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Provisioning and business cycle: Evidence from microfinance institutions

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Abstract

This paper investigates the drivers of provisioning in MFIs and their provisioning behaviour over the course of economic cycles. Using a sample of 6148 firm-year observations from 1474 MFIs worldwide over 2001-2014, we uncover a negative relationship between MFIs' provisioning and the business cycle, in other words, MFIs adjust their provisioning in a pro-cyclical manner, meaning that they fail to accumulate more provisions during periods of economic booms to be used to sustain their lending activities during recessions. Our results also show that some characteristics of both MFIs and their clientele, such as the depth of outreach, the capital adequacy ratio and the number of borrowers per loan officer, are significantly associated with the level of provisions in MFIs.

Keywords: MFI, microfinance, loan loss provision, business cycle, credit cycle

JEL Classification: G21, G23

1. Introduction

The latest 2007-2009 global financial crisis has intensified the debate on effective risk management and appropriate bail-out policies for stable and resilient financial systems (BCBS, 2011). Despite the ongoing debate on how to better regulate financial institutions, unfortunately, the policies put forth by international regulatory bodies, such as the Bank for International Settlements and the Financial Stability Board, are primarily designed for banks, and less attention has been paid to microfinance institutions (MFIs). MFIs are non-negligible financial intermediaries in the financial system of less-developed-countries (LDCs) and emerging economies.[1] Unlike banks, they are often better suited to deal with the information asymmetries, which undermine the credit market in LDCs, and are efficient in dealing with micro-loan costs (Mahjabeen, 2010). While banks are relatively more reluctant to grant uncollateralized loans in low-income communities in LDCs, there are many MFIs, which provide valuable financial services in these countries. Therefore, the stability of microfinance institutions is of paramount importance for inclusive growth and financial stability. Risk management in MFIs remains, however, a major challenge for their sustainability, as evidenced by the successive reports of the Center for the Study of Financial Innovation (CSFI).[2]

This paper aims to study provisioning behaviour of MFIs, especially its relationship with business cycles. Provisioning is the accounting process by which MFIs set aside revenue to cover expected loan losses on their loan portfolio. This reserve is valuable because it provides these institutions with a revenue buffer against anticipated loan losses. In the banking system, provisions for loan losses are estimated based on well-developed internal credit risk models. In addition, banks are subject to stringent and rigorous capital adequacy rules. As recommended by the BCBS (2010) and Christen et al. (2012), the provisioning schedule for delinquent microloans should be even more aggressive than the

[1] The 2015 Microcredit Summit report shows that the total number of customers served by MFIs worldwide grew continuously between 1997 and 2013. As of December 31, 2013, 3,098 microfinance institutions (MFIs) reported reaching 211,119,547 borrowers, 114 million of whom were living in extreme poverty (Reed, 2015). Of these poorest clients, 82.6% are women.

[2] Indeed, the CSFI ranks risk management as number two among the risks faced by MFIs, and concerns about the quality of risk management in service providers continues to rise in the rankings, despite the large amount of work being put into it. In 2012, this Banana Skin ranking was number six, in 2014 number four.

schedule for delinquent secured bank loans to reflect the lack of collateral requirements.[3]

Most previous studies associate MFIs loan portfolio quality to innovative loan contract designs such as joint liability contracts, regular repayment schedules, dynamic incentives, social sanctions, social relations that may help avoid information asymmetry between the MFI and borrowers and provide incentives for borrowers to repay loans (Armendáriz and Morduch, 2010; Besley and Coate, 1995; Chowdhury, 2005; Griffin and Husted, 2015; Stiglitz, 1990). Moreover, the existing literature on the effectiveness of credit risk management schemes in MFIs shows that loan repayment performance depends on the loan officer abilities and role in the loan decision making process, especially in information collection (Agier, 2012), and loan officer subjectivity (Agier and Szafarz, 2013). In contrast, our study is the first that explicitly examines the drivers of provisioning in MFIs and their provisioning behavior through the economic cycles. Our main contributions are twofold: (1) we study whether the provisioning behavior in the microfinance industry depends on MFIs idiosyncratic factors or aggregate (systematic) factors? (2) We study whether MFIs actively manage their provisioning through the business cycle and the credit cycle, by controlling for MFIs idiosyncratic factors? In other words, we examine whether the provisions set by MFIs are pro-or counter-cyclical?

Investigating provisioning behaviour is of particular interest in the microfinance sector for at least three reasons. Firstly, the current trends towards the commercialization of microfinance is associated with a decline in the use of joint liability contracts and creates incentives for some borrowers to take multiple loans which may cause a deterioration in MFIs' loan portfolio quality. Indeed, recently the dramatically increased competition among MFIs in the microfinance sector has become a major challenge for the industry and one of the main explanatory factors for the decline of MFIs' loan portfolio quality. The microfinance crisis that occurred in the Indian state of Andhra Pradesh in October 2010 provides a case study of the adverse effects that competition can have on borrowers'

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[3] In Nigeria, the revised regulatory and supervisory guidelines for microfinance banks (MFBs) impose rules on provisioning. However, in countries like Azerbaijan, Bolivia, Bosnia and Herzegovina, and Kazakhstan, and in some African sub-regions, such as Central Africa and West Africa, where there are specific regulations for microfinance institutions, regulatory rules do not include provisioning requirements and MFIs comply with some best practices recommended by both the Consultative Group to Assist the Poor (CGAP, 2003) and Microrate (2014) (see Appendix 1).

welfare and repayment. Johnson and Meka (2010) reported that 84% of households had two or more loans from different moneylenders and 58% had four or more loans. The Indian crisis illustrates the problem of parallel loans and multiple contracting whose effect on loan repayment performance is evidenced (Baquero et al., 2017; Guha and Chowdhury, 2013; McIntosh and Wydick, 2005; McIntosh et al., 2005). According to de Quidt et al. (2016), increased competition and a shift from non-profit to for-profit lending drives lenders to reduce their use of joint liability loan contracts. To the extent that the use of joint liability contract improves loan repayment performance, we can expect that the trend toward the commercialization of microfinance will lower repayment performance and will increase loan loss provision expenses, at least to some extent.

Secondly, MFIs are double-bottom-line organizations. They seek to earn profit, fight poverty and target disabled people or reach those whose access to borrowing, savings, investment, payment services and insurance is either limited or non-existent. Unlike the banking sector in which there is significant research on banks' provisioning behaviour and strategies (Ahmed et al., 1999; Beatty et al., 1995; Kanagaretnam et al., 2010, 2014; Leventis et al., 2011; Murcia and Kohlscheen, 2016), there are very few studies dealing with the determinants of loan loss provisions expenses in hybrid organizations such as MFIs. To date, existing studies in microfinance do not answer the question of whether MFIs use provisions as a buffer against loan portfolio deterioration.

Thirdly, given the maturity of the microfinance sector, MFIs are now an integral part of the financial system of most developing countries in which they compete with banks, especially through upscaling strategies (Cull et al., 2014; Vanroose and d'Espallier, 2013). MFIs are now well entrenched as a part of expansion in the financial sector (Brière and Szafarz, 2015) and as such are likely to suffer from macro-economic shocks. Unlike banks and other sophisticated financial institutions, they have fewer resources to invest in risk management and in this regard, loan loss provisioning is one of the key credit-risk management tools they can rely on. By building a solid loan loss provision, MFIs can immunize themselves against potential loan losses. Loan loss provisioning is expected to match with expected credit risk-taking and foreseen macroeconomic conditions. As MFIs are also exposed to many of the same sources of macroeconomic risk as banks, a good provisioning practice through economic cycles could protect their business against default.

According to Drehmann et al. (2011), credit risk in financial systems tends to grow gradually in boom periods, and only materializes in downturns. In this regard, good provisioning practice is expected to be countercyclical to allow MFIs, which have less access to liquidity facilities, to stay solvent during bust. Hence, in the absence of a common unified capital adequacy rule such as the Basel capital adequacy requirement for banks, loan loss reserves constitute a good complementary capital buffer. There is, however, less consensus on how macroeconomic factors affect MFIs' performance according to recent studies on international data on MFIs. Some studies claim that MFIs' performance is only weakly correlated with macroeconomic conditions, and hence that MFIs are resilient to economic crisis (Chen et al., 2010; Gonzalez, 2007; Lützenkirchen and Weistroffer, 2012). These studies suggest that MFIs might not be required from a regulatory perspective to set their provision in a countercyclical manner, but instead in a way that potentially reflect their true portfolio risk. However, some recent microfinance studies document strong correlation between vulnerability/crisis in microfinance and the global economic crisis (Ahlin et al., 2011; Wagner and Winkler, 2013). These studies imply that MFIs are vulnerable to macroeconomic risk factors, hence a negative co-movement between provisions expenses and business cycle.

Using a sample of 6148 firm-year observations from 1474 MFIs worldwide over 2001-2014, we uncover a negative relationship between MFIs' provisioning and the business cycle. In other words, MFIs adjust their provision in a pro-cyclical manner, meaning that they fail to accumulate more provisions during periods of economic booms to be used to sustain their lending activities during recessions. The results also show that some characteristics of both MFIs and their clientele are significantly associated with the level of provisions built up. We find evidence that the depth of outreach is negatively associated with provisions, indicating that provision expenses increase when MFI targets disabled borrowers. In addition, we find that provisions are positively correlated with the capital adequacy ratio, suggesting that provisions may be used for capital management purposes. Similar evidence is found in the subsample of regulated MFIs and deposit-taking MFIs, suggesting that when regulation is binding, undercapitalized MFIs use provisions to comply with capital requirements. Finally, we find that the lower the number of borrowers per loan officer, the more the level of provisions increases.

The remainder of the paper is organized as follows. The next section presents the econometric framework, data and variables. Empirical results and analyses are discussed in section 3. We conduct further robustness checks in section 4. We conclude in section 5.

