Default Risk Dynamics in Commercialized Microfinance Institutions: A Smooth Transition Autoregressive Framework

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Abstract: - This paper intends to assess the relationship between the commercialization of microfinance institutions and their portfolio quality using the non-linear smooth transition autoregressive (STAR) model. The main intention of this study is to give an insight into the link between some factors of commercialization and the portfolio quality of MFIs and to justify whether this new trend is responsible for increasing loan defaults. In doing so, we use panel data on 59 MFIs operating in four different regions over a 14-year period. Results show that focusing on profitability as well as increasing competition are positively related to portfolio at risk >30; the indicator of MFIs' repayment risk. Moreover, we find out that the deviation from not-for-profit to for-profit MFIs and from group-based lending to individual lending are also positively associated with PAR30. These results indicate that commercialization seems to be a contributor to the decline of MFIs' portfolio quality and a plausible cause to the decrease of loan default rates.

Key-Words: - microfinance, commercialization, loan default, STAR model.

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1 Introduction

Over the last decades, microfinance has achieved a tremendous development and gained unprecedented widespread public celebration [1]. This industry has been commonly showed as one of the most popular tools to offer access to financial services for poor households, who have long been deemed "unbankable". In the last few years, however, the microfinance institutions (MFIs)1are entrapped by many deep-rooted problems that work to hamper the achievement of the main goal of eradicating poverty. One of such most prominent problems is the high-risk factor for non-repayment of loans by consumers [2]. The loan repayment default has been termed number one risk that threatens the field of microfinance as the borrowers are principally the low income households, where the majority are self-employed and they do not have any physical collateral nor verifiable credit history [3], [4]. Their lacks of collateral assets, lack of financial records and limited credit history, have made providing loans to them more costly and also very risky [5].

Since 2007, many MFIs have encountered serious loan repayment problems and have experienced a drastic increase in repayment delays and defaults. The number of borrowers has sharply decreased and the defaults rates have amplified. Some microfinance markets in many countries have even undergone crises of delinquency and over-indebtedness such as in Nicaragua, Morocco, Bosnia and Pakistan. However, the most dramatic and thoroughly-documented crisis is the one playing out in the Indian State of Andhra Pradesh that erupted in 2010 [6]. Such events have continued to unfold raising concerns about the future of the whole industry.

The recent wave of microfinance commercialization with the aggressive expansion of for-profit driven model has been considered as a chief factor favoring those current problems as it drastically distorted the equilibrium between philanthropic and financial goals. In fact, the growing focus on profit-making aim has exhorted many MFIs to pursue a short-term profit instead of the social-oriented policy that microfinance industry was already renowned [7]. This has recently led not only to increase repayment defaults but also to trigger the risk of over-indebtedness.

Despite the importance of this topic, only a very few studies have attempted to theoretically investigate the impact of commercialization on default risk in microfinance industry [8], [9].

In this paper we try to fill this gap and to give an insight into the association between microfinance commercialization and the portfolio quality of MFIs and to justify empirically whether this new trend is responsible for increasing loan defaults. To perform a better understanding of this concern, the present investigation stands for an empirical analysis using the nonlinear Smooth Transition Autoregressive (henceforth STAR) model. The rationale behind using non linear models is that the loan repayment behavior of poor households may present asymmetric features due to the fragility of their financial situation which make borrower's repayment decision more vulnerable and more prone to fluctuations. Non linear models are therefore needed to apprehend the dynamic features of the data.

Among the non linear models that have flourished in the applied econometric literature, we chose to use STAR model since it represents a good tool to model non-linear time series as it has an immense capacity to adjust to dynamic behavior of time series which are influenced by occasional and dramatic events such as financial crises, wars and so on [10].

In this research, we seek to contribute towards microfinance studies, notably in currently limited empirical studies in microfinance commercialization, as well as towards non linear model literatures in application of STAR model as an adept methodology in microfinance default repayment assessment. Our paper aims to make a twofold contribution. First, while the loan repayment defaults in microcredit issue has frequently been studied, the impact of microfinance commercialization on default repayment is very poorly studied and to the authors' knowledge, this paper is the first empirical investigation exploring this topic. Second, on the methodological front, we employ STAR model which has not been used earlier in the context of microfinance. The few empirical researches on the loan repayment defaults can be found only with linear models [6], [11]. Hence, this study may contribute to the existent literature by using STAR models to investigate nonlinear portfolio-risk dynamics in the microfinance sector. By identifying regime-dependent effects of microfinance commercialization and competition, the paper provides new insights into how repayment behaviour evolves across different risk environments.

