Quarterly Review of Economics and Finance 92 (2023) 262–273

Contents lists available at ScienceDirect

Quarterly Review of Economics and Finance

journal homepage: www.elsevier.com/locate/qref

Pathways to self-sufficiency in the microfinance ecosystem

Carlos Serrano-Cinca, Beatriz Cuellar-Fernández, Yolanda Fuertes-Callén *

Faculty of Economy and Business Administration, University of Zaragoza, Gran Via, 2, Zaragoza 50005, Spain

ARTICLE INFO

JEL classification:
G11
G18
G21

Keywords:
Strategic groups
Microfinance
Self-sufficiency
Latent trajectories

ABSTRACT

We used latent class growth analysis to study the trajectories followed by microfinance institutions for 10 years. This technique can detect groups of firms that follow different patterns of change over time. We identified groups of institutions that followed the same strategy and iso-performance groups of institutions with the same outcome trajectory. The trajectories were analyzed with categorical regression and decision trees, which constitutes a novel approach to latent class growth analysis. Lending money to the poorest while making a profit is not straightforward and it is challenging for microfinance institutions to be self-sufficient. We found that the most useful strategy was to improve efficiency by lowering operating costs, followed by the control of credit risk. Deviating from the mission also had a positive effect on self-sufficiency, but was a strategy followed by few institutions. Rarely did changes in interest rates or not lending to women prove valuable. The findings are useful for the stakeholders of these institutions and particularly for managers.

1. Introduction

Microfinance institutions (MFIs) provide a wide range of financial services to low-income clients, contributing to their financial inclusion, which is a target listed in eight out of 17 Sustainable Development Goals (United Nations, 2015). But lending money to the poorest while making a profit does not sound straightforward. MFIs can follow different paths to self-sufficiency, such as raising or lowering interest rates (Yunus, 2009), reducing operating costs (Gutiérrez-Nieto et al., 2007), controlling delinquency (Blanco et al., 2013), collecting deposits from clients (Nyanzu et al., 2019), optimizing their financial structure (Tchakoute-Tchuigoua, 2016), and deviating from their missions by targeting non-poor clients (Epstein & Yuthas, 2011). Nevertheless, there are still many gaps in our knowledge about the outcomes of decisions made by MFIs in their attempt to achieve self-sufficiency. In this paper, we analyzed the main strategies followed in search of the most successful ones.

First, we aim to identify the strategies. We start from the concept of strategic groups, which are companies within an industry that follow a similar strategy (McGee & Thomas, 1986), but categorizing the trajectories followed by MFIs over several years according to their similarity. Second, we aim to evaluate the result of their strategic actions – that is, whether they were successful. We focus on operational self-sufficiency, an indicator of success for MFIs that is achieved when financial revenues exceed expenses (DEspallier et al., 2013; Hartarska & Nadolnyak, 2007; Mersland & Strøm, 2010; Nyanzu et al., 2019; Pollinger et al., 2007). Different theories explain how MFIs can achieve self-sufficiency, including life cycle theory, resource dependence theory, and profit-incentive theory (Bayai & Ikhide, 2016). We formulate several hypotheses that relate the strategies adopted by each strategic group in the early years to later achievements in self-sufficiency.

Our study contributes to the literature in two ways. Many researchers studied the relationship between belonging to the same strategic group and performance (Cool & Schendel, 1988; Deephouse, 1999; Athanassopoulos, 2003; Tchakoute-Tchuigoua, 2010; Gong et al., 2021). Cool and Schendel (1988) determined that firms that follow a similar strategy do not necessarily obtain similar performance. Deephouse's (1999) strategic balance theory advises firms to strike a balance between competitive pressures and legitimization through a moderate level of distinctiveness to improve performance. This theory has been widely accepted by researchers and empirically verified, but with context limitations (Gong et al., 2021). In the field of microfinance, many researchers have focused on studying statistically significant relationships between MFI self-sufficiency and various determinants, such as leverage (Hartarska & Nadolnyak, 2007), corporate governance (Galema et al., 2012), interest rates (DEspallier et al., 2013), and outreach (Quayes, 2012). However, the pattern of MFI behavior may not be homogeneous, and MFI subgroups may exhibit different profiles of change and stability. We advance beyond exploring the factors that explain self-sufficiency by modelling the various strategies followed by subgroups of MFIs and

* Corresponding author.
E-mail address: yfuertes@unizar.es (Y. Fuertes-Callén).

https://doi.org/10.1016/j.qref.2023.10.007
Received 27 April 2023; Received in revised form 22 September 2023; Accepted 23 October 2023
Available online 26 October 2023

analyzing the performance of each strategy. We modelled the trajectories using latent class growth analysis (LCGA), a statistical technique employed to identify groups of subjects that follow similar trajectories of a single indicator of interest (Liou, 2020; Revilla & Fernández, 2013).

Second, we not only obtained trajectory typologies for each independent variable (the strategies) but also for the dependent variable (the self-sufficiency outcome). We named the latter "iso-performance groups". We related strategic groups to iso-performance groups by comparing the trajectories of the independent variables with the trajectory of the outcome. We found that the most successful strategy is to improve efficiency by reducing operating costs, followed by controlling credit risk. Other strategies were not as common or were simply not effective. Such findings are useful for managers and stakeholders of these institutions. We used categorical regression models (CATREG; Gifi, 1990) and classification and regression trees (CART; Breiman et al., 1984). This is a novel approach by our study since the traditional way to perform a multi-trajectory analysis using LCGA is by relating trajectory groups to the level finally reached by an outcome variable (Nagin et al., 2018; Van de Schoot et al., 2017; Van der Nest et al., 2020).

2. Prior literature and hypothesis development

MFIs provide financial services to people excluded from the financial system (Yunus, 2009). They offer microcredit to achieve financial inclusion, and many also collect savings. Most institutions adhere to the double bottom line objective of reducing poverty and obtaining profits simultaneously. The problems besetting the microfinance sector include mission drift (Epstein & Yuthas, 2010), high-interest rates leading to poverty penalties (Agnihotri, 2013), poor quality of governance (Galema et al., 2012), and the need for donations to survive (DEspallier et al., 2013). Studies with randomized control trials have revealed the limited impact of microfinance, arguing that for microcredit to be successful it must be accompanied by other initiatives (Banerjee et al., 2015). It should not be forgotten that microcredit is simply a debt to start a business and that many of the ventures are not successful.

MFIs follow different strategies for running their businesses and achieving self-sufficiency. Self-sufficiency is reached when financial revenue is greater than expenses; therefore MFIs can act on both sides. First, MFIs can implement strategies that increase financial income by expanding the number of clients. One way of achieving this is to deviate from their social mission by targeting non-poor clients. In this case, the average loan size can be fairly high. They may also offer financial products not designed to fight poverty and reduce lending to vulnerable groups such as women. The main justification for mission drift comes from resource dependency theory, which states that organizations must find the means to access key resources to survive; hence reducing the high transaction costs of granting numerous small loans may be a solution for many MFIs (Serrano-Cinca & Gutiérrez-Nieto, 2014). The weight the MFI gives to serving the poor and country-specific parameters regarding the cost of reaching the poor also matter (Armendáriz & Szafarz, 2011). Occasionally, mission drift can be explained by stakeholder theory, e.g. loan officers who stray from the mission by ignoring management guidelines (Serrano-Cinca et al., 2016).

The mission drift strategy has been criticized for being harmful to the poorest clients, particularly women (Frank et al., 2008), although in some cases it may be justified. Sometimes, the MFI simply supports clients in their growth, which causes loans to grow in size. This is very much in line with the life cycle theory, which justifies MFIs changing their original mission over their lifetime (Hoque et al., 2011). In addition, targeting the non-poor does not necessarily mean the MFI has stopped serving the poor, but rather they have expanded their clientele to include other niches (Armendáriz & Szafarz, 2011). Shareholders may pressure the MFI for profit (Bogan, 2012), but the expansion of clientele served can be a way of making a profit that compensates for the institution's unprofitable loans. In this case, the profit-incentive theory may justify MFIs deviating from their mission as a way to achieve their laudable ultimate goal.

However, deviating from the mission does not always have a positive effect on MFI performance. First, it can cause MFIs to lose grants and donor funds. In addition, changes in strategy that affect the organization's mission sometimes generate negative effects on financial performance due to the chaos that arises (Naranjo-Gil et al., 2008). In any case, several studies have agreed that mission drift does not affect the entire sector but rather certain institutions (Mersland & Strøm, 2010; Mersland et al., 2019). Based on this discussion, our first hypothesis is:

H1. . There is a positive relationship between increasing MFI loan size and achieving self-sufficiency.

Another strategy to increase financial revenue is to act on the interest rates charged on loans. The MFI can decide to either increase or decrease the interest rate. MFIs have high margins and their customers bear high interest rates, which can be justified from the point of view of investment theory, which supports a positive relationship between financial risk and lending rates (Modigliani & Miller, 1958). Another justification for increasing interest rates is the high cost of processing many small loans. In the absence of a perfectly competitive market, the conditions imposed by financial institutions are sometimes abusive, which was denounced by Yunus (2009), who called them financial sharks. In fact, local authorities closed some MFIs, in part because of their interest rates (Basharat et al., 2015). Whatever the cause, high interest rates lead to a poverty penalty, a situation whereby the poor pay more for their loans than other clients (Agnihotri, 2013).

