microfinance clients and their businesses. Results indicate that the program has a limited capacity to help borrowers to improve their business conditions.

Using a LCM model, we estimate the probability of a borrower of moving from one segment of microfinance operations to another. These segments are also defined in terms of the physical and economic characteristics of the businesses concerned, and the socio-economic characteristics of the owners and their families. The desirable result would be a higher likelihood of businesses migrating to a better segment instead of staying in the same cluster, or migrating to a worse segment. Our results show a strong probability of businesses either of remaining in the same segment (especially for the cluster with the worst economic conditions) or migrating to a segment where the business conditions are worse. Overall, less than one fourth of clients in the sample considered transit to better economic conditions while participating in the CrediAmigo program, so we cannot claim that borrowers' businesses are benefiting.

The profiles of the five segments differ in various ways: segments 3 and 4 spend more money on the various costs, but also obtain the best results and their business conditions are better in terms of their administrative control and the level of their activity. This finding suggests that business costs might be a good predictor of its profitability (Chliova et al., 2015).

An interesting finding regards spending for the family: when the business conditions improve, living conditions for the family improve as well (Newman et al., 2014; Garikipati, 2017; Dutta & Banerjee, 2017). Another socio-economic aspect worth noting is that the segments where borrowers are better educated are also those with better business conditions (Staniewski, 2016; Dutta & Banerjee, 2017). There is also a relationship between performance in the various segments and gender: the proportion of men is highest in the best-off segment, i.e. cluster 4 (Garikipati, 2017; Hermes et al., 2011).

The worst-off clusters tend to borrow in joint liability groups. This may be a way for them to gain the trust of the program providers even if single entrepreneurs are not wholly reliable (Khavul, 2010; Giné & Karlan, 2014). On the other hand, borrowers whose businesses are faring better do not want to stay in groups with other people, who may raise the risk of them having to pay for another defaulting borrower (Khavul, 2010; Giné & Karlan, 2014). This result is similar to Quidt et al. (2018) that discover a decline in joint liability groups because programs prefer to offer an individual credit to the best clients. Borrowers in better-off clusters have more installments to pay on their loans and tend to prefer the Capital de Giro Solidario product. Another intriguing finding is that the segments associated with better results are largely active in the services sector.

The outcome of the present research reinforces previously published findings that argue that credit is not the only tool for alleviating poverty (Newman et al., 2017). We find that people who have a better education, good administrative control, and a higher-level business activity achieve better economic results (Banerjee et al., 2015b; Garikipati, 2017). As for the profit for the bank, we find it makes a loss in the worst segments, suggesting that the institution is not always able to pinpoint the real poor, while it offers credit opportunities even to borrowers at risk of failure. Meanwhile, the bank charges the better-off clients in the other segments more, and this may be one of the reasons why these borrowers are unable to improve. It would seem that the program judges as important to give all types of client (even the poorest) a chance, but the cost of this choice is covered by demanding more from borrowers in better economic conditions – so the bank ultimately profits anyway.

Gutierrez-Goiria et al. (2017) recognize that it is very important to approach correctly each target market in order to obtain an efficient result; we show that each group has different features that can only be attended with specific mechanisms (Morduch, 2000; Newman et al., 2017). Looking for better strategies with reference to each target segment can be done to reverse this result. In this way, the program has the opportunity to review its strategy and suggest new products (Imai & Azam, 2012; Shapiro, 2015). It is especially important to recognize that clients need to be prepared to use correctly the credit they are offered. Actions should be taken to find ways to give clients more information, and to help them to improve their business skills. The CrediAmigo program can be considered sustainable because it makes a profit overall, and it also acts as a social agent, offering credit and helping people in need. On the other hand, this program cannot be seen as an example of a win-win situation because borrowers' economic conditions are not improving (Mersland & Strøm, 2010). For a win-win situation to occur, both borrowers and the program must benefit, or at least there must be a trade-off between the social outreach and the financial stability of the program. CrediAmigo needs to ascertain why some borrowers' social welfare does not improve, and identify ways to help these clients. Generally speaking, clients stay in the program for more than nine years and their businesses are more than 10 years old. It seems that borrowers who stay in the program for longer begin to see the loan as a source of income instead of a resource for investment. In fact, those who stay longer in the program become more dependent on this money (Van Rooyen et al., 2012). Further longitudinal studies are needed to analyze this behavior in more detail (Van Rooyen et al., 2012; Garikipati, 2017).