2. Methodology, data and variables

2.1. Econometric model

To respond to our research questions, we follow Murcia and Kohlscheen (2016) and model MFIs' loan loss provisioning in a dynamic partial adjustment framework. Specifically, we assume that MFIs target a long-term loan loss provision (LLP) level and adjust toward it on a yearly basis depending on their realized losses, portfolio quality and macroeconomic conditions. As the amount of realized profit is limited in each period, MFIs are more likely to report some of their expenses adjustment to their LLP. Following the banking literature on partial adjustment (see for instance Guidara et al. (2013), Jacques and Nigro (1997), Murcia and Kohlscheen (2016), Rime (2001), Shrieves and Dahl (1992), among many others), this dynamic adjustment behaviour is described as follows:

$$\Delta \mathrm{LLP}_{\mathrm{it}} = \lambda(\mathrm{LLP}^{*}_{\mathrm{it}} - \mathrm{LLP}_{\mathrm{it-1}}) + \eta_{\mathrm{it}}, \qquad (1)$$

where *i* indexes MFIs, and *t* indexes year. Equation (1) reads as follows: Each year, MFIs adjust a proportion λ of the difference between their *desired* (or long-term) loan loss provision level $\mathrm{LLP}^{*}_{\mathrm{it}}$ and their actual loan loss provision $\mathrm{LLP}_{\mathrm{it-1}}$. We assume that the long-term target $\mathrm{LLP}^{*}_{\mathrm{it}}$ is a function of MFIs' characteristics (both aggregate and idiosyncratic factors), and is expressed as follows:

$$\mathrm{LLP}^{*}_{\mathrm{it}} = \alpha_0 + X_{\mathrm{it-1}}\beta^{*} + W_{\mathrm{it}}\gamma^{*}, \qquad (2)$$

where X_{it-1} is the vector of MFI-level variables (size, capital-to-asset ratio, loan portfolio quality, profitability, liquidity, borrowers per loan officer, percentage of female borrowers, and the depth of outreach). W_{jt} is the vector of aggregate variables and includes the GDP growth, the credit-to-GDP gap and a dummy for crisis periods.

Plugging (2) into (1) yields:

$$\Delta \mathrm{LLP}_{\mathrm{it}} = \lambda(\alpha_0 + X_{\mathrm{it}-1}\beta^* + W_{\mathrm{it}}\gamma^* - \mathrm{LLP}_{\mathrm{it}-1}) + \eta_{\mathrm{it}}$$

$$= -\lambda \mathrm{LLP}_{\mathrm{it}-1} + \lambda\alpha_0 + X_{\mathrm{it}-1}\lambda\beta^* + W_{\mathrm{it}}\lambda\gamma^* + \eta_{\mathrm{it}}, \qquad (3)$$

or

$$\mathrm{LLP}_{\mathrm{i,t}} = (1-\lambda)\mathrm{LLP}_{\mathrm{it}-1} + \lambda\alpha_0 + X_{\mathrm{it}-1}\lambda\beta^* + W_{\mathrm{it}}\lambda\gamma^* + \eta_{\mathrm{it}}, \qquad (4)$$

where η_{it} is the idiosyncratic error. To estimate equation (4), we apply the generalized method of moments (GMM) estimator developed for dynamic panel data by Arellano and Bond (1991) and extended by Arellano and Bover (1995) and Blundell and Bond (1998). This estimation method is designed to address several econometric issues in panel data analysis: persistence, endogeneity and omitted variables. To control for the possible endogeneity of the LLP and the MFI-level variables (namely, profitability, portfolio risk, capital-to-asset ratio and size), we use their two-to five-period lags as instruments. We collapse instruments but specify in the GMM-style variables that lag from one to five can be used. As suggested by the Hansen test, the instruments are valid. The method is also suitable for the structure of our dataset which has a large N (1474 MFIs) and small T (14-year period, from 2001 to 2014)[4]. In addition to the system-GMM approach, we estimate the fixed effect and the OLS versions of equation (4) to provide a consistent interval for the true value of λ.[5] In fact the estimation of λ via fixed effect is theoretically downward biased, whereas its estimation via OLS is upward biased. Therefore the true estimated value of λ obtained with system-GMM must lie between the OLS and fixed effect estimations to be valid.

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[4] Many MFIs have limited data as our panel is unbalanced. 25% of MFIs have only one year of data and are therefore automatically removed from the regressions because we use lags. The average number of data points per MFI is 3 and the maximum is 9, so use of system-GMM is justified. More than 70% of the database consists of MFIs with less than five data points.

[5] Following the existing literature (see Lemmon et al., 2008, page 1599, Table VI), we implement the pooled OLS and the fixed effects estimations to provide a range for the estimates with system-GMM. The OLS estimate is upward biased because of the correlation between the lag and the errors, whereas with the within estimator, the coefficient is downward biased because the lag is now correlated with (minus) the lag of the error (see Baum, 2013, page 24 for details).

2.2. Data and variables

2.2.1. Data

The data used in this study come from two main sources. Data for MFI-level variables comes from the Microfinance Information eXchange (The MIX) database, which is growing in use in the microfinance empirical literature (e.g., Bogan, 2012; Servin et al., 2012; Tchakoute Tchuigoua, 2016; Vanroose and D'Espallier, 2013; among many others). The MIX is a web-based microfinance platform that provides data on market conditions, individual MFIs' performance and the financial inclusion landscape. As of June 2016, the date on which we gathered the data, the MIX platform discloses information on about 2,000 key microfinance institutions around the world. To the extent that only MFIs wishing to disclose information voluntarily decide to disclose their financial statements to the MIX, working with the MIX data induces a selection bias that we have neglected in this study.

Moreover, the data disclosed by the MIX are of unequal quality. Indeed, the MIX uses a five-point ordinal scale (diamond scale) to classify MFIs according to their level of transparency and reliability of information. The highest diamond levels (four and five) indicate that the organization has supplied audited financial statements and/or is rated by ratings agencies specialized in rating MFIs. To address the issue of data reliability, we focus on MFIs with a disclosure rating of at least four and five diamonds on the MIX. The financial statements of these MFIs are certified by the auditors, and for some of them, by the big four accounting firms. Besides the fact that their financial statements are audited, those at level five are rated by rating agencies.

Focusing on MFIs with reliable data from the perspective of MIX enables us to build an unbalanced panel of 6148 MFI-year observations for a total of 1474 MFIs over 2001-2014. As reported in Appendix 3, the sample includes MFIs from six main regions of the world defined by the MIX: Africa (301 MFIs), East Asia and the Pacific (178 MFIs), Eastern Europe and Central Asia (223 MFIs), Latin America and Caribbean (438 MFIs), Middle East and North Africa (57 MFIs) and South Asia (278 MFIs).

Country-level data come from the World Bank's Global Financial Development database (GFD)[6] and World Development Indicators database (WDI), whereas data on the credit-to-GDP gap comes from the website of the Bank for International Settlements (BIS).

Table 1 below gives a summary of the sample distribution by year. In total, we have a sample of 6148 spanning from 2001 to 2014. As mentioned above, the sample countries can be found in Appendix 3, where the number of observations per country is provided. The data are unevenly distributed across the years, hence an unbalanced panel sample.

(Insert Table 1 here)

We have three important types of MFIs in our database as shown in Table 2: banks (51.5%), cooperatives or credit unions (12.3%) and NGOs (36.2%). Bank MFIs include rural bank MFIs, NBFIs (non-bank financial institutions) and other bank MFIs. In terms of their regulatory status, we have 67.6% regulated MFIs as opposed to 32.4% non-regulated MFIs in the sample.

(Insert Table 2 here)

2.2.2. Variables

Dependent variable.

The dependent variable is the loan loss provision ratio (LLP) which measures loan loss provision as a percentage of the total outstanding loan portfolio.

MFI-level variables.

MFI-level variables are those that are traditionally used in microfinance studies (Cull et al., 2011, 2014; Galema et al., 2011; D'Espallier et al., 2017; Tchakoute Tchuigoua, 2016, among many others).

MFI size: As noted by the Basel Committee on Banking Supervision (2010) and Christen et al. (2012) one distinctive feature of microfinance activities is that lending processes tend to be highly decentralized and depend heavily on soft information and strong relationships between MFIs and borrowers. Relationship lending literature suggests that small size appears to be a feature of the banks that extensively use soft information

[6] Website: http://data.worldbank.org/data-catalog/global-financial-development.

and engage in relationship lending. Small banks are in a better position than large ones to collect and act on soft information and are more likely to lend to informationally opaque borrowers (Berger et al., 2005). We thus assume that smaller MFIs are those that are involved in monitoring-intensive lending and make use of soft lending technologies such as joint liability contracts whose efficiency in improving loan repayment performance is well documented. We thus expect size to be positively correlated with loan loss provision expense. *Size* is measured by the natural logarithm of the book value of assets.

The capital adequacy ratio: MFIs, whether they are subject to prudential regulation or not, may have incentives to engage in capital management. We thus expect a positive relationship between capital adequacy ratios and LLP expenses. For MFIs that are subject to the regulation and supervision of banking authorities, provisions may be used to manipulate their capital adequacy ratio in order to comply with regulatory requirements and prudential rules. Results in the banking sector are mixed. Some studies using US banks data find support for a negative relationship between loan loss provision and the Tier 1 capital, suggesting evidence that banks have incentives to decrease provisions in order to avoid violation of capital requirements (Ahmed et al., 1999; Beatty et al., 1995; Beatty and Liao, 2014). Using data on European-Union Banks, Leventis et al. (2011) find no evidence indicating that provisions are used for capital management. For non-regulated MFIs, especially those that are subsidies-dependent, such as microfinance NGOs, we may expect them to engage in capital management in order to give a signal of financial solidity to donors. Trussel and Parsons (2007) show that financial reporting related to financial stability is key in determining donations to charitable organizations. In this study, MFI capitalization is measured by the equity-to-assets ratio, the so-called capital adequacy ratio (CAR). It is similar to the sum of tier 1 and tier 2 capital. Unfortunately, the MIX database does not allow us to distinguish between tier 1 and tier 2.

Risk: The risk of the loan portfolio (non-performing loans) is captured by the *portfolio at risk at 30* days (PAR30) which shows the share of the portfolio affected by outstanding payments when there is a risk that they will not be repaid within thirty (30) days. We expect a positive association between the MFI loan portfolio quality and LLP expenses.

Profitability: Provisions are now recognized as a tool for earnings management in banks (Ahmed et al., 1999; Kanagaretnam et al., 2010, 2014; Leventis et al., 2011) and the microfinance industry (Microrate, 2014). The commercialization movement has allowed MFIs to access external financing in order to sustain their growth. On the external financing market, MFIs compete fiercely to access funds on advantageous conditions and, for this purpose, may manipulate their accounts in order to meet the eligibility criteria. To the extent that there is an informational problem between MFIs and investors, MFI managers may lower provisions to increase earnings. As noted by the Microrate (2014), microfinance NGOs may also have incentives to overprovision in order to hide profit that could undermine access to donors' funding. We may thus expect a negative relationship between profitability and loan loss provisions. Profitability is measured by the *return on assets* (ROA).