In contrast, the reduction of interest rates has two positive social consequences: the increase of the institution's outreach and the reduction of clients' interest payments. Moreover, unjustified interest rate increases are not ethically acceptable (Hudon et al., 2020). In addition, MFIs are gradually adopting computerized pricing systems, which are an effective management tool that helps cut interest rates (Durango et al., 2021). However, firms do not act in isolation but rather within a competitive environment, operating in a complex network of market relationships (Gómez et al., 2017). The strategy of acting on interest rates to increase financial income may have worked in uncompetitive markets, but the current context of the microfinance sector is characterized by increased competition. Hence, our second hypothesis is:

H2. . *There is a positive relationship between increasing interest rates and achieving self-sufficiency.*

Life cycle theory supports the notion that MFI managers gain experience over time, which allows MFIs to evolve from being small, inefficient, and unsustainable to being large, efficient, and self-sustainable (Bayai & Ikhide, 2016). Improving the efficiency of MFIs by reducing expenses through the use of an appropriate information system can be a good way to achieve self-sustainability (Serrano-Cinca & Gutiérrez-Nieto, 2014). In addition, Basharat et al. (2015) recognized that financial efficiency leads to lower prices, which translates into attractive interest rates for clients. For all these reasons, reducing expenses to improve self-sufficiency is a challenge for MFIs.

Expenses can be one of three types: operating expenses (which include both personnel and administrative costs), net loan loss provision expenses (which are an allowance for potential uncollected loans and loan payments), and financial expenses (which are the interest paid for funds). Operating expenses have always been seen as a significant issue for MFIs (Gutiérrez-Nieto et al., 2007). A loan of a few dollars must be managed by a credit officer, entered into the computer system, and monitored for the duration of the debt. Personnel expenses are a vital item within MFIs' operating expenses. Productivity can be increased through technology, but also through wage moderation. For these reasons, the following hypothesis is proposed:

H3. . *There is a positive relationship between increasing efficiency and productivity and achieving self-sufficiency.*

The second item on which an MFI can act to reduce costs is net loan loss provision expenses, which involve reducing non-performing loans. Microcredit developed credit methodologies to minimize defaults, such as group lending, in which group members act as guarantors for each other (Yunus, 2009). Other innovations have also appeared, such as compulsory savings that replace collateral, dynamic incentives that give borrowers access to future loans, and regular repayment programs that pay off previous loans by acquiring new ones (Gutiérrez-Nieto et al., 2007).

In addition, MFIs developed credit-scoring systems that proved to be very effective (Blanco et al., 2013). The use of these systems becomes general when the institution reaches the maturity phase, according to the life cycle theory (Mia et al., 2019). Adopting credit-scoring systems reduces capital requirements and credit losses, thus increasing self-sustainability (Durango et al., 2021). The group lending approach, dynamic incentives, regular repayment schedules, and collateral substitutes, together with the use of credit-scoring systems, have all allowed MFIs to have default levels similar to those of banks (Gutiérrez-Nieto et al., 2007). Based on the aforementioned discussion, our fourth hypothesis is:

H4. . *There is a positive relationship between reducing delinquency and achieving self-sufficiency.*

Another method of reducing financial costs and improving sustainability is collecting deposits, which is a relatively inexpensive source of funding for MFIs (Nyanzu et al., 2019). In addition, by offering them micro-savings, MFIs broaden the portfolio of financial services for their clients, thus favoring their financial inclusion. However, not all MFIs can collect deposits, only those that are regulated. There are several types of financial regulatory agencies, and the banking supervisory authority is the most restrictive. A regulated NGO can also collect deposits, but many choose to transform into a bank. Life cycle theory suggests that the desire to grow justifies MFIs evolving from their birth phase as NGOs to mature as banks (Hoque et al., 2011).

Transforming an NGO into a bank increases the size of loans and decreases the percentage of women borrowers (Frank et al., 2008), but financial expenses for the institution are also reduced, which translates into a decrease in interest rates for clients (DEspallier et al., 2017). DEspallier et al. (2017) found that some MFIs with the lowest self-sustainability values were able to increase their self-sufficiency after such a transformation. However, not all arguments favor the regulation of institutions. First, there is a risk that MFIs will lose their essence. In addition, regulated institutions face regulatory pressures and high exposure to economic uncertainties (Tchakoute-Tchuigoua et al., 2020). Transforming from an NGO to a bank is the kind of deep strategic change that can lead to institutional disarray and have a negative impact on financial performance (Naranjo-Gil et al., 2008). Hartarska and Nadolnyak (2007) found that regulatory involvement does not directly affect performance in terms of operational self-sustainability. Consequently, the following hypothesis is proposed:

H5. . *There is a positive relationship between collecting deposits and achieving self-sufficiency.*

Finally, the literature has also discussed whether there is an optimal financial structure for MFIs (Bogan, 2012; Tchakoute-Tchuigoua, 2016). Sources of funding for MFIs are linked to stages of development, which is very much in line with the life cycle theory. Most MFIs start as NGOs that fund operations with grants and concessional loans from donors, but as the MFI matures private debt capital becomes available, and in the later stage of the MFI's evolution, traditional equity funding becomes available (Fehr & Hishigsuren, 2006). Therefore, life cycle theory supports the tendency of MFIs to be equity funded, increase capital leverage, and rely less on donations (Bogan, 2012). Donations are perceived as money that is "too easy" and that discourages efficiency improvements; as a consequence, the use of donations reduces self-sufficiency (Bogan, 2012).

As with any financial institution, capital strength (measured by equity to total assets, a regulatory solvency ratio) improves the MFI's resilience, enabling it to cope with future risks. Although financial slack can sometimes be considered a sign of inefficiency (Kar, 2012), becoming a solvent MFI is positive and improvements in solvency are often followed by improvements in self-sufficiency. Based on this discussion, our last hypothesis is:

H6. . *There is a positive relationship between strengthening the financial structure and achieving self-sufficiency.*

3. Empirical study

3.1. Sample and data

Microfinance Information eXchange (MIX) provided the data for the study. MIX publishes financial data standardized across the MFI industry, which is available in the World Bank's Data Catalogue. The data included information from 1999 to 2017 on 3652 MFIs. We selected 10 years from each MFI that provided a complete data series to avoid missing data. The final sample consisted of 534 MFIs. Table 1 displays the sample characteristics of the MFIs in the analysis, categorized by geographic area, age, and type of institution. Notably, 39.3% are located in Latin America, 17.5% in Eastern Europe and Central Asia, and 13.3% in Africa. In terms of type, 18.9% are banking entities, 31.6% are NGOs, and the remainder are credit unions or cooperatives. Additionally, 71.9% are regulated and 62.9% have over 8 years of experience.

Table 2 illustrates the variables used and their definitions. The dependent variable was operating self-sufficiency (OSS), which is the ratio of financial revenues to expenses. An MFI is self-sufficient if its OSS is greater than one. We used nine independent variables. The yield of gross loan portfolio (YIELD) reflects the spread charged by the financial institution. Mission drift was measured using two variables: the average loan balance per borrower (ALS/GNI) and the percentage of women borrowers (WOMEN). The strategy of collecting deposits was measured by the ratio of deposits to total assets (DEP), whilst the operating expense ratio (EXPENSE) was obtained as operating expense over gross loan portfolio. Additionally, labour productivity (PROD) was calculated by dividing the number of loans outstanding by the number of employees. The average salary within a company (SALARY) was obtained by dividing the personnel expenses by the number of employees. The write-off ratio (WOFF) measures the percentage of MFI loans removed from the gross loan portfolio because they are unlikely to be repaid. Finally, the financial structure of the institution was measured by the capital assets ratio (CAR).

Table 3 presents the descriptive statistics and Pearson's correlation coefficients for the winsorized data. Winsorizing is a common practice in financial data analysis to reduce the impact of outliers, extreme values,

Table 1
Sample characteristics of MFIs. N = 534.

MFI Type	%	*Num.*
Banks	18.91%	101
NGO	31.65%	169
Others	49.44%	264
Geographic area	%	Num.
Africa	13.30%	71
East Asia and the Pacific	8.80%	47
Eastern Europe and Central Asia	17.42%	93
Latin America and The Caribbean	39.33%	210
Middle East and North Africa	4.12%	22
South Asia	17.04%	91
Age	%	Num.
New (1–4 years)	17.40%	93
Young (4–8 years)	19.70%	105
Mature (+8 years)	62.90%	336
Regulation characterization	%	Num.
Regulated	71.91%	384
Non Regulated	28.09%	150

Table 2
Variables employed and their definition.

Financial characteristic	*Definition*
Operational self-sufficiency (OSS)	Financial Revenue to (Financial Expense + Net Loan Loss Provision Expense + Operating Expense)
Yield of gross portfolio (YIELD)	Financial Revenue from Loan Portfolio to Gross Loan Portfolio
Average loan balance per borrower (ALS/GNI)	(Gross Loan Portfolio to Number of Active Borrowers) to GNI per capita
Percentage of women borrowers (WOMEN)	Number of Women Borrowers to Number of Active Borrowers
Deposits to loans ratio (DEP)	Total Deposits to Gross Loan Portfolio
Operating expense ratio (EXPENSE)	Operating Expense to Gross Loan Portfolio
Labour productivity (PROD)	Number of Loans Outstanding to Number of Employees
Average salary (SALARY)	Personnel Expense to Number of Employees
Write off ratio (WOFF)	Value of Loans Written-off to Gross Loan Portfolio
Capital assets ratio (CAR)	Total Equity to Total Assets

and data errors (Barber & Lyon, 1996). All the observations were winsorized at the 1st and 99th percentiles, based on all the firm-year data.