Even the program cannot reach a win-win situation, we could not say that mission drift happens, because it still focuses on the poor and on female borrowers. Form the data reported in Table 2, we note that the profit of the business diminished over the year; this might be an indication that the number of poor people who enter the program increases. Moreover, the percentage of women also increased in the reference period. In sum, this research proves that not reaching a win-win situation does not necessarily imply mission drift.

8. CONCLUSION

The topic of microfinance is generating a lively debate in the reference literature on its efficacy (Khavul, 2010; Bateman & Chang, 2012; Garikipati, 2017; Cull & Morduch, 2017; Seng, 2018), and many researchers acknowledge its importance and the value of social participation in poverty alleviation (Newman, et al., 2014; Banerjee et al., 2015a; Banerjee et al., 2015b; Chen et al., 2017). Previous reports have been unable to demonstrate that it is effective in helping people emerge from poverty, but there is a consensus that microfinance gives to the poor entrepreneurs a greater degree of freedom to make choices and obtain financial investments, since they do not have access to formal banks (Newman et al., 2014; Mersland & Strøm, 2010; Garikipati, 2017).

The present study charts the evolution in the socio-economic conditions of clients of a microcredit program in Latin America, using LCM models to analyze a longitudinal dataset containing information on over 12,000 clients, observed for a period of 15 years. Based on variables relating to the businesses, the owners and their families, and on the type of microfinance products involved, our results delineate five homogeneous segments of financial operations.

Our findings show that the business conditions of most borrowers did not improve over time; they remained in the same segment or regressed towards a worse one. Borrowers with longer-term dealings with the program show that access to credit did not help them to emerge from poverty; it was more likely for them to become reliant on loans to manage their business.

While the results prove that the institution improves its financial condition and that the borrowers do not, we cannot say that the mission has been diverted: the institution still focuses on the poor and female borrowers. Thus, it is suggested that the concept of mission drift should be expanded beyond the institution's vision, because although the institution does not move away from the primary goal of serving the poor and women, it does not do so effectively. Further studies might seek to analyze mission drift also considering the evolution of the beneficiaries by their bias and not only by the bias of the institution.

Finally, a limitation of this study has to be acknowledged: the sample was not compared with entrepreneurs operating outside the program, it is impossible to say for sure than any decline was not due to external factors. Future research could concentrate on comparing samples such as ours with entrepreneurs involved in other programs or uninvolved in any microfinance schemes to see how they evolve over time in terms of their personal and business conditions; for this scope experiment designs and statistical techniques to evaluate policies should be employed. Another possible future line of research concerns the win-win situation: an effort to elucidate the main factors influencing transitions between segments could shed light on what MFIs can do to improve their strategies to achieve this desirable outcome. Our data contain only information about the clients that stay in the program, which is a limitation of this study, no information is collected on the effect of microfinance for those who exit the program. A future study could focus on this topic.