Liquidity: We measure *liquidity* (LIQ) by the ratio of immediately available liquid assets to the book value of MFI assets.

To the extent that the level of provisioning is strongly linked to the MFI's lending activity, we consider it important to account for the distinctive features of MFIs in loan allocation that are likely to affect loan repayment performance and provisioning. In addition to MFI-specific financial characteristics, we thus include the variable *borrowers per loan officer* (LO) to capture the fact that loan activity is labour intensive in MFIs. We also consider the fact that MFIs are double-bottom-line institutions; in that respect, we introduce two variables: the *depth of outreach* (DEPTH) variable, measured by the average loan size per borrower scaled by the per capita gross national income (GNI), which captures the fact that MFIs target the poorest customers; and the *percentage of female borrowers* (FEMALE), measured by the share of female borrowers among active borrowers of the MFI. Unfortunately, due to the unavailability of data on the MIX database over the period covered by the study, we find it difficult to gather data on outstanding loans by credit method (i.e., individual loans, group loans, village banks loans) or the distribution of loans by type (i.e., household financing, enterprise finance, education, loan to SMEs, loan to microenterprises).

Macroeconomic variables.

To investigate the cyclical behaviour of MFIs' provisioning, we complement the business cycle variable with the credit cycle variable because financial crises are frequently preceded by episodes of rapid credit growth. Indeed, several recent studies in the economics literature have pointed out that abnormal credit growth can be taken as an indication of increased risk-taking behaviour by the financial sector and can therefore be used as a leading indicator of financial crises (e.g., Drehmann et al., 2011; Gourinchas and Obstfeld, 2012; Jorda et al., 2011; Schularick and Taylor, 2012). We predict that prudent or forward-looking MFIs might build their provisioning based on a proper assessment of their loan portfolio and anticipated macroeconomic conditions. There is clear evidence in the literature that losses and defaults are higher during recessions (see for example Boar et al. (2017) and Murcia and Kohlscheen (2016)). Therefore, it is desirable that MFIs enter recession with sufficient provisions to maintain the level of their lending activities. This is possible only if MFIs adjust their provision in a countercyclical manner by increasing their provision during booms so that they have sufficient loss absorption capacity during bust. Our main proxies for economic performance are the real GDP per capita growth (GDPCG), the real GDP growth (GDPG), the economic crisis indicator (CRISIS) and the credit-to-GDP growth (CGDPG). We use both GDP growth and per capita GDP growth to capture variations in country income level. Indeed, while GDP is a gross measure of country income level, per capita GDP provides a relatively good indication for the welfare improvement, and constitutes a better measure since one main goal of MFIs is to ease access to financial services in order to alleviate poverty. Credit-to-GDP growth is used to capture the credit cycle. The economic crisis indicator (CRISIS) is a dummy variable equal to one if the banking sector faced a crisis and zero otherwise.

The loan loss provision is countercyclical if MFIs' loan loss provision is positively related to the economic performance indicator. Indeed, financial sector regulators are now considering macroprudential regulation of the capital ratio to cool down the economy when it is in an upswing, and to stimulate the economy when it is in a downturn (e.g., Boar et al., 2017). To achieve that, financial institutions are expected to increase their capital buffers during periods of excessive credit build-up, in other words, when the probability of an upcoming crisis is higher. One of the main leading economic measures to achieve that has been proved to be the credit-to-GDP gap. This indicator is expected to provide an early warning signal for an upcoming crisis. As MFIs belong to the financial sector (Brière and Szafarz, 2015), in particular for those that are regulated, it is expected that they adopt a prudential loan loss provisioning behaviour. In this regard, loan loss provision will be countercyclical if positively related to the credit-to-GDP gap. The link between provisions and the economic cycle seems to have been little explored in the microfinance literature. Unlike research done in the banking sector (Laeven and Majnoni, 2003; Murcia and Kohlscheen, 2016), the existing literature in microfinance does not allow us to qualify the relationship between provisions and the economic cycle.

Table 3 provides a summary of the definition and description of the variables used in the study, as well as the sources of the data.

(Insert Table 3 here)

3. Results

3.1. Descriptive statistics

Table 4 presents the descriptive analysis of the variables used in the study. Panel A summarizes the descriptive statistics for the full sample and panel B provides the statistics for the sub-samples of MFIs split by type and regulatory status. MFIs on average hold a loan loss provision ratio (LLP) of 1.9%, in other words, they put aside revenue equal to 1.9 percent of their gross loan portfolio value to cover their expected losses. This proportion is consistent with actual MFI write-offs of 1.7%. The observed 2012 values in the 2014 Microrate report vary by 0.5 to 2.7 percent depending on geographical location of the MFIs; the loan loss provision ratio is lower in South Asia, East Asia & Pacific at close to 0.5%, whereas in the Middle East and North Africa, and Latin America and the Caribbean, the ratio is close to 2.5%.

Our sample average MFI loan loss provision ratio is above the value reported for the banking sector, reflecting the fact that microloans are not conventionally collateralized or backed by unconventional collateral (Christen et al., 2012). For example, Ahmed et al. (1999) finds an average of 0.8% for a sample of US bank holding companies, Leventis et al. (2011) report an average value of 0.61% for European Union commercial banks, and

Bushman and Williams (2012) find an average of 0.4% among an international sample of banks from 27 countries.

(Insert Table 4 here)

When we further investigate the LLP rates by MFI type and MFI regulatory status, we find that, although the average LLP rates are more or less identical across sub-groups of MFIs (as shown in panel B of Table 4), there is however a difference in the LLP distribution depending on the MFI regulatory status and type (see Figure 1). The tail of the distribution is relatively heavier for regulated MFIs than among their non-regulated peers (panel A of Figure 1), which seems to indicate different behaviour in their provisioning. We also observe a heavy tail for bank MFIs compared to other types of MFIs (cooperatives and credit unions, and NGOs) as shown in panel B of Figure 1. Note however that most regulated MFIs are bank MFIs in the majority of the countries, which explains why we observe more or less similar behaviours for the other two groups of MFIs.

(Insert Figure 1 here)

At the control variables level, the differences observed for LLP in terms of the distributions of the sub-groups of MFIs subsist. For instance, regulated and bank MFIs are larger in size, more liquid and more profitable than the other subgroups of MFIs. The average asset size of MFIs in our database is 63 million USD, with 22 million USD for non-regulated and 82.7 million USD for regulated MFIs. By MFI type, average asset size is respectively 100 million USD for banks, 42.2 million USD for cooperatives and credit unions and 19.2 million USD for NGOs. As for the liquidity ratio (LIQ), on average MFIs hold 15.3% of their assets in "non-earning" liquid assets. This proportion is 16.3% for regulated MFIs and 13.4% for non-regulated MFIs. By type, banks are more liquid with a liquidity ratio of 16.6%, followed by NGOs (14.1%) and cooperatives and credit unions (13.5%).

The average capital-to-asset ratio of MFIs is 32%; surprisingly, non-regulated MFIs hold a higher capital-to-asset ratio (40.5%) than their regulated peers (27.9%). NGOs are the best capitalized MFIs with a CAR ratio of 36.5%, followed by microfinance banks (29.9%) and cooperatives and credit unions (26.3%). On average, portfolio at risk (30 days) is equivalent to 5.3% of MFIs' portfolios. There is no significant difference in portfolio quality between regulated and non-regulated MFIs. Concerning MFI type however, we find that cooperatives and credit union MFIs have the highest level of portfolio risk (6%), followed by bank MFIs (5.5%) and NGO MFIs (4.8%). NGOs, because of their non-profit orientation, seem to have the least risky loan portfolio and at the same time hold a higher capital ratio than the other types.

The average *depth of outreach* (DEPTH) for the full sample is 1.93. The higher the value of this indicator, the higher the proportion of wealthy borrowers served by the MFI. The index is higher for regulated and bank MFIs, implying that these groups of MFIs target wealthier borrowers, while NGOs and also cooperatives and credit union MFIs are more oriented toward poor borrowers, especially NGO MFIs which have a very low value of DEPTH. On average, each loan officer monitors 337 borrowers. This number is 345 for regulated MFIs and 322 for non-regulated MFIs. Banks and NGO MFIs have fewer borrowers per loan officer (326 and 329 respectively) compared to cooperatives and credit union MFIs (418). Finally, female borrowers represent almost two-thirds of MFI clientele (65.4%). Non-regulated MFIs serve more female borrowers (71.5%) than regulated MFIs (62.3%). By MFI type, NGOs serve more female borrowers, followed by banks (61.2%), then cooperatives and credit unions (50.4%).

Table 5 presents the Pearson correlation matrix between the variables. We focus our analysis mainly on the relation between the dependent variable (LLP) and the control variables. MFIs' size, portfolio at risk (30 days) and capital-to-asset ratio are positively related to LLP, while MFIs' profitability (ROA), liquidity (LIQ), number of borrowers per loan officer (LO), proportion of female borrowers (FEMALE) and depth of outreach ratio (DEPTH) have a negative correlation with it. More importantly, the economic cycle indicators (credit-to-GDP growth for credit cycle, and GDP and per capita GDP growth for business cycle) are negatively related to LLP.

(Insert Table 5 here)

The negative relationship between the GDP growth (business cycle) and LLP can be observed in Figure 2 and seems to indicate that the two variables move in opposite to each other. Although there is a strong correlation of 82% between GDP growth and per capita GDP growth, the correlation is not perfect, meaning that per capita GDP brings additional information not necessarily captured by GDP alone. The correlation between LLP and its lag is 50%, an indication of possible persistence in loan loss provisioning. Except for these high correlations, the correlations between all the other variables are less than 40%, hence the risk of multicollinearity is low.

(Insert Figure 2 here)

3.2. Multivariate analysis

The estimation results of equation (4) are reported in Table 6. Before jumping into the analysis of the main results, let us mention that the system-GMM method employed fits well with the data: first, the AR (1) test confirms the presence of autocorrelation (p-value equals 0.00), whereas the AR (2) test strongly rejects the presence of autocorrelation of higher order in the residuals (p-value equals 0.80). In addition, the Hansen J test confirms that our instruments are valid and robust (p-value equals 0.20). Moreover, our assumption about the dynamic nature of MFIs' loan loss provisioning is valid. We find that the average annual adjustment between *desired* ($\mathrm{LLP}_{\mathrm{it}}^{*}$) and *realized* ($\mathrm{LLP}_{\mathrm{it-1}}$) loan loss provision of MFIs from one year to the next is about 60%. This finding is supported by the persistence of the loan loss provision seen in the correlation table (Table 5), where we report a 50% positive correlation between previous year's LLP and current level of LLP, an indication of a persistence and dynamic adjustment of LLP over time by MFIs. The value of λ lies between the OLS and the fixed effects estimates (see first line of Table 6, columns 1 to 3). Now let's focus on our main research questions.