3.2. Obtaining iso-performance groups

Iso-performance groups are groups of MFIs that followed the same trajectory in terms of the dependent variable (OSS), revealing their path of success or failure in achieving self-sufficiency. Fig. 1 shows the evolution of the OSS for the sample of 534 MFIs analyzed. The figure highlights with the letter A the average trajectory of all of them, which has hardly changed over time. However, the figure allows us to see that there are many different OSS trajectories. For example, trajectory B stands out at the top, which is an MFI with a downward trajectory, or trajectory C at the bottom, which is an MFI that, starting from a situation of non-self-sufficiency, has improved over the years. We can conclude that the microfinance sector is not homogeneous and the trajectories of MFIs differ among themselves. It seems interesting to know what strategy C has followed, how many MFIs are similar to it, and how they managed to be self-sufficient.

We used LCGA to identify homogeneous subpopulations of MFIs within the larger heterogeneous population. The LCGA model for trajectory specifications was formulated as follows (Van der Nest et al., 2020):

$$y_{it}^{k} = \beta_0^k + \beta_1^k X_{it} + \beta_2^k X_{it}^2 + \varepsilon_{it}^k \tag{1}$$

where $k = 1, \ldots, K$ is the trajectory group; $t = 1, \ldots, T$ is the time point; $i = 1, \ldots, n$ is the subject, Y_{it} is the predicted value of subject i at time point t, X_{it} is the predictor value of subject i at time point t, β_o is the intercept term of the model, β_1 is the linear slope, β_{o2} is the quadratic slope, and ε is the error term. The parameters are specific to each subgroup, as shown by the superscript k. Therefore, one subgroup may exhibit a linear average growth, while another group may have a better fit on a quadratic growth curve. It is assumed that error variances are normally distributed and uncorrelated with other residuals. We used *traj*, a Stata plugin, to estimate group-based trajectory models (Jones & Nagin, 2013).

We followed the guidelines established by a Delphi study to conduct a latent trajectory analysis (Van de Schoot et al., 2017). The final model selection requires the number of trajectories that best describes the data to be determined, an issue that remains unresolved (Van der Nest et al., 2020). The researcher selects the number of latent trajectories by

Table 3
Descriptive statistics and Pearson's correlation coefficients. N = 534.

Variables	Mean	Std. Dev.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) OSS	1.163	0.205	0.473	2.135	1								
(2) YIELD	0.252	0.198	0.006	1.588	-0.116	1							
(3) ALS/GNI	0.682	1.094	0.022	12.577	-0.037	-0.171	1						
(4) WOMEN	0.642	0.24	0.004	1	0.043	0.166	-0.355	1					
(5) DEP	0.36	0.475	0	2.846	-0.139	-0.131	0.331	-0.248	1				
(6) EXPENSE	0.228	0.157	0.035	.866	-0.408	0.706	-0.172	0.165	-0.018	1			
(7) PROD	140.978	91.072	7.182	497.191	0.169	-0.106	-0.376	0.475	-0.206	-0.171	1		
(8) WOFF	0.036	0.136	0	2.008	0.073	-0.002	-0.055	0.061	-0.023	0.034	0.009	1	
(9) CAR	0.302	0.194	-.025	.975	0.247	0.240	-0.173	0.104	-0.413	0.301	0.062	0.106	1

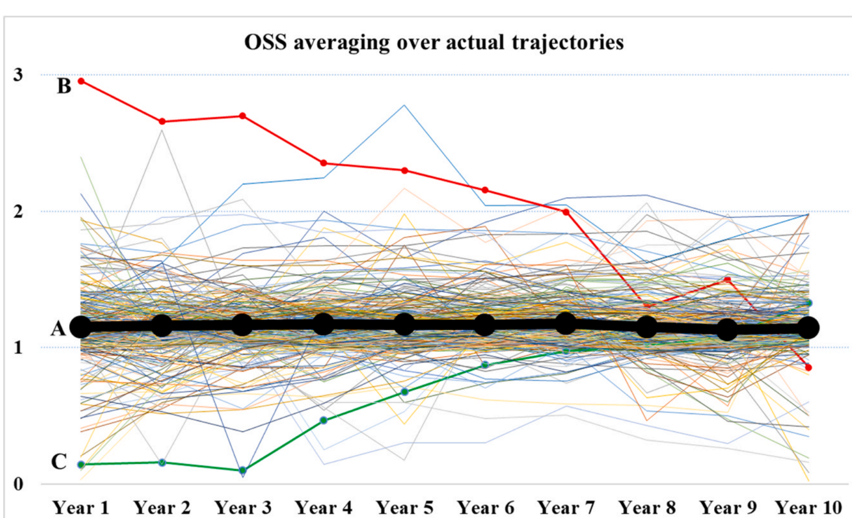

Fig. 1. Ten-year evolution of the OSS for the sample of 534 MFIs. Letter A shows the average trajectory, B is an MFI with a downward trajectory, and C is an MFI that, starting from a situation of non-self-sufficiency, improved over the years.

analyzing one or more criteria. The Bayesian information criterion (BIC) is the most highly recommended method to determine the number of trajectories (Van de Schoot et al., 2017). However, theoretical evaluation and proper judgment also matter in deciding the final number. Therefore, we conducted a profile analysis on parallelism, level difference, convergence, and flatness to clarify the similarities and differences between the groups detected.

We tested models ranging from one to 10 groups; Table 4 shows the results of the profile analysis. First, we analyzed whether the trajectories of the two groups were parallel and at the same level. Additionally, two groups should be combined into one if they follow parallel trajectories that share the same level. We performed a MANOVA test to examine the parallelism between groups, and a Scheffé test for pairwise difference among levels. All groups in Table 4 show significant differences in level. We used the notation $G_{(OSS)}$=n to refer to the MFIs in group n. The only parallel trajectories were between $G_{(OSS)}$= 1 and $G_{(OSS)}$= 4, between $G_{(OSS)}$= 1 and $G_{(OSS)}$= 5, and between $G_{(OSS)}$= 2 and $G_{(OSS)}$= 5, but the differences in level were sufficiently marked to consider them as different groups. As a result of both tests, although the BIC criteria identified five groups, we expanded the number to seven.

Fig. 2 displays the results of the latent trajectory analysis for the dependent variable OSS. $G_{(OSS)}$= 1 and $G_{(OSS)}$= 2 were formed by entities that were not self-sufficient but significantly improved over time, although only $G_{(OSS)}$= 2 achieved self-sufficiency. Both groups were small, comprising 2.4% and 8.1% of the sample, respectively; we labelled them "not yet self-sufficient" and "became self-sufficient". The largest group was $G_{(OSS)}$= 3, which accounted for 49.7% of MFIs. They were self-sufficient institutions that followed a stable but downward trajectory, and we labelled the group as "slowly declining". $G_{(OSS)}$= 4 was also large, accounting for 26.5% of the sample, comprising self-sufficient institutions that followed a stable trajectory but, unlike the previous group, they were "slowly improving". $G_{(OSS)}$= 5 (4.1%) followed a "concave trajectory", characterized by notable growth at first and then a slight decrease. At the end of 10 years, this group achieved the highest OSS value of all the groups. Finally, $G_{(OSS)}$= 6 (6.8%) and $G_{(OSS)}$= 7 (2.2%) started from high OSS positions and followed a downward trajectory, although the first is convex ("steeply declining") and the second is concave ("strongest declining"). However, they are still self-sufficient despite the decline.

It is quite common to find that firms' financial ratio values are adjusted to the industry average. This happens because sometimes the management targets a certain value for the financial ratio to avoid deviating from the sector, and at other times it is because external market forces lead the financial ratio to an equilibrium value (Canarella et al., 2013). We tested whether the OSS trajectories converged or exhibited a flat pattern (Table 4). We first tested for sigma and beta convergence; then, we performed multivariate tests for differences in OSS means to test for flatness. The results revealed a mean-reverting process in OSS (negative estimated beta coefficient). The Lichtenberg (1994) test rejected the hypothesis of no convergence, whereas the multivariate tests found that $G_{(OSS)}$= 3, $G_{(OSS)}$= 4, and $G_{(OSS)}$= 5 followed a flat profile.

Table 5 shows the financial characteristics of the MFIs for each of the seven iso-performance groups. The table shows the average values for the first three years and the last three years for each variable and group. A sparkline depicts the time evolution of each variable for each group. Notably, the table shows that the success of $G_{(OSS)}$= 2 is reflected in an increase in OSS, rising from 0.68 to 1.10. Since the threshold for considering an MFI self-sufficient is 1, it is correct to label it as "became self-sufficient."

The table provides an initial examination of the financial attributes of the MFIs within each of the seven iso-performance groups. For instance, our first hypothesis examined the relationship between the strategy of deviating from their social mission, as assessed by the average loan size (ALS/GNI) trajectories, and the OSS trajectories. This relationship could firstly be assessed visually by comparing the ALS/GNI time path with the OSS time path. Table 5 shows the average values for each independent variable and iso-performance group for the first 3 years and the last 3 years. Successful MFIs in $G_{(OSS)}$= 2 increased their loan size from an average of 0.52 in the first 3 years to 0.55 in the last 3 years, a 5.77% increase. However, even more noteworthy is the reduction in operating expenses (EXPENSE), which decreased from 0.48 to 0.27. This is a substantial 43.75% decrease. Although visual inspection can be informative, we found it appropriate to use analytical techniques to explore the relationship between iso-performance groups and strategies.

3.3. Obtaining strategic groups

We employed the LCGA approach to identify strategic groups among MFIs, considering their trajectories with respect to independent variables. The number of groups generated for each of the nine independent variables varied between five and seven. Subsequently, each MFI was assigned to a specific subgroup based on its trajectory pattern for each variable. Fig. 3 shows the results of the latent trajectory analysis for all independent variables, whereas Table 6 portrays an exploratory analysis with the characteristics of the groups obtained for each independent variable. The table and figure reveal the different patterns observed for

Table 4

Profile analysis results for OSS iso-performance groups.