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TABLES

Table 1 – Descriptive statistics of the variables used for the analysis

DIMENSIONS	INDICATORS	Mean/Percentage	Standard deviation
Dependent variables relating to the business and the operation	**Administrative control**		
	No control	9.4%	
	Precarious	41.4%	
	Adequate	10.7%	
	Satisfactory	38.4%	
	Level of the activity		
	Subsistence	21.5%	
	Simple accumulation	55.3%	
	Extended accumulation	23.0%	
	Small business	0.2%	
	Profit	547.27	454.90
	Payments for materials	897.16	1,055.52
	Payments for employees	26.98	115.61
	Payments for transport	25.38	62.61
	Payments for water and light	20.60	34.24
	Payments for taxes and duties	4.12	27.85
	Total operational costs	115.05	217.05
	Other expenses for the family	187.07	144.70
	Other costs	37.97	98.99
	Total assets	1,5513.19	1,8356.60
	Current assets	2,364.02	3,960.69
	Total paid	758.93	717.36
	COVARIATES		
Variables relating to the business	**Type of activity**		
	Street vendor	9%	
	Peddler	3.2%	
	Shop	26.9%	
	Home delivery	23.3%	
	Working from home	37.7%	
	Activity sector		
	Retail	91.6%	
	Industry	2.2%	
	Services	6.2%	
	Place of business		
	Street vendor	28.1%	
	Owned	57.3%	
	Rented	14.6%	
	Age of business	11.38	7.57
	Additional earnings	231.81	243.91
Variables relating to owners and their families	**Gender**		
	Male	34.3%	
	Female	65.7%	
	Education		
	Illiterate	5%	

	4th grade completed	32.4%	
	8th grade completed	28.2%	
	12th grade completed	30%	
	University graduate	4.2%	
	Marital status		
	Married	50.2%	
	Single	39.1%	
	Widowed	10.7%	
	Age	43.30	12.24
Variables relating to the operation	**Year of operation:**		
	2003-2008	30.2%	
	2009-2013	45.1%	
	2014-2017	24.7%	
	Years in program	9.54	3.34
	Number of borrowers in the joint liability group	4.36	1.95
	Number of installments	5.54	2.56
	Product		
	Capital de Giro Solidario	32.4%	
	CrediAmigo Comunidade	0.2%	
	Giro Popular Solidário	57.5%	
	GiroInveste	5.5%	
	Investimento Fixo	4.3%	
	Solidarity group		
	Yes	90.2%	
	No	9.8%	
	Profit for the bank	7.31	86.28

Table 2 – Descriptive statistics of operations, clients profit, number of women and joint liability groups by years

Year	Number of operations	Number of clients	Business profit first year	Program profit	Program profit first year	Percentage of women	Percentage of women who entered	Joint liability group (%)
2003	5101	1910	1626,10	-197,81	-192,7	53,29	62,2	98,6
2004	8839	3047	1602,34	-143,20	-229,64	52,10	67,0	97,9
2005	9401	3045	*	-53,42	*	54,27	*	95,0
2006	11552	3936	1669,00	-31,40	-156,29	62,80	67,1	93,3
2007	13642	4766	1584,46	-53,18	-180,02	64,00	67,6	91,2
2008	17056	6392	1489,82	-42,04	-165,77	64,83	68,2	90,8
2009	17072	6447	1280,14	26,28	63,66	65,00	63,6	88,1
2010	18465	7517	1276,75	57,38	-163,79	65,51	62,6	87,6
2011	21290	9339	1304,89	25,03	-169,09	65,88	65,8	87,7
2012	19934	8787	1087,67	-10,24	-152,52	66,39	71,4	87,6
2013	21328	9881	1071,93	17,86	-144,45	65,00	61,1	88,1
2014	22408	10850	1316,53	159,29	-8,88	**	62,7	89,7
2015	21186	9999	936,07	157,43	-8,17	67,00	58,2	90,1
2016	10006	6841	921,87	181,40	-41,42	67,02	55,2	92,2