The remainder of this paper is organized as follows: Section 2 explores theoretically the relation between microfinance commercialization and loan repayment. Section 3 investigates the methodology and describes the database and variables using in the study. Section 4 gives empirical results and interpretations. The last section provides conclusion.

2. Commercialization, competition and difficult of repayment: a theoretical standpoint:

Microfinance was considered as an overwhelming success story with competitive financial returns and high growth rates that accordingly attract many more commercial investors. Under this new commercial approach, earning profits became a crucial aim for the best part of MFIs leading them to more emphasize on wealthier borrowers, to extensively use individual loans instead of group loans contracts, which has been the cornerstone of microfinance and to move into urban instead of rural areas [12]. Actually, with an increasing focus on financial sustainability, some MFIs have deeply changed their operations and gone as far as to totally substitute their social aims for financial goals. MFIs are steadily shifting towards middle and higher income target groups while leaving behind its original client base. The researchers argue that, with the objective to attain self-financial sustainability, MFIs try to obtain economies of scale by making all their efforts in serving wealthier borrowers. This turn towards better-off clients goes hand in hand with a deviation from rural to urban areas where better-off clientele are most concentrated. Likewise, the shift into urban areas as well as towards better-off clients heightens the dispersion of the individual lending contracts since wealthier borrowers find it more suitable to be engaged in individual contracts more than to be included into groups [13], [14], [15].

One of Other outcomes following the growing role of commercialized institutions is the increasing competition among MFIs. In an effort to reach larger number of clients, microfinance industry scales up encouraging the entry of new MFIs into the market. This new entry leads substantially to increase the competition.

The literature investigating the effects of increasing competition on MFIs remains highly controversial.

On the one hand, the competition in microfinance industry was broadly considered as being beneficial for both borrowers and institutions as it normally decreases interest rates and enhances service and product quality [16], [17]. Competition may also contribute to better-functioning markets by promoting allocative and technical efficiency, enhancing consumer protection and encouraging MFIs to reduce operational costs and diversifying financial products, including savings, insurance and deposit services [1], [18].

On the other hand, an opposing view argues that intensified competition may weaken borrower screening and monitoring, leading to deteriorating repayment behavior and increasing default rates [19], [20]. Since microfinance relies heavily on soft information and close lender–borrower relationships rather than physical collateral, increasing competition may undermine these relationships by reducing incentives for careful screening and long-term client engagement.

In highly competitive pressure, MFIs are incentivized to expand lending to riskier borrowers without requiring physical collateral in order to increase market share, thereby deteriorating portfolio quality. Moreover, in the absence of effective credit information-sharing mechanisms, competition may facilitate multiple borrowing, as clients can contract loans from several MFIs simultaneously [1], [19].

Empirical evidence on the effect of multiple borrowing remains mixed. While some studies suggest that multiple loans may temporarily improve repayment, support institutional efficiency or finance investment projects [21], [22], [23], a growing body of research indicates that excessive multiple borrowing often exceeds borrowers' repayment capacity, increasing delinquency and default risk [24], [25], [26], [27].

As a result, over-indebtedness has emerged as a central risk and the darker side of microfinance commercialization as it threatens both portfolio quality and institutional stability [28]. It can occur with growing competition and arises when borrowers accumulate debt beyond their capacity to repay, leading to persistent repayment difficulties [29]. Over-indebtedness can impede the growth of financial sector by damaging lender-borrower relationships and increasing subsequently risks for donors, investors and the sector of microfinance as a whole [30].

Based on these arguments above, we expect a negative association between microfinance commercialization and the quality of the loan portfolio caused by increased default rates. The growing profit-oriented behavior associated with the deterioration of lending portfolios of MFIs is a crucial issue that some experts in the microfinance have articulated their frustration.

3 Methodology:

3.1 Data and sample selection

To conduct this study, our dataset is provided by Mix Market (MIX)2 which is the largest data source on microfinance compiling information on more than 2000 MFIs.

In this platform, MFIs are classified into five categories conforming to the transparency of their information and their degree of reliability. The MIX database uses a diamond ranking system where the disclosure score ranges from level one to five to estimate the completeness and transparency of information delivered by MFI's. The higher the number of diamonds, the higher is the level of disclosure.

After eliminating MFIs providing incomplete data by neglecting all units for which any of the inputs are missing, we detain information for 59 MFIs across 21 countries. Obviously, the size of the sample is relatively small and this is due to the fact that only few MFIs with 4 and 5 diamonds have complete information during the period of study. The sample includes MFIs from four main regions where microfinance is more concentrated and level of poverty is higher: Africa (14 MFIs), Latin America

(20 MFIs), Asia (12 MFI's) and Middle East and North Africa (13 MFIs).