	Parallelism Level							Flatness		Convergence
	$G_{(OSS)}$= 1	**$G_{(OSS)}$= 2**	**$G_{(OSS)}$= 3**	**$G_{(OSS)}$= 4**	**$G_{(OSS)}$= 5**	**$G_{(OSS)}$= 6**	**$G_{(OSS)}$= 7**			
$G_{(OSS)}$= 1	–	2.9***	3.85***	1.58	1.43	4.37***	6.63***	**$G_{(OSS)}$= 1**	8.68***	Sigma (σ_1^2/σ_{10}^2) = 6.82
$G_{(OSS)}$= 2	-0.293***	–	33.5***	18.49***	1.71	36.4***	15.43***	**$G_{(OSS)}$= 2**	21.37***	CV1 = 0.428
$G_{(OSS)}$= 3	-0.410***	-0.117***	–	4.16***	11.04***	13.33***	17.09***	**$G_{(OSS)}$= 3**	1.05	CV(2–9) = 0.304
$G_{(OSS)}$= 4	-0.593***	-0.300***	-0.183***	–	4.54***	18.24***	14.81***	**$G_{(OSS)}$= 4**	1.50	CV10 = 0.165
$G_{(OSS)}$= 5	-0.867***	-0.574***	-0.457***	-0.274***	–	11.91***	6.11***	**$G_{(OSS)}$= 5**	0.91	Beta (β) = −0.075***
$G_{(OSS)}$= 6	-0.743***	-0.450***	-0.332***	-0.150***	0.124***	–	3.83***	**$G_{(OSS)}$= 6**	20.58***	R^2 = 0.876
$G_{(OSS)}$= 7	-1.171***	-0.878***	-0.761***	-0.578***	-0.304***	-0.428***	–	**$G_{(OSS)}$= 7**	8.40***	T1 = 13.42***

Levels (below the diagonal): Scheffé test for pairwise difference among all possible comparisons.

Parallelism (above the diagonal): F-values of MANOVA analysis to check for parallelism in each pair of groups.

Flatness: Multivariate tests on differences of OSS means by year and by group.

Convergence: σ convergence measured by the ratio of variances of the OSS values by group, the first and last year, and by coefficients of variation (CVt=desv.st/mean).

β convergence was measured using the Lichtenberg (1994) T1-statistic $= \dfrac{R^2}{1+\beta} \sim F(N-2, N-2)$ where N is the number of groups, β is the beta coefficient, and R^2 is the fit value obtained from regression $\ln(OSS_T) = \alpha + (1+\beta) \quad \ln(OSS_1) + u$

* p < 0.10; ** p < 0.05; *** p < 0.01

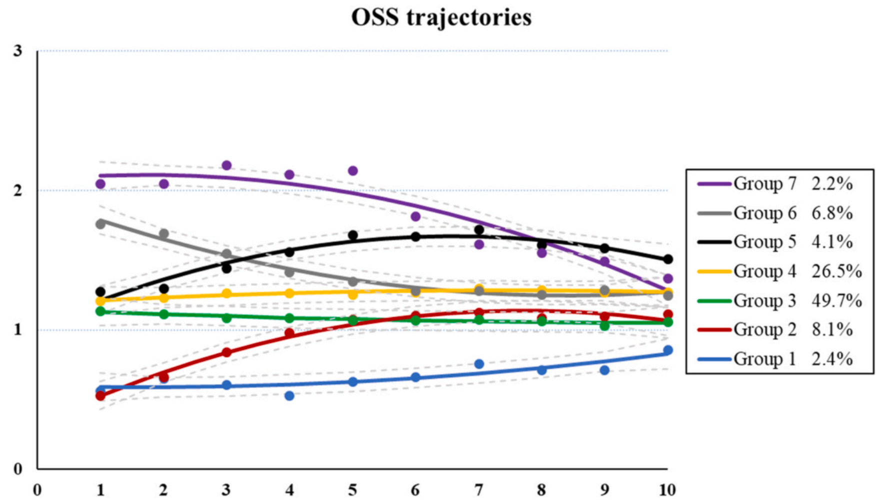

Fig. 2. Iso-performance groups of institutions that followed the same trajectory in terms of self-sufficiency (OSS). Seven estimated OSS trajectories and 95% confidence intervals are shown.

each of the independent variables, which correspond to upward, downward, maintenance, and sometimes concave or convex trajectories.

The strategic groups obtained from certain variables only showed differences in level (WOMEN, YIELD). This suggests that MFIs do not radically change the percentage of loans made to women. The same can be said of their margin strategy (YIELD), except for the severely minor group 6 (1.3%). Other variables revealed many changes. For example, some of the trajectories revealed notable changes in strategy in terms of loan size (ALS/GNI), increases or decreases in operating costs (EXPENSE), and improvements or worsening in the level of solvency (CAR), productivity (PROD), and delinquency (WOFF). Finally, on other occasions, the trajectories never decreased. For example, neither group included MFIs that stopped collecting deposits (DEP) or lowered employee salaries (SALARY).

3.4. Relationship between strategies and outcome

We created a multivariate table that includes information about the nine subgroups to which each MFI belonged for each trajectory variable, along with the iso-performance group. For example, the first MFI belonged to iso-performance group $G_{(OSS)}$= 2, labeled “became self-sufficient.” It also belonged to $G_{(EXPENSE)}$= 5, labeled “radical reduction in expenses,” and $G_{(ALS/GNI)}$= 2, labeled “keep the social mission.” We treated the other independent variables similarly. The evidence suggests that MFI number 1 achieved self-sufficiency by reducing its expenses without giving up its social mission. Much can be learned by visualizing the relationships between MFI membership in strategic and iso-performance groups, but it is better to use an appropriate analysis technique. Therefore, the next step was to relate the trajectories of the independent variables (strategic groups) to the trajectories of the dependent variable (iso-performance groups). This is how we tested the hypotheses and arrived at our final conclusions. However, it is worth noting that the groups are categorical variables, which cannot be ordered meaningfully. As a consequence, standard analytical techniques, such as multiple linear regression, are not applicable. We therefore used classification and regression tree (CART) and categorical regression analysis (CATREG).

CART is a decision tree technique used to relate a dependent categorical variable to a set of independent categorical variables, allowing the identification of complex non-linear relationships between trajectories (Breiman et al., 1984). The algorithm aims to maximize within-node homogeneity and stops when predefined criteria are met, limiting the tree size and minimum cases per node. The Gini index is the splitting criterion for the growth of a CART. As a results, CART provides decision rules that best explain the variation in a single categorical variable by recursively splitting the data into more homogeneous subsets, using variable combinations. Table 7 shows the results of a CART decision tree that included the iso-performance group as the dependent variable and the strategic groups as independent variables.

CART was very useful in identifying the features that distinguish MFIs in each subgroup. For instance, we previously noted that the first MFI in the sample belonged to $G_{(OSS)}$= 2, labeled “became self-sufficient,” and to $G_{(EXPENSE)}$= 5, labeled “’radical reduction in expenses.” CART found this to be common, with 27.9% of $G_{(OSS)}$= 2 MFIs also appearing in $G_{(EXPENSE)}$= 5, resulting in a straightforward rule: If $G_{(EXPENSE)}$= 5 THEN $G_{(OSS)}$= 2. Similarly, we determined that the primary characteristic of MFIs in $G_{(OSS)}$= 1, “improving but not yet self-sufficient,” was their delinquency control strategy. Table 7 presents the rules classifying each iso-performance group and the percentage of MFIs adhering to these rules.

CART also serves to specify the differences between iso-performance groups. At first, $G_{(OSS)}$= 1 and $G_{(OSS)}$= 2 were not self-sufficient entities, but $G_{(OSS)}$= 2 achieved self-sufficiency. $G_{(OSS)}$= 1 included 13 “not yet self-sufficient” MFIs; the decision tree detected that eight of these (65.5%) belonged to $G_{(WOFF)}$= 6, which is a small group with only 38 MFIs that significantly lowered delinquencies. It seems clear that what distinguishes $G_{(OSS)}$= 1 is the strategy to control delinquency. $G_{(OSS)}$= 2 included 43 MFIs labelled as “became self-sufficient”. The decision tree detected that 12 of them (27.9%) belonged to the $G_{(EXPENSE)}$= 5; this is a small group of 20 MFIs that achieved a dramatic decrease in operating expenses. $G_{(OSS)}$= 1 and $G_{(OSS)}$= 2 exhibit similar levels and trajectories for most variables, but the biggest difference is the strategic commitment that $G_{(OSS)}$= 2 made to lowering operating costs.

$G_{(OSS)}$= 3 labelled “slowly declining” and $G_{(OSS)}$= 4 labelled “slowly improving” are similar, but the trajectory of $G_{(OSS)}$= 4 is slightly better than that of $G_{(OSS)}$= 3. Both groups stand out for their control over operating costs, because most of their MFIs belong to EXPENSE groups 1 and 2. The main feature that differentiates them is productivity. Most of the members of $G_{(OSS)}$= 3 (35.4%) belong to $G_{(PROD)}$= 1, with the lowest productivity. In contrast, most of the members of $G_{(OSS)}$= 4 (28.9%) belong to $G_{(PROD)}$= 2, in the next level of productivity.

It is also interesting to examine the differences between $G_{(OSS)}$= 5, which follows a “concave trajectory”, $G_{(OSS)}$= 6 “steeply declining”, and $G_{(OSS)}$= 7 “strongest declining”. At the beginning of the period, the most self-sufficient was $G_{(OSS)}$= 7, followed by $G_{(OSS)}$= 6 and $G_{(OSS)}$= 5. The ranking position changed at the end of the period. The decision rules that best explain $G_{(OSS)}$= 5 refer to the strong control of delinquency, as well as the control over salaries. There are also differences in solvency.