* Nobody entered in 2005

** There is not this information on MIX

Table 3 - CrediAmigo products

Product	Purpose	Interest Rate	Terms	Periodicity	Warranty	Rule
Capital de Giro Solidário	Loans from US$ 525.00 to 3,750.00 for solidarity groups	Effective interest rate of 2% a month + TACs (Opening Credit Rate) 3% on value released	4 - 12 months	Fixed monthly payments	Joint liability group of 3 to 10 people, each acting as guarantor for the others.	-
CrediAmigo Comunidade	Loans from US$ 25.00 to 250.00	Interest rate of 1.2% a month + TACs (Opening Credit Rate) 3% on value released	4 - 12 months	-	Joint liability group of 11 to 30 people, each acting as guarantor for the others	Up to 20% of the members of the Community Bank are initiating production activities
Giro Popular Solidário	Loans from US$ 25.00 to 250.00	Interest rate of 1.7% a month + TACs (Opening Credit Rate) 3% on value released	4 - 12 months	Fixed monthly payments	Joint liability group of 3 to 10 people, each acting as guarantor for the others	Up to 20% of the members of the Community Bank are initiating production activities. The others must have been in activity for at least 6 months
GiroInveste	Loans from US$ 75.00 to 3,750.00	Interest rate of 2.% a month + TACs (Opening Credit Rate) 3% on value released	up to 24 months	Fixed monthly payments	Guarantor who pays if the client fails to do so	Clients need to have been in business for at least 6 months, be operating normally, and show a knowledge of their activity
Investimento Fixo	Loans from US$ 75.00 to 2,000.00	Interest rate of 2.% a month + TACs (Opening Credit Rate) 3% on value released	up to 24 months	Fixed monthly payments	Guarantor who pays if the client fails to do so	Clients need to have been in business for at least 6 months, be operating normally, and show a knowledge of their activity

Table 4 – Measures of model fit

# of latent states	Log-likelihood value	BIC	# of parameters	% of classification errors	R^2
3	-19.417.994.7428	38,836,837.0914	90	10.33	0.6763
4	-18.695.165.3247	37,391,489.0440	123	17.29	0.6392
5	-18.479.695.4852	36.960.878.9894	158	17.80	0.6395
6	-18.373.855.3285	36,749,547.1362	195	22.22	0.5650

Table 5 – Size of latent states

# of clusters	1	2	3	4	5	6
3	67.74%	22.94%	9.33%	-	-	-
4	47.82%	29.51%	13.12%	9.56%	-	-
5	27.74%	46.97%	10.47%	5.57%	9.26%	-
6	2.86%	7.06%	27.62%	10.98%	47.20%	4.29%

Table 6 - Profiles of the latent states – 5 clusters solution

	State					
	1	**2**	**3**	**4**	**5**	**Overall**
Size	0.2774	0.4697	0.1047	0.0557	0.0926	
Administrative control						
No control	0.0937	0.1094	0.0585	0.0518	0.1209	0.0972
Precarious	0.4185	0.4467	0.3343	0.3141	0.4644	0.4206
Adequate	0.1081	0.1054	0.1105	0.1100	0.1032	0.1068
Satisfactory	0.3798	0.3384	0.4967	0.5241	0.3115	0.3754
Level of the activity						
Subsistence	0.1372	0.3781	0.0189	0.0131	0.2780	0.2420
Simple accumulation	0.6420	0.5608	0.3891	0.3386	0.6204	0.5575
Extended accumulation	0.2203	0.0610	0.5861	0.6402	0.1015	0.1993
Small business	0.0005	0	0.0059	0.0081	0.0001	0.0013
Profit						
Mean	541.78	305.33	954.38	3,644.65	469.84	504.54
Payments for materials						
Mean	839.15	406.06	1,634.80	2,402.68	803.32	810.08
Payments for employees						
Mean	0	0	86.99	179.29	21.137	21.57
Payments for transport						
Mean	20.82	8.58	46.13	95.84	22.84	22.34
Payments for water and light						
Mean	17.97	11.01	38.51	57.23	13.30	18.79
Payments for taxes and duties						
Mean	0	0	0	47.60	7.00	3.34
Total operational costs						
Mean	76.31	19.60	267.00	531.56	83.11	97.25
Other expenses for the family						
Mean	188.50	138.10	263.41	319.42	162.94	178.38
Other costs						
Mean	37.51	0	95.36	151.58	18.81	31.19
Total assets						
Mean	14,092.63	8,252.28	2,8422.90	4,0380.38	1,1178.99	1,4173.85
Current assets						
Mean	1,950.20	873.45	4,989.21	8,100.72	1,443.12	2,085.60
Total paid						
Mean	769.80	436.83	1,377.60	1,460.89	555.74	701.22
COVARIATES						
Type of activity						
Street vendor	0.076	0.050	0.072	0.144	0.271	0.090
Peddler	0.033	0.024	0.038	0.054	0.035	0.032
Commercial point	0.260	0.152	0.465	0.532	0.270	0.269
Home delivery	0.254	0.309	0.131	0.077	0.133	0.233
Working from house	0.377	0.464	0.294	0.194	0.292	0.377
Activity sector						
Retail	0.933	0.943	0.867	0.816	0.902	0.916