3.2 Variables description:

3.2.1 Dependent variable:

In this current study, our goal is to examine the effect of the commercialization of MFIs on their loan repayment rates. In the literature, three measurements are usually used to measure rates of MFI loan repayment namely Write-off ratio, portfolio at risk 90 days (PAR 90)3and portfolio at risk 30 days (PAR 30).

In our study, we choose to use Portfolio at risk > 30 which is defined by the value of all loans outstanding that have one or more installments of principle past due more than 30 days. This indicator is formulated as "the ratio between the value of outstanding loans with arrears over 30 days plus rescheduled or restructured loans and the total adjusted gross loan portfolio" [31]. PAR 30 is considered as an early indicator of default problems which may allow MFIs to monitor the credit risk of their outstanding portfolios avoiding, subsequently, unexpected losses. This indicator is broadly used in empirical studies as a measure of delinquent loans [32], [33], [34], [35].

3.2.2 Independent variables:

According to [36], the key principles of commercial approach to microfinance are profitability, competition and regulation. Therefore, we use these three variables as proxies for microfinance commercialization.

Profitability: this variable is given by two leading financial indicators: the operational self-sufficiency (OSS)4 and the return on assets (ROA)5 [37], [38], [39]. As MFIs commercialization indicates more focus on making profit, we hypothesize that profitability indicators are positively associated with PAR30.

Competition: to empirically measure the impact of competition on repayment risk, we have to build a proxy for it. According to the empirical literature on bank competition, we apply Lerner Index which is computed to explore the competitive behavior of institutions and it is defined as "the difference between output price and marginal cost of production scaled by price" [40], [41], [42]. This index measures the degree of firm's market power.

Generally, the value of Lerner index is ranged between 0 and 1. This index is an inverse measure of competition. Thereby, a higher value means greater market power and lower level of competition.

However lower values correspond to weak market power and more competitive market conditions. Consequently, a decline in the Lerner index should be interpreted as an increase in competition.

In this study, our main hypothesis suggests that increased competition among MFIs may maximize the risk of default. Hence, we expect that Lerner index and PAR30 are negatively associated.

Regulation: according to [36], regulated MFIs are closely associated with increasing commercialization. Then, we foresee that repayment strategies might differ between regulated and unregulated institutions and we expect that regulated MFIs may have increased default rates. In doing so, we assess the effect of regulation by including a dummy variable on whether the MFI is regulated or not.

Profit status: The profit status variable is binary coded. This indicated that MFIs of the sample are registered either as non-profit or as for-profit institution. We hypothesize that for-profit oriented MFIs are more likely to suffer high repayment defaults than their peers.

3.2.3 Other explanatory variables:

According to [12], commercialization may be jointly occurred with main changes in MFI business model such as switching lending towards individual contracts, operating in urban areas instead of rural areas and focusing less on women clients [15]. These changes might have important effects on the quality of the portfolio. To identify these effects, three other variables are incorporated which can be employed to find out which MFI methodology is more risky than the others.

Individual lending: this variable is measured by the share of individual contracts in the total portfolio of an MFI. We hypothesize that MFIs with a higher share of individual contracts have a higher default risk.

Rural lending: it is expected that MFIs which have upper share of their rural allocated portfolio are likely to have lower default rates than MFIs that have more contracts in urban areas. This variable is measured by the share of rural contracts in the total portfolio of an MFI.

Percentage of female borrowers: : several studies of microcredit programs have shown that female customers considerably do better than men in terms of repayment and they often reveal stronger willingness to repay their loans [43], [44]. Thereby, we hypothesize that the percentage of women borrower are negatively associated with PAR30.

3.3 Econometric model

The interest in nonlinear time series models has been, over the last decades, progressively increasing. Many studies have already stated that business cycle exhibits nonlinear characteristics and economic dynamic reality shows asymmetric processes [45]. This nonlinearity in time series is due to many reasons such as changing policy regimes, changing agents' behaviors, technological changes, etc.

The nonlinear modelling method that we are going to use belongs to the group of regime-switching models and, as above mentioned, is known as the smooth transition autoregressive (STAR) model. This model was initially introduced in its univariate form by [46] and developed later by [45] and [47].

Although the dataset has a panel structure, the STAR model is applied within a univariate time-series framework. This choice reflects the nonlinearity in portfolio-at-risk behavior that is common across MFIs. In order to control for unobserved cross-sectional heterogeneity, unobserved MFI-specific effects are removed using a fixed-effects transformation. The fixed-effects-adjusted series are then aggregated across MFIs to construct a representative time series, on which the univariate STAR model is estimated. This strategy reconciles the panel nature of the data with the STAR methodology while keeping nonlinear time dynamics.