(Q1). Are MFIs' loan loss provisioning driven idiosyncratically or systematically?

Our analysis suggests that both variables related to idiosyncratic and aggregate factors affect MFIs' loan provisioning behaviour. We find that idiosyncratic factors such as the size and the level of capitalization of MFIs have positive effects on MFIs' level of LLP, whereas profitability is negatively associated with LLP. Surprisingly, we find no significant impact of MFIs' portfolio risk (PAR30) in their LLP targeting behaviour, which raises concern about the alignment between their portfolio quality and their provisioning behaviour. Concerning systematic or aggregate forces behind MFIs' loan loss provisioning, we find that the level of the GDP per capita growth is negatively associated with MFIs' loan loss provisioning.

Regarding the level of capital, we would have expected that MFIs with lower LLP hold a larger capital-to-asset ratio, and vice versa, to hedge against unexpected credit risk, hence a substitution effect between LLP and CAR. This is not the case as the relation between LLP and CAR is rather positive, suggesting that better capitalized MFIs tend to hold higher levels of LLP as well, which suggests a complementary effect between the two variables. Beyond the issue of complementarity, this positive relationship between provisions and the capital adequacy ratio provides evidence that regulatory pressure may give MFIs incentives for capital management. This positive relationship between capital and LLP is opposite to findings for banks – the analyses of Ahmed et al. (1999), Beatty et al. (1995) and Beatty and Liao (2014) for example, suggest that unlike MFIs, banks lower their LLP to meet their capital requirements.

The positive effect of the size on MFIs' LLP is supported by Murcia and Kohlscheen (2016) based on a sample of banks from emerging markets. The lower provisioning from smaller MFIs might be explained by the fact that they use soft lending technologies, which generate better repayment performance and therefore require lower provision expenses. Our descriptive analysis in sub-section 3.1 supports this finding, as smaller-sized NGOs are the most capitalized type of MFIs. Regarding aggregate or systematic variables, our analysis suggests that the growth in GDP per capita is negatively associated with the MFIs' LLP target. We discuss in detail the implication of this finding below when we discuss our second research question.

(Insert Table 6 here)

(Q2). Are MFIs' provisioning behaviour pro-cyclical or countercyclical?

Our analysis suggests that aggregate forces such as the growth in the GDP per capita are associated with MFIs' loan loss provisioning behaviour. We report in the introduction that MFIs now belong to the financial sector (Brière and Szafarz, 2015) and as such are likely to suffer from macro-economic shocks. In our model we evaluate (equation 3) both the credit cycle and the business cycle effects on how MFIs adjust towards their loan loss provision (LLP) target. Our analysis suggests that MFIs' LLP is negatively associated with the GDP per capita growth. Unlike the commonly used GDP growth, per capita GDP growth captures variations in a country's income level and therefore provides a relatively good indication of the welfare improvement, and constitutes a better measure since one main goal of MFIs is to ease access to financial services in order to alleviate poverty. This relation between MFIs' LLP and the GDP per capita is in line with the literature suggesting that macroeconomic variables influence MFIs' credit growth (Wagner and Winkler, 2013) and performance (Ahlin et al., 2011). Our finding supports the fact that MFIs do not build their LLP in booms when profit and earnings are high. Therefore, if their provisioning is very low when they enter recession, they are likely to suffer from unexpected losses and experience failure. This is in sharp contrast with the Basel III conservative buffer requirement suggesting that banks build sufficient buffer in booms so that they can avoid costly capital adjustment when the economy contracts. As we document a positive relation between capital-to-asset ratios and LLPs, our analysis by transitivity might suggest that those with low LLPs in booms they might also hold low capital, something that can weaken their ability to absorb both expected and unexpected losses more likely to occur in recession.

The above analysis is only valid if we can provide evidence on MFIs' asset deterioration in recession. Existing evidence on microfinance loan portfolio performance through the business cycle suggests that MFIs' portfolios are resilient to economic crisis (Chen et al., 2010; Lützenkirchen and Weistroffer, 2012). This literature claims that the observed decline in MFIs' performance (profitability and loan portfolio quality) over 2007-2010 is at most weakly correlated with domestic macroeconomic conditions. In line with these anecdotal results, Gonzalez (2007) finds that there is no evidence suggesting a strong (in magnitude) and statistically significant relationship between changes in country national income growth and MFIs' portfolio risk. This may be explained by the fact that MFIs are less profit oriented, and thus lend to poor people whose activities are less affected by the boom-bust cycle.

This analysis would suggest that MFIs might not be required from a regulatory perspective to set their provision in a countercyclical manner, but instead in a way that reflect their true portfolio risk. Based on the assumption that MFIs' portfolios are immunized from macroeconomic risk, it can be argued that MFIs will be better off even with a pro-cyclical LLP and that there is no need to require them to adjust their capital in a countercyclical manner. However, this argument is only valid for smaller MFIs as they target a very concentrated and well-known clientele. We suspect that for large MFIs with portfolios similar to banks, it is expected that their portfolio risk looks different from the rest of MFIs and therefore deteriorate in periods of recession. For this type of MFI, it may be important to implement a countercyclical buffer. We conduct further analyses below in the robustness check section to explore that.

4. Robustness check

In this robustness check section, we investigate the provisioning behaviour by MFIs in a static framework. Specifically, we use alternative simple panel estimation methods such as a fixed effects model and a random effects model to test our main findings. In particular, we test our findings to verify if they are specific to the dynamic framework implemented above. More detailed information on these alternative models is given in Appendix 2. We also exploit the fact that static models can be used with short samples to investigate how our results change when we conduct the analysis using different subsamples based on the type and the regulatory status of MFIs.

Table 7 presents the regression results of the determinants of LLP. All our main previous findings are confirmed. As in the dynamic model, we find no significant impact of the portfolio quality (PAR30) on the level of provision. Also, the negative relation between the LLP and the macroeconomic environment is confirmed. In addition to the size and the capital-to-asset ratio found above to influence significantly LLP, we find that other factors are also significant when we do not include the lag of the dependent variable in the static model regression. We find evidence that MFIs' clientele has a significant effect on their provisioning behaviour. Indeed, MFIs targeting wealthy borrowers (i.e. with high value of outreach depth) will tend to provision less, probably because they expect less default from these borrowers. We also test how MFIs' ability to monitor and/or service borrowers (proxied by the ratio of borrowers per loan officer, LO) affects their loan loss provisioning. Contrary to our initial belief, labour-intensive MFIs with more loan officers to service their clients (low level of LO) hold higher LLP. This may be due to the fact that loan officers have diversified missions that go beyond loan monitoring. It also suggests that MFIs with a lot of social activities may have many loan officers, but they do not necessarily "*monitor*" clients more heavily.

(Insert Table 7 here)

We conduct further analysis by dividing the MFI sample into sub-groups. First, we divide the sample into regulated MFIs (those that are subject to formal regulation) and non-regulated MFIs. We expect that regulation could distort the provisioning behaviour of regulated MFIs toward better risk management practice. Second, we split the sample of MFIs into three subgroups based on their ownership type (microfinance banks or privately owned MFIs, microfinance NGOs, and cooperatives and credit union MFIs). We re-estimated our regression using those sub-samples in order to investigate whether determinants of provisioning behaviour vary by MFI ownership type and regulatory status. From the results presented in Table 8 below, we find that regulated MFIs' loan loss provision increases with their size and capital ratio. Similar results are found with bank MFIs and NGO MFIs where the coefficients of these two variables are significant. Particularly, for NGO MFIs, we find a strong positive relationship between their LLP and their capital level, consistent with the result for the full sample analysis, suggesting that more capitalized NGO MFIs simultaneously hold higher levels of LLP. To the contrary, cooperatives and credit unions' LLP are negatively related to their size and capital ratio. The fact that cooperatives and credit union MFIs with higher capital-to-asset ratios hold less LLP supports the argument of a substitution effect between LLP and capital adjustment for these institutions.

There is also evidence that microfinance banks' loan loss provisioning are negatively related to their portfolio at risk (PAR30), suggesting that MFIs with higher portfolio risk hold less LLP. This is even questionable as microfinance banks' LLP is not only unrelated to the level of their capital-to-asset ratio, but is also negatively related to the business cycle. Intuitively, this suggests that riskier microfinance banks are more likely to enter economic downturn with a low level of LLP. However, unlike microfinance banks, for the case of microfinance cooperatives and credit unions, we find a positive relationship between their portfolio at risk (PAR30) and their LLP. For microfinance NGOs, we find no relationship between their LLP and their portfolio risk, and even a negative relation between their LLP and per capita GDP growth, an indication that some microfinance NGOs, mainly the less capitalized ones, may face important challenges, should a major crisis occur.

(Insert Table 8 here)

5. Conclusion

The current debate on macroprudential regulation for financial stability is more directed towards banks, and less attention is being paid to microfinance institutions. Since MFIs are less sophisticated in managing credit risk, loan loss provision constitutes one important tool protecting against failure. The purpose of this paper is to understand if the loan provisioning practice in MFIs for credit risk management purposes is forward looking and cyclical. We mainly study how they build their reserves, and if those reserves account for macroeconomic and idiosyncratic business risks. For that purpose, using a sample of 6148 firm-year observations from 1474 MFIs worldwide over 2001-2014, we uncover a negative relationship between MFIs' provisioning and the business cycle. In other words, MFIs adjust their provision in a pro-cyclical manner, meaning that they fail to accumulate more provisions during periods of economic booms to be used to sustain their lending activities during recessions. Our results also show that some characteristics of both MFIs and their clientele are significantly associated with their level of provisions. We find evidence that the depth of outreach is negatively associated with provisions, indicating that provision expenses increase when an MFI targets disable borrowers. In addition, we find that provisions are positively correlated with the capital adequacy ratio, suggesting that provisions may be used for capital management purposes. Similar evidence is found in the subsample of regulated MFIs and deposit-taking MFIs, suggesting that when regulation is binding, undercapitalized MFIs use provisions to comply with capital requirements.

Finally, we find that the lower the number of borrowers per loan officer, the higher the level of provisions.

This study is crucial, as it will contribute to the debate on how to design appropriate macroprudential regulation for the whole financial system, especially regulations targeting microfinance institutions, without altering their double-bottom-line orientation.