Table 5
The first section shows an exploratory analysis of the seven iso-performance groups obtained using self-sufficiency (OSS). The remaining sections show the financial characteristics of MFIs in each of the seven iso-performance groups.

	Full sample	G(OSS)=1	G(OSS)=2	G(OSS)=3	G(OSS)=4	G(OSS)=5	G(OSS)=6	G(OSS)=7
OSS	n= 534	n= 13 (2.4%)	n= 43 (8.1%)	n=274 (49.7%)	n=135 (26.5%)	n= 22 (4.1%)	n= 35 (6.8%)	n= 12 (2.2%)
1st 3 years	1.16	0.61	0.68	1.11	1.23	1.34	1.67	2.09
Last 3 years	1.15	0.76	1.10	1.05	1.28	1.57	1.26	1.47
Time path								
YIELD								
1st 3 years	0.26	0.45	0.33	0.25	0.23	0.20	0.24	0.28
Last 3 years	0.24	0.28	0.30	0.23	0.23	0.20	0.23	0.25
Time path								
ALS/GNI								
1st 3 years	0.55	0.40	0.52	0.58	0.47	0.76	0.55	0.56
Last 3 years	0.60	0.51	0.55	0.64	0.52	0.83	0.53	0.47
Time path								
WOMEN								
1st 3 years	0.65	0.68	0.66	0.63	0.67	0.62	0.65	0.73
Last 3 years	0.64	0.64	0.67	0.62	0.66	0.65	0.62	0.63
Time path								
DEP								
1st 3 years	0.22	0.09	0.22	0.26	0.19	0.16	0.14	0.06
Last 3 years	0.26	0.15	0.24	0.31	0.23	0.17	0.18	0.08
Time path								
EXPENSE								
1st 3 years	0.25	0.64	0.48	0.34	0.44	0.76	0.55	0.88
Last 3 years	0.21	0.49	0.27	0.26	0.38	0.33	0.59	0.70
Time path								
PROD								
1st 3 years	140.85	91.50	109.32	136.07	160.61	126.92	168.75	138.34
Last 3 years	140.77	96.13	127.30	128.08	166.70	158.10	162.59	140.28
Time path								
SALARY								
1st 3 years	7,741.37	6,629.04	7,608.65	8,411.23	7,484.57	5,539.97	6,098.87	5,842.56
Last 3 years	10,211.30	8,675.33	8,635.01	11,048.06	9,829.68	7,435.99	9,609.13	9,555.27
Time path								
WOFF								
1st 3 years	0.02	0.05	0.04	0.02	0.02	0.01	0.02	0.02
Last 3 years	0.02	0.04	0.03	0.03	0.01	0.02	0.02	0.03
Time path								
CAR								
1st 3 years	0.33	0.36	0.41	0.28	0.31	0.47	0.43	0.61
Last 3 years	0.29	0.33	0.29	0.24	0.32	0.46	0.36	0.63
Time path								

For example, $G_{(OSS)}$= 7 has a very high level because its MFIs are mainly included in $G_{(CAR)}$= 5, which has the highest ratio value. However, holding too high a solvency ratio may mean idle resources (Kar, 2012).

Finally, we used CATREG analysis (Van der Kooij et al., 2006) to relate the trajectories of the dependent variable OSS to the trajectories of the independent variables. CATREG falls within the framework of regression with transformations (Van der Kooij et al., 2006). This is a statistical method that transforms categorical data into numerical values using the non-linear methods of optimal scaling (Meulman et al., 2019). Optimal scaling seeks the most suitable quantifications for both dependent and independent variables, ensuring that they are optimal for the regression model by maximizing the multiple correlation. The alternating least squares method estimates the regression coefficients by maximizing the squared multiple regression coefficient (Young et al., 1978). This results in a linear regression equation that is optimized for the transformed variables. The dependent variable was the iso-performance group, while the independent variables represented the strategic groups. Table 8 shows the standardized beta coefficients, bootstrap standard error estimates, and the Pratt relative importance index (PRI), which is equivalent to the product of the regression coefficient and the zero-order correlation. We subsequently used the LASSO (least absolute shrinkage and selection operator) method to select a parsimonious model to identify the essential variables (Tibshirani, 2011).

The strategies followed explained a significant proportion of variance in self-sufficiency trajectories. PRI indicator was used to assess the relative importance of variables in the model, which sums to 100% across all variables. PRI was highest for EXPENSE, which indicates that cost-cutting is the most important strategy to ensure self-sufficiency (PRI = 52.4%). Control of delinquency (WOFF) was the other crucial variable

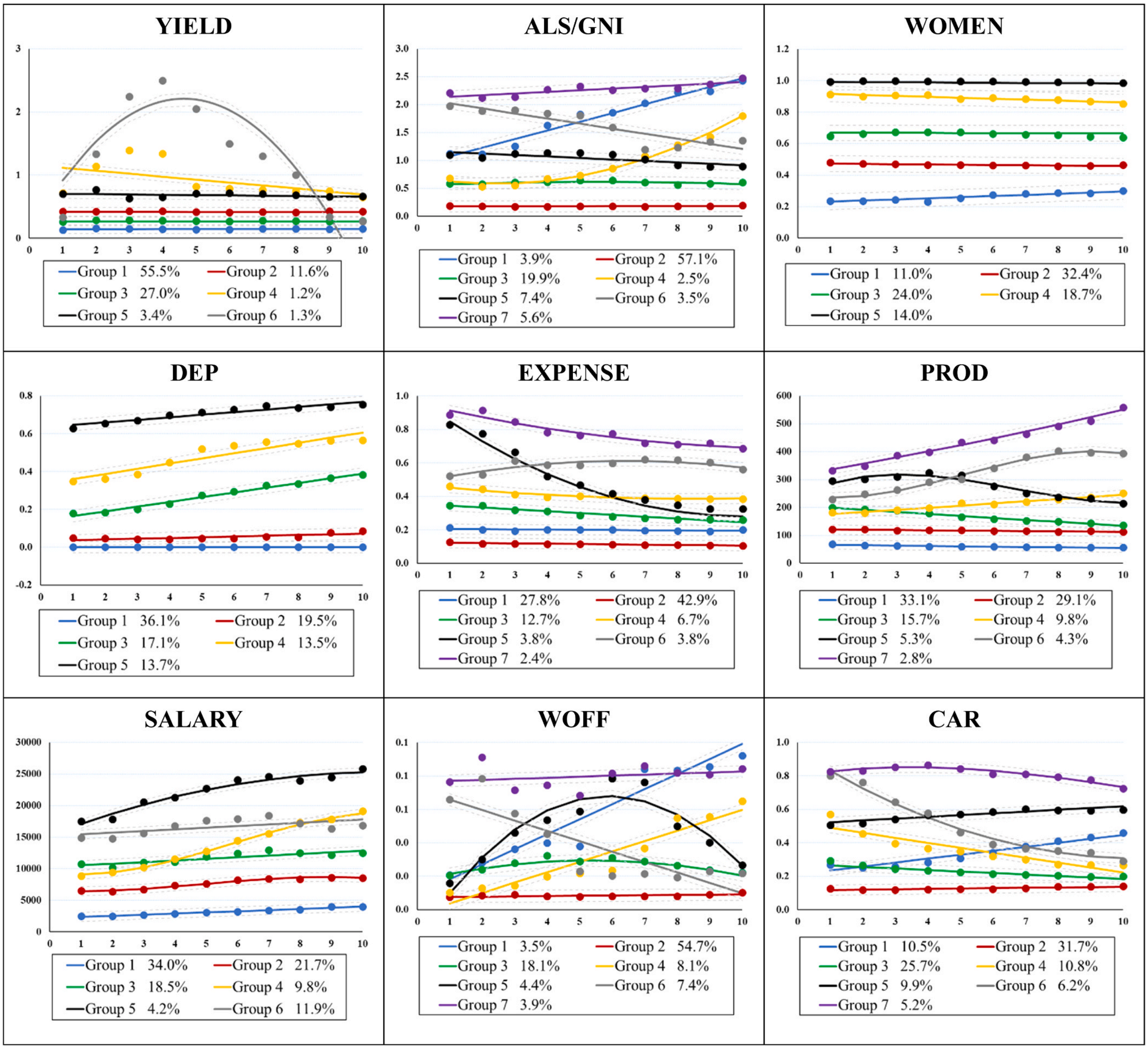

Fig. 3. Strategic groups. Estimated trajectories for the nine independent variables with 95% confidence intervals.

(PRI = 23.0%). Both variables were included in the parsimonious model, obtained by applying the LASSO technique. The regression results provided strong evidence in favor of H3 and H4. The p value for both EXPENSE and WOFF was well below the significance threshold at 0.01, indicating a highly significant relationship. The variables that measure productivity (PROD), solvency (CAR), and mission drift (ALS/GNI) also had significant beta coefficients, at the 0.01 level for PROD and CAR and at the 0.05 level for ALS/GNI. Additionally, PROD exhibited a PRI of 11.8%, CAR registered a PRI of 9.4%, and ALS/GNI had a PRI of 1.8%. Hence, our data also support H1 and H6. The rest of the variables had non-significant coefficients, indicating that they did not notably contribute to the model. Thus, our data support H2 and H5. A tolerance study was carried out that rejected the presence of multicollinearity.