The STAR model can be showed as a continuous mix of two AR (k) models and by a weighted function that defines the nonlinearity degree [48].

A general STAR model for a univariate time series y_t can be expressed as follows:

$$y_t = \emptyset x_t + \varphi x_t G(s_t;\gamma,c) + \varepsilon_t t = 1,2,\dots,T \qquad (1)$$

Where,

$\emptyset = (\emptyset_0, \emptyset_1, \dots, \emptyset_p)'$ and $\varphi = (\varphi_0, \varphi_1, \dots, \varphi_p)'$are the parameter vectors.

$x_t = (1 - \tilde{x_t})' = (1, x_{1t}, x_{2t}, \dots, x_{pt}) = (1, y_{t-1}, \dots y_{t-i}; z_{t-1}, \dots, z_{t-j})'$ represents the vector of explanatory variables including lags of the endogenous and exogenous variables, while ε_t is defined as a sequence of independent identically distributed errors($\varepsilon_t \sim iid(0,\sigma^2)$).

$G(s_t;\gamma,c)$ is named a transition function that characterizes the STAR model. It is a continuous function that is limited between zero and one.

$s_t$is the transition variable that is assumed to be the lagged endogenous variable ($s_t = y_{t-d}$; with d is the number of lags of transition variable). This parameter can also be an exogenous variable ($s_t = z_t$) or a linear time trend ($s_t = t$).

The parameter γ is the smoothness parameter, it is also called the slope parameter, which represents the shape of shift from a regime to another and it determines the speed of transition between the two regimes of the model [49].

The parameter c is the threshold parameter which identifies the location and the midpoint of the transition function.

[47] specified two different transition functions in STAR models: the logistic STAR model (LSTAR) and the exponential STAR model (ESTAR).

Using LSTAR, the transition function is given by:

$$G(s_t;\gamma,c) = (1 + exp\{-\gamma(s_t - c)\})^{-1} \quad ,\gamma > 0 \qquad (2)$$

It can be interpreted that the logistic function allows for smooth and continuous transition between two extreme regimes and it varies monotonously from 0 to 1 as s_t raises. The parameter c defines the threshold between regimes and the parameter γ describes the speed of the regimes adjustment and identifies the smoothness of the transition in the value of the logistic function. As γ increases largely($\gamma \to \infty$), the transition of $G(s_t;\gamma,c)$ from 0 to 1 becomes roughly instantaneous at $s_t = c$. While, if $\gamma = 0$, the corresponding equation becomes linear. Hence, the logistic function implies an asymmetric adjustment of y_t to its past values depending on the value of the transition variable s_t, to be below or above the threshold c. The LSTAR transition function is of S-shape around c and it monotonically increases producing an asymmetric adjustment process toward the equilibrium.

Using the ESTAR, the transition function is specified as:

$$G(s_t;\gamma,c) = 1 - \exp\{-\gamma(s_t - c)\}^2 \quad ,\gamma > 0 \qquad (3)$$

This function has the property that $G(s_t;\gamma,c) \to 1$ both when $s_t \to -\infty$ and $s_t \to +\infty$, while $G(s_t;\gamma,c) = 0$ for $s_t = c$. Hence, the ESTAR model suggests that two regimes have similar dynamics and it is characterized by a symmetric adjustment in both direction of $s_t - c$. The transition function of ESTAR has a form of U-shape around c and it yields to a symmetric adjustment towards the equilibrium.

Both functions become steeper when γ becomes larger (γ → ∞), which means that the speed of the transition becomes faster.

[47] has developed an appealing modelling cycle of STAR model which is composed of the following sequence of steps:

Step 1: Specifying the order p for the autoregressive model

Step 2: Testing linearity against STAR

Step 3: Choosing between LSTAR and ESTAR models

Step 4: Estimating and evaluating the STAR model

The first step consists on determining the adequate lag length of order p of deterministic autoregressive part of model (AR (p)). This order p should be when the corresponding residuals are roughly white noise and it can be selected by various order selection criteria, for example the Akaike Information Criterion [AIC] and the Schwarz Information Criterion [SIC]. Further, the presence of autocorrelation is assessed by the Ljung-Box statistics.

The second step consists on testing linearity against STAR for different values of delay parameter. We can express the null hypothesis of linearity as:

$$\begin{cases} H_0 : \varphi = 0 \\ H_1 : \varphi \neq 0 \end{cases}$$

However, under the null hypothesis, the investigating problem is characterized by the existence of unidentified nuisance parameters [47], [50]. Alternatively, the null hypothesis becomes$H_0^{'}: \gamma = 0$ against$H_1^{'}: \gamma > 0$, but it, in addition, produce a linear model and under which the parameters $c$and φ still unidentified.