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Table 1: Sample distribution by year

This table presents the distribution of our sample by year of observation. Statistics are based on an unbalanced panel of 6148 MFI-year observations for a total of 1474 MFIs over 2001-2014.

Year	Nb. obs.	Percent
2001	126	2.05
2002	202	3.29
2003	303	4.93
2004	410	6.67
2005	493	8.02
2006	546	8.88
2007	552	8.98
2008	648	10.54
2009	553	8.99
2010	611	9.94
2011	624	10.15
2012	501	8.15
2013	338	5.5
2014	241	3.92
Total	6,148	100

Table 2: Proportion of MFIs by type and by their regulatory status

This table presents the proportion of the different types of MFIs and the proportion of regulated versus non-regulated MFIs in the database.

MFI type (%)			Regulatory status (%)	
Banks	Coop/credit unions	NGOs	Regulated	Non-regulated
51.5	12.27	36.22	67.58	32.42

Table 3: Variables definition and description

	Variable	Description
Loan loss provision expense ratio	LLP	Net loan loss provision expense/average gross outstanding portfolio Net loan loss provision expense= Loan loss provision expense and write-off minus Recovery from Loans written off Source: MIX
Assets	SIZE	Log of total assets Source: MIX
Equity	CAR	Capital adequacy ratio = Equity-to-Total assets Equity includes equity plus supplementary capital sources, such as loan loss reserves, asset reserves and subordinated debt. Source: MIX
Risk: portfolio at risk at 30 days	PAR30	(Outstanding balance on arrears over 30 days + Total gross outstanding refinanced (restructured) portfolio)/Total gross portfolio Measurement of portfolio quality. It shows the share of the portfolio affected by outstanding payments when there is a risk that they might not be repaid. The threshold is < 10% given that financial guarantees in microfinance are not always sufficient Source: MIX
Profitability	ROA	Return on assets = Net operating income/ Average assets Source: MIX
Liquidity	LIQ	Liquidity = Liquid assets / Total assets Source: MIX
Labour intensive	LO	Number of borrowers per loan officer Source: MIX
Depth of outreach	DEPTH	Average loan size per borrower scaled by the per capita gross national income (GNI). Source: MIX
Female	FEMALE	% of female borrowers as a share of all active borrowers of the MFI
Regulation	REG	Regulation dummy, is 1 if the MFI is regulated and 0 otherwise Source: MIX
Credit cycle	CGDPG	Credit-to-GDP (= Total credit / GDP) growth Source: BIS
Crisis	Crisis	Dummy, is 1 if the banking sector faces a crisis and 0 otherwise Source: GFD & WDI
Economic Growth	GDPG	Real gross domestic product growth Source: GFD & WDI
	GDPCG	Real gross domestic product per capita growth Source: GFD & WDI

Note : MIX = Microfinance Information eXchange database. GFD = Global Financial Development database of the World Bank. WDI = World Development Indicators of the World Bank. BIS = Bank for International Settlements.

Table 4: Summary statistics

This table presents the summary statistics of our variables for the full sample (panel A) and by MFI type and MFI regulatory status (panel B). Statistics are based on an unbalanced panel of 6148 MFI-year observations across a total of 1474 MFIs over 2001-2014. The ***dependent variable*** is the loan loss provision ratio (LLP) measured as a percentage of the outstanding loan portfolio. ***MFI-level variables*** include: the *Size,* measured by the natural logarithm of the book value of assets; the *capital adequacy ratio* (CAR) measured by the equity-to-assets ratio, the *portfolio at risk at 30* days (PAR30) which is the share of the portfolio affected by outstanding payments, the *return on assets* (ROA) which is the profitability measure, the *liquidity* (LIQ) measured by the ratio of immediately available liquid assets to the book value of MFI assets, the *borrowers per loan officer* (LO) captures the quality of monitoring, the *depth of outreach* (DEPTH) variable, which measures the fact that the MFI targets the poorest clients, and the *percentage of female borrowers* (FEMALE) measured by the share of women among active borrowers of the MFI. ***Macroeconomic variables*** include: the *real GDP per capita growth* (GDPCG), the *real GDP growth* (GDPG), and the *credit-to-GDP growth* (CGDPG).

Panel A. Sample statistics for the full sample

Variable	**Obs**	**Mean**	**SD**	**Min**	**Max**
LLP	5,525	0.019	0.014	0.000	0.060
SIZE	6,096	16.017	1.969	6.359	22.446
CAR	6,088	0.320	0.414	-18.353	17.753
PAR30	5,606	0.053	0.118	0.000	5.485
ROA	5,569	0.018	0.111	-3.453	0.728
LIQ	5,100	0.153	0.126	0.000	0.891
LO	4,905	337	1036	0	67418
DEPTH	2,546	1.925	60.489	0.000	3034.180
FEMALE	5,418	0.654	0.265	0.000	1.272
GDPCG	3,555	0.037	0.035	-0.193	0.285
GDPG	3,555	0.052	0.040	-0.193	0.339
CGDPG	3,530	0.056	0.125	-1.152	1.194

Panel B. Sample statistics by MFI type and MFI regulatory status

	MFI regulatory status		MFI type		
Variable	Non-regulated	Regulated	Banks	Coop/CU	NGO
LLP	0.019	0.019	0.019	0.018	0.018
SIZE	15.368	16.328	16.591	15.695	15.333
CAR	0.405	0.279	0.299	0.263	0.365
PAR30	0.050	0.054	0.055	0.060	0.048
ROA	0.015	0.020	0.019	0.019	0.018
LIQ	0.134	0.163	0.166	0.135	0.141
LO	321.817	345.108	329.459	417.583	326.344
DEPTH	0.675	2.173	3.271	0.643	0.065
FEMALE	0.715	0.623	0.612	0.504	0.760

Table 5: Correlation matrix

This table presents the Pearson correlation matrix of our variables. Statistics are based on an unbalanced panel of 6148 MFI-year observations for a total of 1474 MFIs over 2001-2014. The ***dependent variable*** is the loan loss provision ratio (LLP) measured as a percentage of the outstanding loan portfolio. ***MFI-level variables*** include: the *Size,* measured by the natural logarithm of the book value of assets; the *capital adequacy ratio* (CAR) measured by the equity-to-assets ratio, the *portfolio at risk at 30* days (PAR30) which is the share of the portfolio affected by outstanding payments, the *return on assets* (ROA) which is the profitability measure, the *liquidity* (LIQ) measured by the ratio of immediately available liquid assets to the book value of MFI assets, the *borrowers per loan officer* (LO) captures the quality of monitoring, the *depth of outreach* (DEPTH) variable, which measures the fact that the MFI targets the poorest clients, and the *percentage of female borrowers* (FEMALE) measured by the share of women among active borrowers of the MFI. ***Macroeconomic variables*** include: the *real GDP per capita growth* (GDPCG), the *real GDP growth* (GDPG), the credit-to-GDP growth (CGDPG) and the *economic crisis indicator* (CRISIS), a dummy variable equal to 1 if the banking sector faced a crisis and 0 otherwise. The prefix “L.” in front of a variable designates the lag of the variable. * $p<0.05$.

	LLP	L.LLP	L.SIZE	L.CAR	L.PAR30	L.ROA	L.LIQ	LO	FEMALE	DEPTH	L.GDPCG	GDPCG	L.GDPG	GDPG	L.CGDPG	CGDPG	CRISIS
LLP	1																
L.LLP	0.4992*	1															
L.SIZE	0.0598*	0.0360*	1														
L.CAR	0.0246	-0.0001	-0.3359*	1													
L.PAR30	0.0694*	0.0866*	-0.0132	-0.0211	1												
L.ROA	-0.0687*	-0.0959*	0.1091*	0.0608*	-0.0223	1											
L.LIQ	-0.0133	0.0425*	0.1270*	-0.032	0.0293	-0.0859*	1										
LO	-0.0333*	-0.1211*	0.0811*	-0.0787*	-0.0042	0.0567*	-0.0324	1									
FEMALE	-0.0811*	-0.1020*	-0.1860*	0.0033	-0.0547*	-0.0046	0.0171	0.0311*	1								
DEPTH	-0.0064	-0.0289	0.0651*	0.0038	-0.0176	-0.0092	-0.0316	0.0495*	-0.0302	1							
L.GDPCG	-0.0312	-0.1353*	0.0289	0.021	-0.0699*	0.0351	-0.0281	-0.0158	-0.0195	0.0699*	1						
GDPCG	-0.1390*	-0.0989*	-0.0027	0.0584*	-0.0304	0.0316	0.034	0.0128	0.0163	0.008	0.4417*	1					
L.GDPG	-0.0331	-0.1095*	0.0111	0.0212	-0.0644*	0.0118	0.0186	0.0147	-0.0162	0.0603*	0.8439*	0.3644*	1				
GDPG	-0.1160*	-0.0855*	-0.0294	0.0421*	-0.0307	0.0121	0.0473*	0.0208	0.0251	0.0043	0.3807*	0.8215*	0.2571*	1			
L.CGDPG	0.0259	-0.0376	0.0398	0.0381	-0.0938*	0.0399	-0.0006	-0.0662*	-0.1044*	0.0567	0.1911*	0.0885*	0.1068*	0.0099	1		
CGDPG	-0.0252	-0.0106	0.0228	0.0668*	-0.0714*	0.0308	-0.0153	-0.0789*	-0.1035*	-0.0157	0.2288*	0.2090*	0.1814*	0.1321*	0.3833*	1	
CRISIS	0.0176	0.0175	0.0881*	-0.0426*	0.0167	-0.0006	-0.0118	-0.0083	-0.0267	-0.001	-0.035	-0.0245	-0.0424	-0.0138	-0.019	-0.1006*	1

Table 6: System-GMM, OLS and fixed effects (FE) estimation of the dynamic adjustment of LLP by MFIs