3.5. Robustness issues

Our study did not include the trajectories of MFIs that lived less than 10 years or disclosed reports of less than 10 years to MixMarket, which may cause a bias. Another related problem is that we excluded MFI trajectories with missing data. We conducted three additional analyses to ensure the robustness of the results. First, we used the entire series of years from 1999 to 2017, retrieving all available information by taking trajectories from three to 19 years, and MFIs with missing data. Model 2 in Table 9 shows the results. Compared with the original model (Model 1), the percentage of missing data was extremely high, 70.7%. The total number of trajectories increased for each variable. When estimating the categorical regression, the goodness of fit decreased, but the operating expense ratio (EXPENSE) remained statistically significant and was identified by the LASSO method as the variable with the greatest explanatory power.

The second analysis consisted of taking all possible 10-year trajectories, from 2008 to 2017, even if data were missing (Model 3). The percentage of missing data was extremely high, 62.1%. The EXPENSE ratio remained statistically significant and was found to be the independent variable with the greatest explanatory power, with YIELD being the second variable to enter the model. We repeated the analyses with different time periods and shorter trajectories, and in all of them the EXPENSE ratio was the most closely related to OSS. WOFF was usually

Table 6
Exploratory analysis of each of the strategic groups obtained for each independent variable. The first section shows an exploratory analysis of the seven iso-performance groups.

OSS	**Full sample**	**G(OSS)=1**	**G(OSS)=2**	**G(OSS)=3**	**G(OSS)=4**	**G(OSS)=5**	**G(OSS)=6**	**G(OSS)=7**
	n= 534	n= 13 (2.4%)	n= 43 (8.1%)	n=274 (49.7%)	n=135 (26.5%)	n= 22 (4.1%)	n= 35 (6.8%)	n= 12 (2.2%)
1st 3 years	1.16	0.61	0.68	1.11	1.23	1.34	1.67	2.09
Last 3 years	1.15	0.76	1.10	1.05	1.28	1.57	1.26	1.47
Time path								
YIELD	**Full sample**	**G(YIELD)=1**	**G(YIELD)=2**	**G(YIELD)=3**	**G(YIELD)=4**	**G(YIELD)=5**	**G(YIELD)=6**	
	n= 534	n=306(57.3%)	n= 62(11.6%)	n= 135(25.3%)	n=6 (1.1%)	n= 18 (3.4%)	n= 7 (1.3%)	
1st 3 years	0.26	0.14	0.43	0.28	1.08	0.70	1.30	
Last 3 years	0.24	0.15	0.42	0.27	0.71	0.67	0.31	
Time path								
ALS/GNI	**Full sample**	**G(ALS/GNI)=1**	**G(ALS/GNI)=2**	**G(ALS/GNI)=3**	**G(ALS/GNI)=4**	**G(ALS/GNI)=5**	**G(ALS/GNI)=6**	**G(ALS/GNI)=7**
	n= 534	n=21 3.9%	n=305 57.1%	n=107 19.9%	n=14 2.5%	n=38 7.4%	n=19 3.5%	n=30 5.6%
1st 3 years	0.55	1.17	0.18	0.59	0.59	1.09	1.92	2.16
Last 3 years	0.60	2.30	0.18	0.59	1.50	0.90	1.31	2.38
Time path								
WOMEN	**Full sample**	**G(WOMEN)=1**	**G(WOMEN)=2**	**G(WOMEN)=3**	**G(WOMEN)=4**	**G(WOMEN)=5**		
	n= 534	n=58 (10.9%)	n=175 (32.8%)	n=127 (23.8%)	n=100 (18.7%)	n=74 (13.9%)		
1st 3 years	0.65	0.24	0.47	0.66	0.91	1.00		
Last 3 years	0.64	0.29	0.46	0.65	0.87	0.99		
Time path								
DEP	**Full sample**	**G(DEP)=1**	**G(DEP)=2**	**G(DEP)=3**	**G(DEP)=4**	**G(DEP)=5**		
	n= 534	n=193(36.1%)	n=104 19.5%)	n=92 (17.2%)	n=72 (13.5%)	n=73 (13.7%)		
1st 3 years	0.22	0.00	0.07	0.22	0.48	0.73		
Last 3 years	0.26	0.00	0.09	0.37	0.57	0.75		
Time path								
EXPENSE	**Full sample**	**G(EXPENSE)=1**	**G(EXPENSE)=2**	**G(EXPENSE)=3**	**G(EXPENSE)=4**	**G(EXPENSE)=5**	**G(EXPENSE)=6**	**G(EXPENSE)=7**
	n= 534	n=147(27.5%)	n=229(42.9%)	n=69 (12.9%)	n=36 (6.7%)	n=20 (3.7%)	n=20 (3.7%)	n= 13 (2.4%)
1st 3 years	0.25	0.20	0.12	0.34	0.44	0.76	0.55	0.88
Last 3 years	0.21	0.19	0.11	0.26	0.38	0.33	0.59	0.70
Time path								
PROD	**Full sample**	**G(PROD)=1**	**G(PROD)=2**	**G(PROD)=3**	**G(PROD)=4**	**G(PROD)=5**	**G(PROD)=6**	**G(PROD)=7**
	n= 534	n=179(33.1%)	n=153 (29.1%)	n=84 (15.7%)	n=52 (9.8%)	n=28 (5.3%)	n=23 (4.3%)	n= 15 (2.8%)
1st 3 years	140.85	64.57	120.00	193.65	183.95	301.53	247.07	355.82
Last 3 years	140.77	56.44	113.34	142.66	238.79	227.62	397.77	520.41
Time path								
SALARY	**Full sample**	**G(SALARY)=1**	**G(SALARY)=2**	**G(SALARY)=3**	**G(SALARY)=4**	**G(SALARY)=5**	**G(SALARY)=6**	
	n= 534	n=181(33.9%)	n=117(21.9%)	n=99 (18.5%)	n=52 (9.7%)	n=22 (4.1%)	n=63 (11.8%)	
1st 3 years	7,741.37	2,544.52	6,541.93	10,628.88	9,506.61	18,613.71	15,108.33	
Last 3 years	10,210.38	3,811.10	8,493.75	12,377.12	18,086.34	24,746.73	16,801.83	
Time path								
WOFF	**Full sample**	**G(WOFF)=1**	**G(WOFF)=2**	**G(WOFF)=3**	**G(WOFF)=4**	**G(WOFF)=5**	**G(WOFF)=6**	**G(WOFF)=7**
	n= 534	n=300(56.2%)	n=90(16.9%)	n=31(5.8%)	n=33(6.2%)	n=22(4.1%)	n=32(6.0%)	n=26(4.9%)
1st 3 years	0.02	0.03	0.01	0.02	0.01	0.03	0.07	0.08
Last 3 years	0.02	0.09	0.01	0.02	0.06	0.04	0.02	0.08
Time path								
CAR	**Full sample**	**G(CAR)=1**	**G(CAR)=2**	**G(CAR)=3**	**G(CAR)=4**	**G(CAR)=5**	**G(CAR)=6**	**G(CAR)=7**
	n= 534	n=54 10.1%	n=174 32.6%	n=134 25.1%	n=57 10.7%	n=51 10.1%	n=33 6.2%	n=28 5.2%
1st 3 years	0.33	0.26	0.12	0.27	0.47	0.52	0.74	0.84
Last 3 years	0.29	0.43	0.14	0.20	0.27	0.60	0.84	0.76
Time path								

the second variable to appear in the parsimonious models, although not always, since in some periods other variables joined EXPENSE, like YIELD and SALARY. All this suggests that the results are quite robust to biases.

The question arises as to what extent the relationships found imply causality. It is usually assumed that temporal precedence is essential to define causation. It seems reasonable to think that the strategies followed by a company affect its performance. However, we cannot discard reverse causality because it is probable that the causal pathway between some independent variables and OSS goes in both directions. A low OSS may lead to changes in strategy and encourage MFI management to take actions such as increasing loan size, changing interest rates, or raising

Table 7
Classification and regression tree results. The rules that best classify each of the iso-performance groups are shown, as well as the percentage of MFIs.

Iso-performance group	Percentage (N)	Rule	Rule percentage (N)
$G_{(OSS)}$= 1	2.4% (13)	If $G_{(WOFF)}$= 6 THEN $G_{(OSS)}$= 1	61.5% (8)
$G_{(OSS)}$= 2	8.1% (43)	If $G_{(EXPENSE)}$= 5 THEN $G_{(OSS)}$= 2	27.9% (12)
		If $G_{(EXPENSE)}$= 4,5,7 AND $G_{(WOFF)}$= 2,3,6 THEN $G_{(OSS)}$= 2	34.9% (15)
$G_{(OSS)}$= 3	51.3% (274)	If $G_{(PROD)}$= 1 THEN $G_{(OSS)}$= 3	35.4% (97)
		If $G_{(EXPENSE)}$= 1,2 AND $G_{(PROD)}$= 1 THEN $G_{(OSS)}$= 3	25.6% (70)
		If $G_{(EXPENSE)}$= 1,2 AND $G_{(PROD)}$= 1,2 THEN $G_{(OSS)}$= 3	44.9% (123)
$G_{(OSS)}$= 4	25.3% (135)	If $G_{(PROD)}$= 2 THEN $G_{(OSS)}$= 4	28.9% (39)
		If $G_{(EXPENSE)}$= 2 AND $G_{(PROD)}$= 2,3 THEN $G_{(OSS)}$= 4	34.8% (47)
		If $G_{(EXPENSE)}$= 1,2 AND $G_{(PROD)}$= 2,3 THEN $G_{(OSS)}$= 4	40.7% (55)
$G_{(OSS)}$= 5	4.1% (22)	If $G_{(WOFF)}$= 2 THEN $G_{(OSS)}$= 5	77.3% (17)
		If $G_{(WOFF)}$= 2 AND $G_{(EXPENSE)}$= 1,2 THEN $G_{(OSS)}$= 5	69.6% (16)
		If $G_{(WOFF)}$= 2 AND $G_{(SALARY)}$= 1 THEN $G_{(OSS)}$= 5	50.0% (11)
$G_{(OSS)}$= 6	6.6% (35)	If $G_{(WOFF)}$= 2 AND $G_{(EXPENSE)}$= 1,2 THEN $G_{(OSS)}$= 6	60.0% (21)
		If $G_{(WOFF)}$= 2 AND $G_{(YIELD)}$= 1 THEN $G_{(OSS)}$= 6	42.9% (15)
$G_{(OSS)}$= 7	2.2% (12)	If $G_{(CAR)}$= 5 THEN $G_{(OSS)}$= 7	50.0% (6)

deposits. The direction of causality can be strengthened by using a longitudinal design with measures of the independent variables that precede measures of OSS. We performed a new analysis by lagging the independent variables (Model 4 in Table 9). The trajectories of the independent variables were calculated using the data from the first five years, while the subsequent five years were used to calculate the OSS trajectories. Although the goodness of fit decreased, the categorical regression continued to highlight the importance of EXPENSE, which was the only variable selected when using the LASSO method. Based on the results of this study, if a causal relationship were to be established, it would be between cost reduction and increased self-sufficiency.