[51] argued to solve the problem of the presence of nuisance parameters that may complicate the origin of the asymptotic distribution of the test statistics, by replacing the transition function $\mathrm{G}(\mathrm{s_t}; \gamma, \mathrm{c})$by an appropriate Taylor series approximation. In this case, we can test linearity by carrying out a Lagrange Multiplier (LM)-type test with an asymptotic Khi-deux distribution under the null hypothesis.

If the linearity hypothesis is rejected, the next step will consist on selecting the right form of the transition function either ESTAR or LSTAR. [47] considered a sequence of null hypotheses as follows:

$$H_{03}: \beta_3 = 0$$
$$H_{02}: \beta_2 = 0 | \beta_3 = 0$$
$$H_{01}: \beta_1 = 0 | \beta_3 = \beta_2 = 0$$

Using an F-test, Teräsvirta (1994) noted that the rejection of H_{03} would mean the elimination of the ESTAR specification since the cubic power of s_t in a first order approximation of $\mathrm{G}(\mathrm{s_t}; \gamma, \mathrm{c})$ is equal to 0. Moreover, the failure to reject H_{02} is considered as evidence in favor of LSTAR model. Likewise, the elimination of H_{01} after accepting H_{02} points also to LSTAR model whereas accepting H_{01} after rejection of H_{02} supports the choice of ESTAR transition function [52].

Briefly, the expansion for the ESTAR transition function has the quadratic form, so if the ESTAR is suitable, it will be likely to exclude all the terms in the cubic expression [48].

Once the transition function has been chosen, the fourth step in the modeling cycle consists on estimating the STAR model's parameters using the nonlinear least squares (NLS) or the maximum likelihood estimation under the hypothesis of normally distributed errors [53]. Further the model should be subject to misspecification tests in order to evaluate the properties of the fitted model [50]. Indeed, the adequacy of the model is determined by carrying out some tests to verify the remaining heteroskedasticity and correlation in the residuals such as the Ljung-Box test, Breush Godfrey test and McLeod-Li test.

4 Empirical results and interpretations:

4.1 Model specification:

We estimated, based on Akaike Information Criterion and Ljung-Box statistics for autocorrelation, different AR models and then chose the appropriate order of auto-regression p. Results reveal that an AR (p) model with 1 lagged first difference is more adequate. Table 1 (Appendix) shows the AR (1) model results.

The Table 2 (Appendix) below gives the estimated statistics of the Ljung-Box test of no error serial correlation.

The p-values show that the null hypothesis of no serial dependence autocorrelation is accepted. This points out that the AR (1) model has white noise residuals. Thus, the nonexistence of correlation in the residuals of the estimated parameters provides evidence that AR (1) is adequate in modelling the data series.

4.2 Testing linearity and selecting the transition function:

This stage consists on testing linearity against STAR model for different values of the delay parameter d using the LM-type statistics. The delay parameter is specified by selecting the value that minimizes the p-values of the linearity tests. As reported by results displayed in Table 3 (Appendix), the delay parameter, d = 1 is the best to be chosen because it has the smallest p-value among the other delay parameters.

As a measure to determine whether the nonlinear specification is appropriate, we apply the overall significance F-test. Results show that the null hypothesis of linearity is not accepted for all the variables at 10% level of significance which verify the nonlinear structure of the considered variables, except for PROFST and REG that are assumed to be linear and this is arguably, because they are dichotomous variables. This finding confirms that the adjustment process of PAR30 towards the long-run equilibrium is of nonlinear nature. Thus, the model with p=1 and d=1 is a correct representation of the adjustment process of the repayment default.

After testing for nonlinearity, the subsequent stage is to select the nature of the transition function and then choose between LSTAR and ESTAR models.

In our context, the LSTAR specification may detect asymmetric transitions between high and low portfolio risk regimes. The high risk regime is associated with advanced commercialization, and high portfolio default repayment whereas the low risk regime corresponds to periods of moderate commercialization and stable repayment behaviour. Economically, this indicates that once commercialization exceeds a certain threshold, repayment dynamics change asymmetrically, leading to higher and faster deterioration of portfolio-at- risk. However, the ESTAR model detects symmetric adjustments around a long-run equilibrium level of portfolio risk. Deviations from this equilibrium, either downward or upward, incite similar adjustment dynamics that reflect different degrees of portfolio default risk rather than structurally distinct regimes.

The results of model selection process are presented in Table 4 (Appendix).