This table presents the dynamic adjustment estimates of the LLP using three estimation methods: OLS, fixed effects and Blundell-Bond System-GMM. Our results are based on an unbalanced panel of 6148 MFI-year observations for a total of 1474 MFIs over 2001-2014. ***The dependent variable*** is the loan loss provision ratio (LLP) measured as a percentage of the outstanding loan portfolio. ***MFI-level variables*** include: the *Size*, measured by the natural logarithm of the book value of assets; the *capital adequacy ratio* (CAR) measured by the equity-to-assets ratio, the *portfolio at risk at 30 days* (PAR30) which is the share of the portfolio affected by outstanding payments, the *return on assets* (ROA) which is the profitability measure, the *liquidity* (LIQ) measured by the ratio of immediately available liquid assets to the book value of MFI assets, the *borrowers per loan officer* (LO) captures the quality of monitoring, the *percentage of female borrowers* (FEMALE) measured by the share of women among active borrowers of the MFI, and the *depth of outreach* (DEPTH) variable, which measures the fact that the MFI targets the poorest clients. ***Macroeconomic variables*** include: the *Economic crisis indicator* (CRISIS) is a dummy variable which equals 1 if the banking sector faced a crisis and 0 otherwise, the *regulation dummy* (REG), the *credit-to-GDP growth* (CGDPG), the *real GDP per capita growth* (GDPCG) and the *real GDP growth* (GDPG). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	The whole sample			Only regulated MFIs		
VARIABLES	OLS	Fixed effects	Syst-GMM[1]	OLS	Fixed effects	Syst-GMM
L.LLP **(1-λ)**	**0.4970*** **	0.0426	**0.421*** **	**0.488*** **	0.0422	**0.417*** **
	(0.0308)	(0.0460)	(0.0663)	(0.0329)	(0.0496)	(0.0767)
L.SIZE	**0.0009*** **	-0.0002	**0.0018*** **	**0.0009*** **	-0.0001	**0.0019** **
	(0.0002)	(0.0009)	(0.0007)	(0.0002)	(0.0008)	(0.0008)
L.CAR	**0.0039* **	-0.0022	**0.0102** **	0.0024	-0.0025	**0.0095* **
	(0.0020)	(0.0075)	(0.0044)	(0.0023)	(0.0079)	(0.0055)
L.PAR30	0.0050	-0.0013	0.0059	0.0019	-0.0067	0.0012
	(0.0060)	(0.0064)	(0.0179)	(0.0059)	(0.0052)	(0.0152)
L.ROA	**-0.0041*** **	0.0083	**-0.0057** **	-0.0002	-0.0005	-0.0131
	(0.0014)	(0.0064)	(0.0028)	(0.0095)	(0.0154)	(0.0265)
L.LIQ	0.0011	0.0023	0.0003	-0.0009	0.0034	-0.0025
	(0.0038)	(0.0058)	(0.0078)	(0.0042)	(0.00581)	(0.0078)
L.LO	-5.20e-07	4.58e-07	-1.12e-06	-2.46e-07	6.13e-07	-6.70e-07
	(7.49e-07)	(5.20e-07)	(1.07e-06)	(6.37e-07)	(4.31e-07)	(9.67e-07)
L.FEMALE	0.0018	0.0015	0.0002	0.0002	0.0028	0.0007
	(0.0019)	(0.0032)	(0.0028)	(0.0021)	(0.0029)	(0.0029)
L.DEPTH	-2.06e-05	-6.96e-05	0.0002	-1.57e-05	-6.88e-05	0.0003
	(0.0001)	(7.32e-05)	(0.0004)	(0.0001)	(7.03e-05)	(0.0004)
REG	**-0.0028** **		**-0.00261** **			
	(0.0013)		(0.0013)			
CRISIS	-0.0026	**-0.0049** **	-0.0026	**-0.00547*** **	**-0.0051** **	**-0.0045** **
	(0.0028)	(0.0021)	(0.0036)	(0.0016)	(0.002)	(0.0020)
CGDPG	0.0035	-0.0015	-0.002	**0.0048* **	-0.0009	-0.0006
	(0.0020)	(0.0045)	(0.0033)	(0.0028)	(0.0046)	(0.0036)
GDPCG	**-0.0725*** **	**-0.0592** **	**-0.0927*** **	**-0.0751*** **	**-0.0692*** **	**-0.0953*** **
	(0.0210)	(0.0246)	(0.0245)	(0.0220)	(0.0239)	(0.0245)

[1] In the GMM, we use up to 5 lags as instruments but some MFIs cannot be included because roughly 70% of MFIs have less than 5 data points. In addition, our macro variable data is limited as there is no GDP data available for some countries for some years. We also have some variables with limited data points (loan officers and depth of outreach). The fact that we use lags in our fixed and random effects models (to avoid endogeneity issues) also reduces the number of MFIs that can participate. MFI-year observations with even one missing value for any of the variables in the regression are automatically removed. Therefore, our data length is limited to the length of the shortest variable. We also try to run regressions without lags using fixed effects and find that only 715 MFIs out of the 1474 are retained with a total of 2144 MFI-year observations. The unreported results, available from the authors upon request, confirm our findings.

	The whole sample			Only regulated MFIs		
VARIABLES	OLS	Fixed effects	Syst-GMM[1]	OLS	Fixed effects	Syst-GMM
GDPG	0.0147	-0.0056	0.0121	0.0191	-0.0015	0.0154
	(0.0184)	(0.0226)	(0.0239)	(0.0193)	(0.0190)	(0.0232)
Constant	-0.0041	0.0227	-0.0175	-0.0044	0.0204	-0.0205
	(0.0047)	(0.0172)	(0.0136)	(0.0046)	(0.0152)	(0.0156)
Nb. Obs.	931	937	937	787	790	790
R2	0.327	0.045		0.321	0.060	
Ar(1)			0.00			0.00
Ar(2)			0.80			0.403
Hansen J			0.203			0.147
Nb. MFIs		377	377		303	303

Table 7: Fixed effects (FE) and random effects (RE) estimation of the determinants of LLP in MFIs

This table presents the fixed effects and random effects estimates of the determinants of MFIs' loan loss provisions (LLP). Our results are based on an unbalanced panel of 6148 MFI-year observations for a total of 1474 MFIs over 2001-2014. ***The dependent variable*** is the loan loss provision ratio (LLP) measured as a percentage of the outstanding loan portfolio. ***MFI-level variables*** include: the *Size* (SIZE), measured by the natural logarithm of the book value of assets; the *capital adequacy ratio* (CAR) measured by the equity-to-assets ratio, the *portfolio at risk at 30 days* (PAR30) measured by the part of the portfolio affected by outstanding payments, the *return on assets* (ROA) which is the profitability measure, the *liquidity* (LIQ) measured by the ratio of immediately available liquid assets to the book value of MFI assets, the *borrowers per loan officer* (LO) captures the quality of monitoring, the *percentage of female borrowers* (FEMALE) measured by the share of women among active borrowers of the MFI, and the *depth of outreach* (DEPTH) variable, which measures the fact that the MFI targets the poorest clients. ***Macroeconomic variables*** include: the *Economic crisis indicator* (CRISIS) which is a dummy variable equal to 1 if the banking sector faced a crisis and 0 otherwise, the *regulation dummy* (REG), the *credit-to-GDP growth* (CGDPG), the *real GDP per capita growth* (GDPCG) and the *real GDP growth* (GDPG). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	No macro-variables		GDPCG		GDPG		All macro-variables	
	FE	RE	FE	RE	FE	RE	FE	RE
L.SIZE	0.0002	**0.0010****	0.0002	**0.0012****	0.0006	**0.0013****	0.0003	**0.0013****
	(0.0008)	(0.0004)	(0.0014)	(0.0006)	(0.0013)	(0.0006)	(0.0014)	(0.0006)
L.CAR	0.0009	**0.0095*****	-0.0028	**0.0082*****	0.0025	**0.0105*****	-0.0022	**0.0089*****
	(0.0053)	(0.0032)	(0.0104)	(0.0031)	(0.0067)	(0.0032)	(0.0106)	(0.0033)
L.PAR30	-0.0053	**0.0111***	-0.0064	0.0015	-0.0015	0.0109	-0.0059	0.0022
	(0.0058)	(0.0065)	(0.0064)	(0.0059)	(0.0069)	(0.0069)	(0.0064)	(0.0059)
L.ROA	0.0064	-0.0039	-0.0211	**-0.0082*****	0.0046	-0.0031	-0.0192	**-0.0085*****
	(0.0069)	(0.0024)	(0.0190)	(0.0029)	(0.0069)	(0.0021)	(0.0193)	(0.0031)
L.LIQ	-0.0037	-0.0009	0.0021	-0.0027	-0.0036	-7.58e-05	0.0042	-0.00213
	(0.0061)	(0.0052)	(0.0078)	(0.0063)	(0.0064)	(0.0057)	(0.0068)	(0.0064)
LO	-1.60e-06	**-6.16e-06*****	**-7.82e-06****	**-7.78e-06*****	**-2.84e-06**	**-6.64e-06*****	**-8.51e-06****	**-7.99e-06*****
	(3.04e-06)	(1.60e-06)	(3.70e-06)	(2.18e-06)	(3.80e-06)	(1.85e-06)	(3.66e-06)	(2.21e-06)
FEMALE	-0.0038	-0.0005	-0.0074	-0.0038	-0.0055	-0.0015	-0.0069	-0.0035
	(0.0044)	(0.0028)	(0.0047)	(0.003)	(0.0054)	(0.0029)	(0.0047)	(0.0029)
DEPTH	**-0.0004*****	2.17e-06	**-0.0004*****	4.09e-05	**-0.0004****	2.31e-06	**-0.0003*****	4.27e-05
	(0.0002)	(1.74e-06)	(0.0001)	(6.56e-05)	(0.0001)	(2.05e-06)	(9.31e-05)	(5.82e-05)
REG		-5.12e-05		-0.0019		-0.0011		-0.0021
		(0.0022)		(0.0025)		(0.0024)		(0.0025)
GDPCG			**-0.0480***	**-0.0583****			-0.0365	**-0.0531***
			(0.0247)	(0.0236)			(0.0267)	(0.0273)
CRISIS			**-0.0119*****	**-0.0136*****	**-0.0073****	-0.0053	**-0.0113*****	**-0.0132*****
			(0.0028)	(0.0021)	(0.0029)	(0.0054)	(0.0032)	(0.0022)
GDPG					**-0.0428***	**-0.0468****	-0.0137	-0.0077
					(0.0227)	(0.0207)	(0.0337)	(0.0326)
CGDPG							0.0011	0.0014
							(0.0046)	(0.0043)
Constant	0.0196	0.00103	0.0248	0.00532	0.0166	0.00166	0.0228	0.0041
	(0.0147)	(0.00803)	(0.0251)	(0.0101)	(0.0227)	(0.0103)	(0.0254)	(0.0103)
MFI Type	Yes		Yes		Yes		Yes	
Obs.	1,240	1,240	695	695	934	934	687	687
R2	0.009		0.055		0.036		0.063	
Nb. MFIs	429	429	264	264	365	365	263	263