Industry	0.017	0.019	0.028	0.031	0.033	0.022
Services	0.049	0.037	0.106	0.154	0.065	0.062
Place of business						
Street vendor	0.304	0.339	0.165	0.139	0.247	0.281
Owned	0.556	0.537	0.658	0.648	0.596	0.573
Rented	0.140	0.124	0.177	0.212	0.157	0.146
Age of business						
Mean	11.80	9.60	13.57	13.79	11.84	11.4
Additional earnings						
Mean	236.16	197.65	296.37	341.96	174.49	231.80
Gender						
Male	0.320	0.275	0.456	0.507	0.397	0.343
Female	0.680	0.725	0.544	0.493	0.603	0.657
Education						
Illiterate	0.042	0.073	0.023	0.017	0.055	0.050
4th grade completed	0.340	0.332	0.258	0.246	0.394	0.324
8th grade completed	0.279	0.290	0.288	0.271	0.261	0.282
12th grade completed	0.298	0.269	0.373	0.392	0.259	0.300
University graduate	0.041	0.072	0.128	0.071	0.029	0.042
Marital status class						
Married	0.512	0.480	0.526	0.532	0.494	0.502
Single	0.381	0.408	0.379	0.368	0.393	0.391
Widowed	0.107	0.112	0.095	0.099	0.112	0.107
Age						
Mean	43.91	42.50	43.73	43.40	43.59	43.29
Year of operation:						
2003 – 2008	0.288	0.311	0.224	0.246	0.468	0.302
2009 – 2013	0.480	0.423	0.498	0.482	0.379	0.451
2014 -2017	0.233	0.266	0.279	0.272	0.153	0.247
Years in program						
Mean	10.00	8.60	10.16	10.05	10.30	9.5
Number of borrowers in joint liability group						
Mean	4.24	4.72	3.91	3.74	4.40	4.4
Number of installments						
Mean	5.79	5.10	6.06	6.21	5.14	5.5
Product						
Capital de Giro Solidario	0.364	0.179	0.539	0.550	0.277	0.324
CrediAmigo Comunidade	0.003	0.002	0.002	0.001	0.002	0.002
Giro Popular Solidário	0.49,7	0.791	0.285	0.259	0.646	0.575
GiroInveste	0.068	0.013	0.110	0.131	0.040	0.055
Investimento Fixo	0.067	0.014	0.063	0.059	0.034	0.043
Solidarity group						
Yes	0.865	0.973	0.827	80.10	0.925	0.902
Profit for the bank						
Mean	10.20	-25.02	66.14	78,70	-14.69	7.31

Table 7 - Transition probabilities

State[=0]					
	1	**2**	**3**	**4**	**5**
	0,2194	0,5359	0,0383	0,0274	0,1791
State[-1]					
	1	**2**	**3**	**4**	**5**
State					
1	0,7247	0,1121	0,1192	0,0447	0,1459
2	0,1636	0,8517	0,0194	0,0087	0,1522
3	0,0595	0,0059	0,7569	0,1519	0,0514
4	0,0132	0,0022	0,0855	0,7578	0,0344
5	0,0391	0,0281	0,0190	0,0370	0,6161

Table 8 – Transitions between segments – absolute values and percentages

State[=1]	1		2		3		4		5	
State[=0]		%		%		%		%		%
1			303	2.46	**322**	**2.62**	**121**	**0.98**	1,850	15.04
2	**1,079**	**8.77**	**-**	**-**	**128**	**1.04**	**57**	**0.47**	**1,004**	**8.15**
3	28	0.23	3	0.02	**-**	**-**	**71**	**0.58**	24	0.20
4	4	1.48	1	0.00	29	0.23	-	-	12	0.09
5	**86**	**0.70**	62	0.50	**42**	**0.34**	**82**	**0.67**	-	-