The sequence of nested hypothesis outcomes depict that the logistic STAR model is retained for PAR30, ROA, OSS, RURLD and FEM, since the values of H_{03} are the largest among the test statisticsH_{01}, H_{02} and H_{03}.Then, we selected ESTAR model for COMP and INLD, as the p-value of H_{02} is the smallest. Particularly, this finding verified the claim that the asymmetrical adjustment process of default repayment could be well characterized by the monotonic increasing function; the LSTAR model.

4.3 Model estimation:

In this stage, we proceed with the mode estimation using nonlinear least squares method. Table 5 (Appendix) reports the estimation results including nonlinear and linear part of LSTAR model.

With regard to the smoothness parameter, the estimated coefficient $\hat{\gamma}$ (1.462) is positive and significant at the 5% level of significance suggesting the smoothness of the transition between different regimes. The low value of this parameter imposes a slow transition indicating that the adjustment speed towards the equilibrium is fairly slow. As to the threshold parameter which identifies the location of the transition function and represents the point of transition between the two extreme regimes, the estimated coefficient $\hat{c}$ (-9.145) is negative and statistically significant at the 5% level of significance.

Before interpreting the results of the interaction between commercialization and repayment default, we try to assess the adequacy of the estimated model of LSTAR applying the Ljung-Box test for serial correlation in order to test the null hypothesis of no error autocorrelation. Findings are tabulated in Table 6 (Appendix).

The p-values for the residuals lag designate that the null hypothesis of no serial correlation in the model is not rejected and that the estimated model is free from serial correlation problem. This could be concluded that the fitted LSTAR model is adequate.

Back to the Table 5 (Appendix) above, the estimation results of the LSTAR model depict that the estimated value of ROA in nonlinear part (0.5213) is positive and statistically significant at the 1% level which figures out that profitability is positively associated with the rate of defaults in loan repayment and that highly profitable MFIs have a lower portfolio quality. However, the relation between OSS and repayment defaults is negative but insignificant. This result agreed relatively with our prior hypothesis which stipulated that pursuing profitability is more providing greater rate of loan delinquency. These findings are aligned with those of many studies which found that seeking profitability leads to leave behind the poorest and to shift towards more profitable segment of the market instead. This would make the poorest fall into several constraints and taking multiple loans. Therefore, it increases their repayment defaults [1], [54].

By constructing a Lerner index, results reveal that the value of the coefficient is negative and significant at the 10% level. Since Lerner index is inversely related to competition, this result suggests that the rate of defaults is positively correlated with competition. It means that increasing competition leads to declining loan repayment and spiraling default rates. This might be illustrated by the fact that the entry of increasing number of lenders into market may induce asymmetric information which makes information sharing between lenders more difficult [55]. Furthermore, increasing competition in microfinance market may incite lenders to change their behavior by adopting over-aggressive marketing and paying less attention on client’s repayment capacity. This might trigger some borrowers to obtain multiple loans leading, hence, to over-indebtedness. Accordingly, this multiple contracting generates less favorable equilibrium credit contract by raising the borrowers’ debt levels in the MFI portfolio and declining the repayment rate equilibrium among all the loan transactions [19]. Our findings corroborate the results of several studies such as [30], [56] and [26] who stated that increased competition may decline portfolio quality, hasten the market saturation and deteriorate information sharing between MFIs inducing a decrease in repayment performance.

With respect to the regulatory status variable, the result depicts a negative but not significant linear relationship between regulation and delinquent loans.

Econometric outcomes reveal also a positive and significant linear relationship between profit status and delinquent loans. These findings confirm our hypothesis that being for-profit may worsen the loan portfolio quality of MFIs increasing the volume of defaults. Indeed, the profit orientation incites MFIs to focus more on enhancing profitability through increasing the volume of loans and attracting more borrowers. Nonetheless, higher levels of MFI borrowers make getting loans from MFIs excessive.

As for the individual lending, the results demonstrate a statistically significant and positive coefficient indicating that repayment defaults are more likely to occur under individual liability than group liability. This is due to the fact that individual based-lending schemes may strengthen the moral hazard problems and intensify adverse selection inefficiencies since the individual monitoring is largely costly. However, joint liability under group lending contracts, mainly via peer monitoring and peer selection, can lead to higher repayment rates and can overcome informational asymmetries because group members have better information about each other, have incentives to easily monitor each other and may be possible to impose social sanctions at lower costs. These findings uphold the results of many previous studies which argue that group lending tool is more successful in decreasing borrower defaults than individual lending mechanism [14], [57] and [58].

Finally, results depict that loan repayment delinquencies is negatively but not significantly related to the portfolios allocated in rural areas as well as to the proportion of women borrowers detained by MFIs.