Table 8: Fixed effects (FE) and random effects (RE) estimation of the determinants of LLP by MFI types and regulatory status

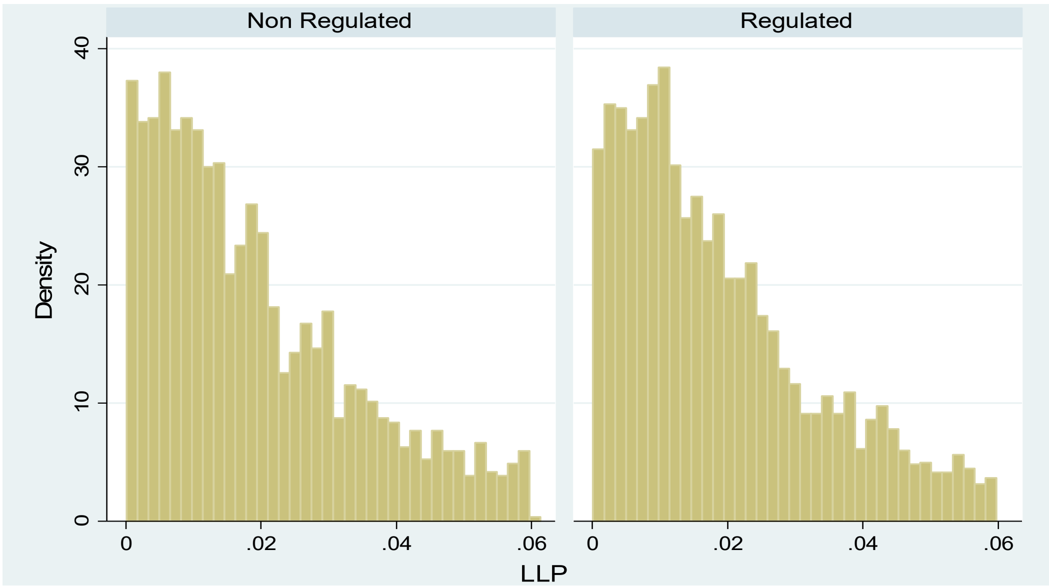
This table presents the fixed effects and random effects estimates of the determinants of MFIs' loan loss provisions (LLP). Our results are based on an unbalanced panel of 6148 MFI-year observations for a total of 1474 MFIs over 2001-2014. ***The dependent variable*** is the loan loss provision ratio (LLP) measured as a percentage of the outstanding loan portfolio. ***MFI-level variables*** include: the *Size* (SIZE), measured by the natural logarithm of the book value of assets; the *capital adequacy ratio* (CAR) measured by the equity-to-assets ratio, the *portfolio at risk at 30 days* (PAR30) measured by the share of the portfolio affected by outstanding payments, the *return on assets* (ROA) which is the profitability measure, the *liquidity* (LIQ) measured by the ratio of immediately available liquid assets to the book value of MFI assets, the *borrowers per loan officer* (LO) captures the quality of monitoring, the *percentage of female borrowers* (FEMALE) measured by the share of women among active borrowers of the MFI, and the *depth of outreach* (DEPTH) variable, which measures the fact that the MFI targets the poorest clients. ***Macroeconomic variables*** include: the *Economic crisis indicator* (CRISIS) which is a dummy variable equal to 1 if the banking sector faced a crisis and 0 otherwise, the *regulation dummy* (REG), the *credit-to-GDP growth* (CGDPG), the *real GDP per capita growth* (GDPCG) and the *real GDP growth* (GDPG). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Regulated MFIs		Bank MFIs		Credit union MFIs		NGO MFIs	
	FE	RE	FE	RE	FE	RE	FE	RE
L.SIZE	-0.0001	**0.0014****	0.0004	**0.0016***	**-0.0102*****	0.0010	0.0026	0.0008
	(0.0015)	(0.0006)	(0.0012)	(0.0008)	(0.0014)	(0.0009)	(0.0024)	(0.0007)
L.CAR	-0.0089	**0.0077****	-0.0151	0.0093	**-0.0538****	0.0152	**0.0195****	**0.0114****
	(0.0110)	(0.0036)	(0.0114)	(0.006)	(0.0238)	(0.0175)	(0.0093)	(0.0047)
L.PAR30	-0.0085	-0.0015	**-0.0148****	-0.0096	**0.138****	**0.110*****	-0.0019	0.0107
	(0.0061)	(0.0058)	(0.0064)	(0.0060)	(0.0535)	(0.0224)	(0.0069)	(0.0075)
L.ROA	-0.0199	-0.0206	-0.0298	-0.0200	**0.0883***	0.0347	-0.0119	**-0.0086*****
	(0.0231)	(0.0145)	(0.0268)	(0.0168)	(0.0502)	(0.0608)	(0.0240)	(0.0022)
L.LIQ	0.0051	-0.0060	-0.0007	-0.0103	**0.0297***	-0.0125	-0.0017	0.0110
	(0.0064)	(0.0064)	(0.0105)	(0.0107)	(0.0149)	(0.0204)	(0.0062)	(0.0102)
LO	**-8.21e-06****	**-5.79e-06*****	**-1.01e-05****	**-6.52e-06****	**-5.08e-06**	**-1.30e-05*****	**-4.36e-06**	**-1.67e-05*****
	(3.66e-06)	(2.09e-06)	(4.34e-06)	(2.96e-06)	(4.50e-06)	(3.68e-06)	(2.22e-05)	(5.98e-06)
FEMALE	-0.0056	**-0.0048***	-0.0109	-0.0047	0.0031	-0.0062	-0.0048	-0.0017
	(0.0046)	(0.0028)	(0.0070)	(0.0032)	(0.0067)	(0.006)	(0.0063)	(0.0099)
DEPTH	**-0.0003*****	6.75e-05	**-0.0004*****	1.46e-05	**-0.0626***	-0.00117	0.0416	-0.0009
	(9.35e-05)	(6.68e-05)	(9.50e-05)	(7.05e-05)	(0.0354)	(0.0051)	(0.0693)	(0.0209)
GDPCG	-0.0384	**-0.0483***	0.0075	-0.0145	-0.122	-0.0100	-0.188	**-0.242*****
	(0.0279)	(0.0287)	(0.0350)	(0.0346)	(0.0704)	(0.0528)	(0.118)	(0.0874)
CRISIS	**-0.0116*****	**-0.0132*****	**-0.0128*****	**-0.0134*****	(Omitted)	(Omitted)	(Omitted)	(Omitted)
	(0.00321)	(0.0024)	(0.0027)	(0.0026)				
REG	(Omitted)	(Omitted)	(Omitted)	**-0.0117****		0.0002		-0.0009
				(0.0059)		(0.0030)		(0.0028)
GDPG	-0.0119	-0.0053	-0.0409	-0.0239	0.0248	-0.0479	0.0240	0.0297
	(0.0362)	(0.0342)	(0.0388)	(0.0388)	(0.0709)	(0.0945)	(0.113)	(0.0754)
CGDPG	-0.0014	1.89e-05	0.0025	0.0019	0.0065	-0.0134	0.0046	0.0086
	(0.005)	(0.0045)	(0.0054)	(0.0053)	(0.0092)	(0.0190)	(0.0097)	(0.0084)
L.CGDPG	0.0058	**0.0068***	**-0.0494****	**-0.0397***	0.0484	-0.0134	0.0105	0.0089
	(0.0042)	(0.0041)	(0.0215)	(0.0224)	(0.0356)	(0.0298)	(0.0097)	(0.0074)
Constant	0.0300	3.85e-05	0.0293	0.0102	0.195***	0.0041	-0.0226	0.0127
	(0.0264)	(0.0104)	(0.0231)	(0.0152)	(0.0208)	(0.0180)	(0.0420)	(0.0133)
Obs.	599	599	397	397	121	121	169	169
R2	0.076		0.103		0.314		0.136	
Nb. CU	218	218	142	142	46	46	75	75

Figure 1: Distribution of the LLP by MFIs' type and regulatory status

These graphs plot the distribution of the LLP for regulated versus non-regulated MFIs (panel A) and by MFI type (banks, NGOs and cooperatives) (panel B).