4. Discussion and conclusions

This paper sought to identify the strategic groups in the microfinance industry, assessing whether the strategic actions taken by MFI groups were successful – that is, whether there was an association between the strategy and improvements in self-sufficiency. The paper first discussed several ways to achieve self-sufficiency, grouping together the MFIs that followed them. We used LCGA, a type of longitudinal latent growth model used when there are several subgroups that share certain characteristics (Liou, 2020) which allows a dynamic analysis (Revilla & Fernández, 2013). In addition to the strategic groups, we obtained iso-performance groups, defined as institutions whose outcomes followed similar trajectories. Thus, our research contributes to the literature, firstly by identifying strategic groups in the microfinance sector, and secondly by relating them to self-sufficiency.

We formulated six hypotheses regarding the relationship between various strategies (increasing MFI loan size, raising interest rates, enhancing efficiency and productivity, reducing delinquency, strengthening the financial structure, and collecting deposits) and the achievement of self-sufficiency. To test these hypotheses, we classified MFIs based on the strategies they pursued and similarly categorized the trajectories of the outcome (OSS). We conducted a preliminary visual interpretation of the results for exploration. However, the testing of the hypotheses linking strategies to performance was conducted using two techniques capable of handling categorical data: decision trees and

Table 8
Categorical regression results for self-sufficiency (OSS trajectories as dependent variable). R^2 = .304; $F(17, 516) = 13.277^{***}$.

	Coefficients		*Pratt's relative importance (PRI) (sum= 100%)*	*Tolerance*		*LASSO Coefficients*	
	Std. β	*Std. error*		*After trans.*	*Before trans.*	*Std. β*	*Std. error*
$G_{(YIELD)}$	-.033	.134	0.9%	.964	.713	.000	.016
$G_{(ALS/GNI)}$	$.103^{**}$	.041	1.8%	.833	.748	.000	.003
$G_{(WOMEN)}$	.043	.049	0.5%	.847	.715	.000	.003
$G_{(DEP)}$	.034	.076	-0.5%	.686	.703	.000	.007
$G_{(EXPENSE)}$	$-.384^{***}$	.187	52.4%	.799	.705	$-.277^{***}$	.129
$G_{(PROD)}$	$.173^{***}$	.046	11.8%	.751	.734	.035	.038
$G_{(SALARY)}$	.083	.078	0.6%	.906	.852	.000	.012
$G_{(WOFF)}$	$-.219^{***}$	.104	23.0%	.826	.833	$-.111^{***}$	.063
$G_{(CAR)}$	$.270^{***}$	.070	9.4%	.691	.718	.058	.077

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 9
Robustness analysis using alternative models. Categorical regression results for self-sufficiency (OSS trajectories as dependent variable).

	Description	N	Missing data	Statistically significant variables	Most important variables using LASSO	R2	F
Model 1	Original model with 10-year trajectories, without missing data	534	0%	EXPENSE, WOFF, PROD, CAR	EXPENSE, WOFF	0.304	13.277^{***}
Model 2	Model using all available MFIs and trajectories, with missing data	2992	70.7%	EXPENSE, CAR	EXPENSE	0.036	7.935^{***}
Model 3	Model with trajectories from 2008 to 2017, with missing data	2992	62.1%	EXPENSE, YIELD, WOFF	EXPENSE, YIELD	0.102	18.699^{***}
Model 4	Model with five-year trajectories for the independent variables and five subsequent years for the OSS	534	0%	EXPENSE, CAR, SALARY	EXPENSE	0.087	4.713^{***}

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

categorical regression. The results derived from decision trees and categorical regression analysis aligned with and provided support for the hypotheses.

We concluded that the most important factor is cost-cutting and productivity gains, a well-considered but difficult strategy to carry out (Gutiérrez-Nieto et al., 2007). Our results show that the coefficients of the independent variables EXPENSE and PROD are statistically significant at the 0.01 level, with a positive relationship between both variables and OSS. According to the Pratt importance measure, EXPENSE emerged as the most important variable, with a notable PRI of 52.4%. Iso-performance $G_{(OSS)} = 2$ dramatically reduced operating expenses and achieved self-sufficiency. However, we did not find a relationship between salary reduction strategies and self-sufficiency ($p > 0.10$). This leads us to recommend that cost savings should not come at the expense of loan officers and other employees. Instead, we suggest exploring alternative avenues, such as the strategic utilization of appropriate technologies, which can be pivotal in the quest for efficiency and the attainment of self-sustainability.

In general, it is assumed that delinquency is not a severe problem for MFIs because of the various credit methodologies they have developed, such as group lending (Yunus, 2009). However, we found that the control of delinquency is another of the variables that count, which supports the development of credit-scoring systems (Blanco et al., 2013). WOFF, which represents control of delinquency, proved to be a statistically significant variable in the regression analysis, with a p-value of < 0.01 and a PRI of 23.0%. Iso-performance $G_{(OSS)} = 1$ made a clear effort to make progress in this aspect, improving their levels of self-sufficiency, albeit without becoming self-sufficient.

The debate about the best strategies for MFIs to be self-sufficient has a long pedigree (Agnihotri, 2013; D'Espallier et al., 2013; Nyanzu et al., 2019; Pollinger et al., 2007). A key discussion focused on the opportunity to deviate from the mission to attract new clients (and not necessarily poor ones) whose profits offset losses on social loans (Mersland & Strøm, 2010; Serrano-Cinca & Gutiérrez-Nieto, 2014). We used ALS/GNI as a measure of mission drift. We found a significant relationship between the trajectories of increasing ALS/GNI and the trajectories of achieving self-sufficiency ($p < 0.05$), but loan size was not the most relevant variable. ALS/GNI had a PRI of 1.8%, suggesting that loan size is a relatively unimportant factor in explaining the performance of microfinance institutions. The mission drift did not affect the percentage of women borrowers, because the trajectories remained parallel over the years. MFIs seem to realize that it is not worthwhile stopping lending to women because it does not improve performance.

It has been widely discussed whether it is worth increasing or decreasing interest rates (Adusei, 2021). Our study found no significant relationship with self-sufficiency. Collecting deposits is a trend across the entire microfinance industry, rather than a strategy followed by a specific group of entities. All of the iso-performance groups increased the deposits collected, but only some improved self-sufficiency. Therefore, we did not find it to be a discriminant variable in explaining self-sufficiency. Increases in leverage can improve the performance of institutions, although they also increase risk, which poses a dilemma (Kar, 2012). We found that the solvency of an institution is related to self-sufficiency ($p < 0.01$). Consequently, it seems reasonable to suggest that MFIs would do well to strengthen their capital structure but without idling resources.

4.1. Limitations and future research

One of the limitations of the study relates to the use of the MixMarket database. Registration with MIXMarket is not mandatory for MFIs, and there is a concern that the results may suffer from selection bias, whether or not the database is representative of the microfinance market (Hartarska & Nadolnyak, 2007). Nevertheless, the database covers the vast majority of organizations of significant size and many studies use it. We recognize that there may be strategies that have not been identified due to the shortcomings of the database. Another limitation of the study relates to the use of self-sufficiency as a measure of MFI success. Given the social nature of many MFIs, one might wonder whether it would be better to measure success in social terms and analyze trajectories in terms of community outreach and impact. This may become a future research direction.

Declaration of Competing Interest

For clarity, we wish to explicitly state that we have no financial, personal, or professional interests that could create a conflict of interest regarding the research presented in this article. All financial and non-financial aspects that might be considered a conflict of interest have been adequately disclosed within the manuscript.

Acknowledgments

This study was funded by the European Regional Development Fund (ERDF), the Spanish Ministry of Education and Science (code PID2022-136818NB-I00), and the Government of Aragon (code S38_23R).

References

Adusei, M. (2021). Interest rate and the social performance of microfinance institutions. *The Quarterly Review of Economics and Finance, 80*, 21–30.

Agnihotri, A. (2013). Doing good and doing business at the bottom of the pyramid. *Business Horizons, 56*(5), 591–599.

Armendáriz, B., & Szafarz, A. (2011). On mission drift in microfinance institutions. *The Handbook of Microfinance, London and Singapore* (pp. 341–366). World Scientific Publishing.

Athanassopoulos, A. (2003). Strategic groups, frontier benchmarking and performance differences: evidence from the UK retail grocery industry. *Journal of Managerial Studies, 40*(4), 921–953.