So far, we can conclude that these results confirm relatively our prior hypothesis that commercialization seems to be a contributor to the decrease of repayment performance and the increase of defaults. Transforming into profit organizations, more focusing on profitability, increasing competition, improving individual lending instead of joint liability, all those constitute key factors of boosting adverse selection and moral hazard problems inciting substantially to multiple borrowing and leading further to over-indebtedness. Consequently, borrowers are pressured to sell off whatever they have, in order to pay back their loans, making them more impoverished than they were before and even bringing them to suicide in some cases [59]. Thus, the commercial trend does not only lead to raise delinquencies and to fuel over-indebtedness crisis but also to lose its good reputation, making the whole industry in a situation in which the value of microfinance for the borrowers as well as the original mission of eradicating poverty is questioned.

5 Conclusion:

In this study, the basic objective is to investigate whether the commercialization of MFIs is a plausible cause of decreasing portfolio quality and raising delinquencies or not. To this end, we applied the STAR model to 59 MFIs operating in Africa, MENA, Asia and Latin America.

Following the modelling cycle given by [47], at the beginning, the results revealed that AR (1) model is appropriate to model the data and the delay parameter d=1 is the best to be chosen. Next, we proceeded to test the linearity of series, then to select the adequate model among LSTAR and ESTAR. Once non linearity was proved and the model was chosen, we performed the non least squares method to estimate model parameters and variables. At this stage, estimates showed that the value of the smoothness parameter coefficient is low and it is positively significant at the 5% level of significance suggesting that the transition between regimes is smooth and the speed of adjustment towards the equilibrium is fairly slow.

Concerning the determinant of MFIs commercialization, the obtained results are mostly plausible and the majority of variables are positively and significantly associated with MFIs repayment risk. Indeed, results show that pursuing profitability instead of focusing on client welfare and transforming into for-profit organization may decrease loan portfolio quality. Likewise, the results of this study give insight that increasing competition may deteriorate repayment rates. Moreover, the spreading of individual contracts instead of joint liability may reinforce loan defaults by increasing asymmetrical information and lead to multiple borrowing as well as to client over-indebtedness. However, insignificant relation is founded between portfolios at risk> 30 days and operational self-sufficient, regulation, rural areas and percentage of female borrower.

From these results, we can conclude that microfinance commercialization and the related emphasis on profitability may be a plausible cause of deteriorating portfolio quality and may have a great contribution in increasing loan defaults. Moreover, commercialization might be an underlying driver for multiple borrowing and over-indebtedness. Therefore, it may endanger the well-being of clients making the microfinance public reputation in question.

Nonetheless, we should not blame solely commercialization for increasing loan defaults. Other internal and external factors may be the main determinants of declining portfolio quality and rising defaults such as MFI’s malpractices and their internal inefficiencies [28]. Therefore, it will be crucial for MFIs to take proper measures to curb such potentially problems and to be strict in removing all the malpractices in order to ensure their sustainability and growth on the one hand and to find ways for better wellbeing of their clients on the other.

Finally, some limitations of the study must to be noted. Actually, there might be some other relevant factors, which significantly influence on the microfinance commercial decisions, notably, the characteristics of loan officers and their interaction with their incentives environment which may influence their lending decision. In this way, further research is warranted to analyze more specifically the impact of personal characteristics of microfinance loan officers on their portfolio decision making. Also, we can, by applying panel-based nonlinear models, integrate computational simulations or exploring experimental data to investigate borrower behavior under varying competitive and institutional conditions.

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APPENDIX

Table 1. Estimation of AR (1) model

Parameters	Coefficients	P-value
Constant	**0.06018**	**0.0000**
PAR30 (1)	**-0.24779**	**0.0000**

Note: PAR30: portfolio at risk 30 days

Table 2. Ljung-B

Lags	Q-statistic	P- value
Q (6)	**9.2813**	**0.6859**
Q (12)	**19.8737**	**0.4671**
Q (18)	**26.1483**	**0.2948**
Q (24)	**36.3975**	**0.1632**

Table 3. Linearity test results

d	Statistics	PAR30	ROA	OSS	COMP	INLD	RURLD	FEM	PROFST	REG
d =1	LM	15.9001 (0.0000)	22.5406 (0.0000)	21.4916 (0.0000)	1.8842 (0.0810)	7.3165 (0.0000)	1.9806 (0.0662)	42.8687 (0.0000)	0 .0000 (1.0000)	0.0041 (1.0000)
d =2	LM	6.3188 (0.0000)	22.0111 (0.0000)	10.2454 (0.0000)	1.2590 (0.2742)	3.9677 (0.0007)	1.8908 (0.0799)	26.7275 (0.0000)	0.0000 (1.0000)	0.0049 (1.0000)
d =3	LM	3.3606 (0.0029)	1.7308 (0.1113)	12.7119 (0.0000)	0.375 4 (0.8947)	4.3064 (0.0003)	0.0528 (0.9994)	7.1813 (0.0000)	0.0037 (1.0000)	0.0341 (1.0000)
d =4	LM	4.879 4 (0.0010)	1.4122 (0.2075)	3.5867 (0.0017)	0.324 0 (0.9244)	4.6799 (0.0001)	0.0413 (0.9997)	4.8448 (0.0001)	0.0061 (1.0000)	0.0026 (1.0000)
d =5	LM	3.8140 (0.0020)	1.2933 (0.2584)	1.6464 (0.1323)	0.2462 (0.9607)	3.8488 (0.0009)	0.1241 (0.9934)	5.5433 (0.0000)	0.0068 (1.0000)	0.0029 (1.0000)
d =6	LM	4.7544 (0.0011)	6.3372 (0.0000)	4.4141 (0.0002)	0.2531 (0.9579)	3.9917 (0.0007)	0.0303 (0.9999)	3.0131 (0.0067)	0.0076 (1.0000)	0.0511 (1.0000)

Note: PAR30: portfolio at risk 30 days; ROA: Return on assets; OSS: Operational self-sufficiency; COMP: Competition; INLD: Individual lending; RURLD: Rural lending; FEM: Percentage of female borrowers; PROFST: Profit status; REG: Regulation.

Table 4. Result of model selection

d	PAR30	ROA	OSS	COMP	INLD	RURLD	FEM

d =1	$\mathbf{H_{01}}$: 4.067 (0.0175) $\mathbf{H_{02}}$: 10.080 (0.0000) $\mathbf{H_{03}}$: 12.167 (0.0000)	$\mathbf{H_{01}}$: 0.999 (0.3687) $\mathbf{H_{02}}$: 15.392 (0.0000) $\mathbf{H_{03}}$: 49.215 (0.0000)	$\mathbf{H_{01}}$: 0.343 (0.7091) $\mathbf{H_{02}}$: 8.480 (0.0002) $\mathbf{H_{03}}$: 54.609 (0.0000)	$\mathbf{H_{01}}$: 0.106 (0.8987) $\mathbf{H_{02}}$: 4.140 (0.0163) $\mathbf{H_{03}}$: 1.406 (0.2457)	$\mathbf{H_{01}}$: 5.492 (0.0043) $\mathbf{H_{02}}$: 9.447 (0.0001) $\mathbf{H_{03}}$: 6.641 (0.0014)	$\mathbf{H_{01}}$: 0.220 (0.8025) $\mathbf{H_{02}}$: 1.088 (0.3373) $\mathbf{H_{03}}$: 4.644 (0.0099)	$\mathbf{H_{01}}$: 9.037 (0.0001) $\mathbf{H_{02}}$: 22.564 (0.0000) $\mathbf{H_{03}}$: 88.872 (0.0000)

Note: PAR30: portfolio at risk 30 days; ROA: Return on assets; OSS: Operational self-sufficiency; COMP: Competition; INLD: Individual lending; RURLD: Rural lending; FEM: Percentage of female borrowers.

Table 5. Estimates of LSTAR model

Variables	Coefficients	T-statistics	P-value
ROA	0.5213	2.8703	0.0042
OSS	-0.2389	-0.7615	0.4465
COMP	-0.3678	-1.8649	0.0948
FEM	-0.4518	-0.3502	0.7262
INLD	0.1941	2.6902	0.0055
RUR	-0.8129	-1.0527	0.2928
$\mathbf{A_0}$	-0.0111	-10.1646	0.0000
PROFST	0.7152	3.6094	0.0003
REG	-0.9813	-0.3234	0.7464
$\mathbf{B_1}$	0.0111	10.2154	0.0000
$\mathbf{B_2}$	1.4183	3.5921	0.0000
GAMA	1.4621	44.5227	0.0000
c	-9.1451	-95.7526	0.0000

Note: PAR30: portfolio at risk 30 days; ROA: Return on assets; OSS: Operational self-sufficiency; COMP: Competition; INLD: Individual lending; RURLD: Rural lending; FEM: Percentage of female borrowers; PROFST: Profit status; REG: Regulation.

Table 6. Ljung-Box statistics

Lags	Q-statistic	P- value
Q (6)	**12.1439**	**0.6738**
Q (12)	**20.4120**	**0.3159**
Q (18)	**28.1131**	**0.2605**
Q (24)	**38.2175**	**0.1462**