Banerjee, A., Duflo, E., Goldberg, N., Karlan, D., Osei, R., Parienté, W., & Udry, C. (2015). A multifaceted program causes lasting progress for the very poor: Evidence from six countries. *Science, 348*(6236), Article 1260799.

Barber, B. M., & Lyon, J. D. (1996). Detecting abnormal operating performance: The empirical power and specification of test statistics. *Journal of Financial Economics, 41*(3), 359–399.

Basharat, B., Hudon, M., & Nawaz, A. (2015). Does efficiency lead to lower prices? A new perspective from microfinance interest rates. *Strategic Change, 24*(1), 49–66.

Bayai, I., & Ikhide, S. (2016). Life cycle theory and financial sustainability of selected SADC microfinance institutions (MFIs). *The Journal of Developing Areas, 50*(6), 121–132.

Blanco, A., Pino-Mejías, R., Lara, J., & Rayo, S. (2013). Credit scoring models for the microfinance industry using neural networks: Evidence from Peru. *Expert Systems with Applications, 40*(1), 356–364.

Bogan, V. L. (2012). Capital structure and sustainability: An empirical study of microfinance institutions. *Review of Economics and Statistics, 94*(1), 1045–1058.

Breiman L., Friedman J.H., Olshen R.A. & Stone C.J. (1984). *Classification and regression trees*. Wadsworth International Group, New York.

Canarella, G., Miller, S. M., & Nourayi, M. M. (2013). Firm profitability: Mean-reverting or random-walk behavior? *Journal of Economics and Business, 66*, 76–97.

Cool, K., & Schendel, D. (1988). Performance differences among strategic group members. *Strategic Management Journal, 9*(3), 207–223.

D'Espallier, B., Goedecke, J., Hudon, M., & Mersland, R. (2017). From NGOs to banks: Does institutional transformation alter the business model of microfinance institutions? *World Development, 89*, 19–33.

D'Espallier, B., Hudon, M., & Szafarz, A. (2013). Unsubsidized microfinance institutions. *Economics Letters, 120*(2), 174–176.

Deephouse, D. L. (1999). To be different, or to be the same? It's a question (and theory) of strategic balance. *Strategic Management Journal, 20*(2), 147–166.

Durango, M. P., Lara-Rubio, J., Galera, A. N., & Blanco-Oliver, A. (2021). The effects of pricing strategy on the efficiency and self-sustainability of microfinance institutions: a case study. *Applied Economics, 54*, 1–16.

Epstein, M. J., & Yuthas, K. (2010). Mission impossible: diffusion and drift in the microfinance industry. *Sustainability Accounting, Management and Policy Journal, 1*(2), 201–221.

Epstein, M. J., & Yuthas, K. (2011). Protecting and regaining clarity of mission in the microfinance industry. *Sustainability Accounting, Management and Policy Journal, 2*(2), 322–330.

Fehr, D., & Hishigsuren, G. (2006). Raising capital for microfinance: Sources of funding and opportunities for equity financing. *Journal of Developmental Entrepreneurship, 11*(2), 133–143.

Frank, C., Lynch, E., & Schneider-Moretto, L. (2008). Stemming the tide of mission drift: microfinance transformations and the double bottom line. *Women's World Bank Focus Note, 4*(1), 1–24.

Galema, R., Lensink, R., & Mersland, R. (2012). Do Powerful CEOs Determine Microfinance Performance? *Journal of Management Studies, 49*(4), 718–742.

Gifi, A. (1990). *Nonlinear multivariate analysis* (2nd ed.), Chichester, UK: Wiley.
Gómez, J., Orcos, R., & Palomas, S. (2017). Do strategic groups explain differences in multimarket competition spillovers? *Strategic Organization, 15*(3), 367–389.
Gong, T. J., Yu, C. M. J., & Huang, K. F. (2021). Strategic similarity and firm performance: Multiple replications of Deephouse (1999). *Strategic Organization, 19* (2), 207–236.
Gutiérrez-Nieto, B., Serrano-Cinca, C., & Mar-Molinero, C. (2007). Microfinance institutions and efficiency. *Omega, 35*(2), 131–142.
Hartarska, V., & Nadolnyak, D. (2007). Do regulated microfinance institutions achieve better sustainability and outreach? Cross-country evidence. *Applied Economics, 39* (10), 1207–1222.
Hoque, M., Chishty, M., & Halloway, R. (2011). Commercialization and changes in capital structure in microfinance institutions: An innovation or wrong turn? *Managerial Finance, 37*(5), 414–425.
Hudon, M., Labie, M., & Reichert, P. (2020). What is a fair level of profit for social enterprise? Insights from microfinance. *Journal of Business Ethics, 162*(3), 627–644.
Jones, B. L., & Nagin, D. S. (2013). A note on a Stata plugin for estimating group-based trajectory models. *Sociological Methods and Research, 42*(4), 608–613.
Kar, A. K. (2012). Does capital and financing structure have any relevance to the performance of microfinance institutions? *International Review of Applied Economics, 26*(3), 329–348.
Lichtenberg, F. R. (1994). Testing the convergence hypothesis. *The Review of Economics and Statistics, 76*(3), 576–579.
Liou, F. M. (2020). A tale of two paths. *Management Decision, 58*(1), 1–15.
McGee, J., & Thomas, H. (1986). Strategic groups: theory, research and taxonomy. *Strategic Management Journal, 7*(2), 141–160.
Mersland, R., & Strøm, R.Ø. (2010). Microfinance mission drift? *World Development, 38* (1), 28–36.
Mersland, R., Nyarko, S. A., & Szafarz, A. (2019). Do social enterprises walk the talk? Assessing microfinance performances with mission statements. *Journal of Business Venturing Insights, 11*, Article e00117.
Meulman, J. J., van der Kooij, A. J., & Duisters, K. L. (2019). ROS Regression: Integrating Regularization with Optimal Scaling Regression. *Statistical Science, 34*(3), 361–390.
Mia, M. A., Lee, H. A., Chandran, V. G. R., Rasiah, R., & Rahman, M. (2019). History of microfinance in Bangladesh: A life cycle theory approach. *Business History, 61*(4), 703–733.
Modigliani, F., & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American Economic Review, 48*(3), 261–297.
Nagin, D. S., Jones, B. L., Passos, V. L., & Tremblay, R. E. (2018). Group-based multi-trajectory modeling. *Statistical Methods in Medical Research, 27*(7), 2015–2023.
Naranjo-Gil, D., Hartmann, F., & Maas, V. S. (2008). Top management team heterogeneity, strategic change and operational performance. *British Journal of Management, 19*(3), 224–234.
Nyanzu, F., Peprah, J. A., & Ayayi, A. G. (2019). Regulation, outreach, and sustainability of microfinance institutions in Sub-Saharan Africa: a multilevel analysis. *Journal of Small Business Management, 57*(2), 200–217.
Pollinger, J. J., Outhwaite, J., & Cordero-Guzmán, H. (2007). The question of sustainability for microfinance institutions. *Journal of Small Business Management, 45* (1), 23–41.
Quayes, S. (2012). Depth of outreach and financial sustainability of microfinance institutions. *Applied Economics, 44*(26), 3421–3433.
Revilla, A. J., & Fernández, Z. (2013). The dynamics of company profits: A latent growth model. *Strategic Organization, 11*(2), 180–204.
Serrano-Cinca, C., & Gutiérrez-Nieto, B. (2014). Microfinance, the long tail and mission drift. *International Business Review, 23*(1), 181–194.
Serrano-Cinca, C., Gutiérrez-Nieto, B., & Reyes, N. M. (2016). A social and environmental approach to microfinance credit scoring. *Journal of Cleaner Production, 112*, 3504–3513.
Tchakoute-Tchuigoua, H. (2010). Is there a difference in performance by the legal status of microfinance institutions? *The Quarterly Review of Economics and Finance, 50*(4), 436–442.
Tchakoute-Tchuigoua, H. (2016). Buffer capital in microfinance institutions. *Journal of Business Research, 69*(9), 3523–3537.
Tchakoute-Tchuigoua, H., Soumaré, I., & Hessou, H. T. (2020). Lending and business cycle: Evidence from microfinance institutions. *Journal of Business Research, 119*, 1–12.
Tibshirani, R. (2011). Regression shrinkage and selection via the lasso: a retrospective. *Journal of the Royal Statistical Society: Series B (Statistical Methodology, 73*(3), 273–282.
United Nations (2015). Transforming our World: the 2030 Agenda for Sustainable Development. Seventieth session of the General Assembly on 25 Sept 2015, A/RES/70/1 UN General Assembly.
Van de Schoot, R., Sijbrandij, M., Winter, S. D., Depaoli, S., & Vermunt, J. K. (2017). The GRoLTS-checklist: guidelines for reporting on latent trajectory studies. *Structural Equation Modeling: A Multidisciplinary Journal, 24*(3), 451–467.
Van der Kooij, A. J., Meulman, J. J., & Heiser, W. J. (2006). Local minima in categorical multiple regression. *Computational Statistics & Data Analysis, 50*(2), 446–462.
Van der Nest, G., Passos, V. L., Candel, M. J., & van Breukelen, G. J. (2020). An overview of mixture modelling for latent evolutions in longitudinal data: Modelling approaches, fit statistics and software. *Advances in Life Course Research, 43*, Article 100323.
Young, F. W., Takane, Y., & de Leeuw, J. (1978). The principal components of mixed measurement level multivariate data: An alternating least squares method with optimal scaling features. *Psychometrika, 43*(2), 279–281.
Yunus, M. (2009). *Creating a world without poverty: Social business and the future of capitalism*. New York: Public Affairs Books.