A. Distribution of the LLP for regulated versus non-regulated MFIs



B. Distribution of the LLP by MFI type (banks, cooperatives and NGOs)

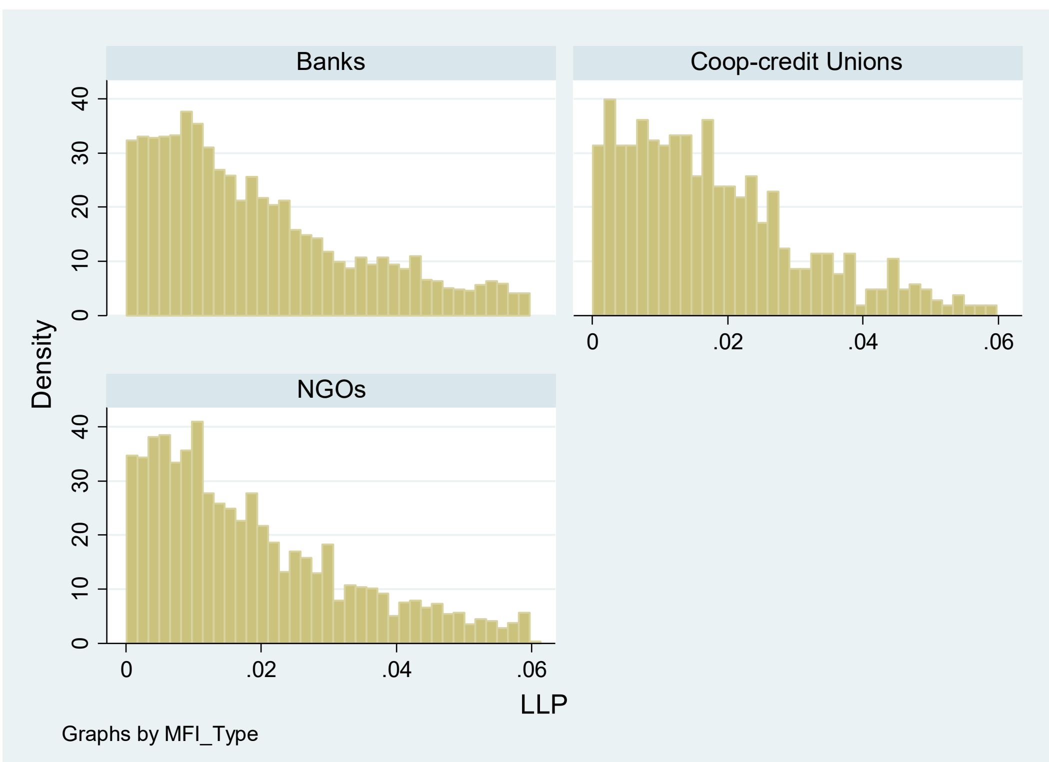
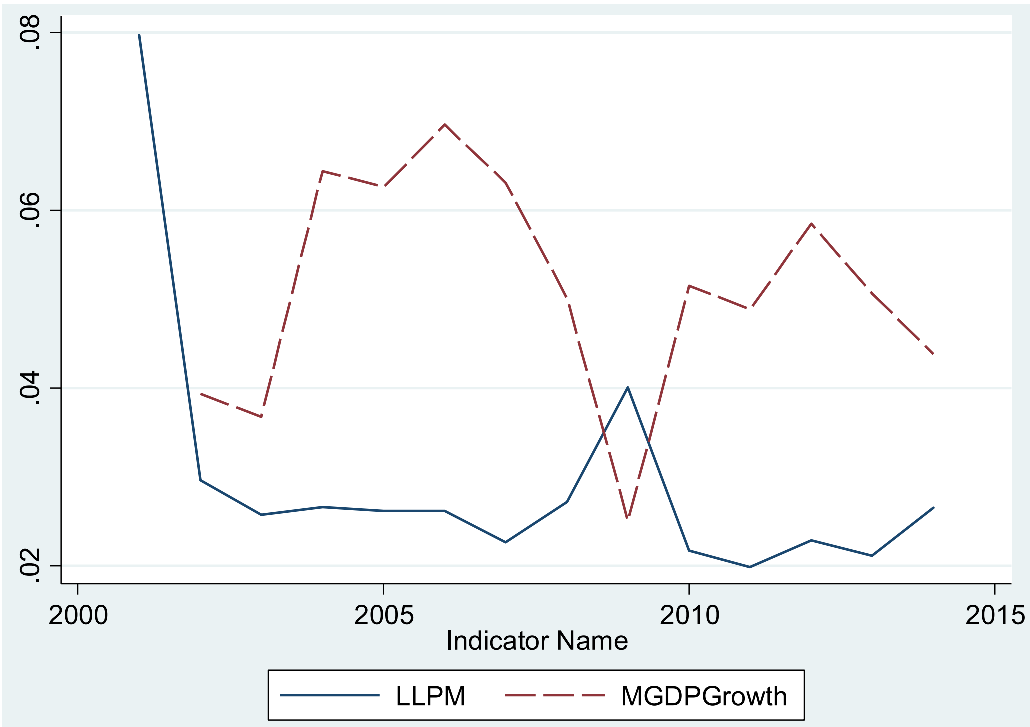


Figure 2: Dynamic of the sample average LLP and average GDP growth

This graph plots the dynamic of the sample average of loan loss provisioning (LLP) and GDP growth (GDPG) over time.



Appendix 1: Provisioning requirements

Days at risk [No. of days missed payment]	Provisioning requirement or allowance for probable losses [%]		
	Nigeria	Microrate (2014)	CGAP (2003)
0	1%	1%	1%
1-30 days	5%	10%	25%
31-60 days	20%	30%	50%
61-90 days	50%	60%	
91 or more days and /or restructured loans	100%	100%	100%

Appendix 2: The fixed and the random effects models

Our basic static model is the following:

$$\mathrm{LLP_{it}} = \alpha_0 + X_{\mathrm{it-1}}\beta + W_{\mathrm{it}}\gamma + \delta_{\mathrm{i}} + \varepsilon_{\mathrm{it}}, \quad (1A)$$

where i indexes MFIs, and t indexes year. $\mathrm{LLP_{it}}$ is the Loan Loss Provision for MFI i at the year t; $X_{\mathrm{it-1}}$ is the vector of MFI-level variables (size, capital-to-asset ratio, loan portfolio quality, profitability, liquidity, borrowers per loan officer, percentage of female borrowers, and the depth of outreach). W_{it} is the vector of country-level variables and includes the GDP growth, the per-capita-GDP growth, the credit-to-GDP gap and a dummy for crisis periods; δ_i is the MFI's individual unobserved effects and captures, among other things, the manager's ability and capabilities. We assume these unobserved individual effects to be correlated with MFI-level variables. ε_{it} is the idiosyncratic error. We are mostly interested in the vector of coefficients (β, γ) which capture respectively the effects of the MFIs idiosyncratic characteristics (X) and the macroeconomic environment variables (W) on the level of loan loss provision ($\mathrm{LLP_{it}}$). However, the quality of the estimated parameters (β, γ) is likely to be affected if equation (1A) is estimated by means of simple Ordinary Least Squares (OLS) ignoring δ_{i}. Therefore, the pooled OLS could lead to biased estimates.

The Least Squares Dummy Variable (LSDV) approach is designed to control for fixed effects by including dummies for each MFI in equation (1A). Unfortunately, this approach requires to estimate N (number of MFIs in the sample) additional coefficients and then is less suitable for our data structure with large N and small T. In this regards, we adopt another approach, which simply removes the impact of fixed effects from the model by subtracting the time average of each variable. This approach is known as the "within" estimator and is written as follows:

$$(\mathrm{LLP_{it}} - \overline{\mathrm{LLP_i}}) = (\mathrm{X_{it-1}} - \bar{X}_{\mathrm{i}})\beta + (\mathrm{W_{it}} - \bar{W}_{\mathrm{i}})\gamma + (\varepsilon_{\mathrm{it}} - \bar{\varepsilon}_{\mathrm{i}}). \quad (2A)$$

Based on the "within" estimator in equation (2A), we can obtain consistent estimates of (β, γ) by estimating a Feasible Generalized Least Squares (FGLS) of equation (2A). Through the "within" framework, we implicitly assume that the fixed effects are correlated with the regressors (X, W). If this hypothesis is relaxed and the fixed effects are assumed random, we can treat the fixed effects as error component and estimate the model differently with random effects model[2]. The random effects model can be viewed as a modified version of the fixed effects model where fixed effects are assumed to follow well-known distribution with constant variance. Consistent estimates of (β, γ) can then be obtained by estimating the following model through FGLS:

$$(\mathrm{LLP}_{\mathrm{it}} - \theta\overline{\mathrm{LLP}}_{\mathrm{i}}) = (\mathrm{X}_{\mathrm{it}-1} - \theta\bar{X}_{\mathrm{i}})\beta + (\mathrm{W}_{\mathrm{it}} - \theta\bar{W}_{\mathrm{i}})\gamma + \{(1-\theta)\alpha_i + (\varepsilon_{\mathrm{it}} - \theta\bar{\varepsilon}_{\mathrm{i}})\}. \quad (3\mathrm{A})$$

It is obvious to observe that in the case where θ =1, the fixed effects (Eq. 2A) and the random effects (Eq. 3A) estimates become equivalent. We report both estimates (fixed and random effects) in Tables 7 and 8.

[2] A good review of fixed and random effects models can be found in Baltagi (2013, chap. 2) and Wooldridge (2013, chap. 14).

Appendix 3: Country sample

Country	Nb. obs.	Percent
Afghanistan	29	0.47
Albania	38	0.62
Angola	5	0.08
Argentina	54	0.88
Armenia	75	1.22
Azerbaijan	108	1.76
Bangladesh	238	3.87
Belize	2	0.03
Benin	58	0.94
Bhutan	3	0.05
Bolivia	188	3.06
Bosnia and Herzegovina	90	1.46
Brazil	109	1.77
Bulgaria	32	0.52
Burkina Faso	17	0.28
Burundi	6	0.1
Cambodia	128	2.08
Cameroon	36	0.59
Central African Republic	1	0.02
Chad	5	0.08
Chile	24	0.39
China, People's Republic of	20	0.33
Colombia	166	2.7
Congo, Democratic Republic of the	26	0.42
Congo, Republic of the	8	0.13
Costa Rica	87	1.42
Cote d'Ivoire (Ivory Coast)	9	0.15
Croatia	7	0.11
Dominican Republic	59	0.96
East Timor	10	0.16
Ecuador	423	6.88
Egypt	64	1.04
El Salvador	117	1.9
Ethiopia	83	1.35
Fiji	2	0.03
Gambia	3	0.05
Georgia	66	1.07
Ghana	75	1.22
Grenada	1	0.02
Guatemala	120	1.95

Guinea	5	0.08
Guyana	1	0.02
Haiti	27	0.44
Honduras	130	2.11
Hungary	3	0.05
India	497	8.08
Indonesia	75	1.22
Iraq	12	0.2
Jamaica	1	0.02
Jordan	53	0.86
Kazakhstan	60	0.98
Kenya	78	1.27
Kosovo	63	1.02
Kyrgyzstan	78	1.27
Laos	13	0.21
Lebanon	21	0.34
Macedonia	32	0.52
Madagascar	35	0.57
Malawi	24	0.39
Malaysia	2	0.03
Mali	45	0.73
Mexico	144	2.34
Moldova	18	0.29
Mongolia	41	0.67
Montenegro	10	0.16
Morocco	48	0.78
Mozambique	37	0.6
Myanmar (Burma)	1	0.02
Namibia	1	0.02
Nepal	172	2.8
Nicaragua	188	3.06
Niger	11	0.18
Nigeria	47	0.76
Pakistan	126	2.05
Palestine	28	0.46
Panama	29	0.47
Papua New Guinea	5	0.08
Paraguay	54	0.88
Peru	289	4.7
Philippines	306	4.98
Poland	13	0.21
Romania	31	0.5
Russia	58	0.94

Rwanda	21	0.34
Samoa	10	0.16
Senegal	46	0.75
Serbia	28	0.46
Sierra Leone	12	0.2
Solomon Islands	2	0.03
South Africa	26	0.42
South Sudan	1	0.02
Sri Lanka	52	0.85
Sudan	2	0.03
Suriname	5	0.08
Swaziland	1	0.02
Syria	6	0.1
Tajikistan	95	1.55
Tanzania	47	0.76
Thailand	7	0.11
Togo	35	0.57
Tonga	6	0.1
Trinidad and Tobago	3	0.05
Tunisia	13	0.21
Turkey	4	0.07
Uganda	70	1.14
Ukraine	13	0.21
Uruguay	5	0.08
Uzbekistan	26	0.42
Venezuela	9	0.15
Vietnam	55	0.89
Yemen	21	0.34
Zambia	16	0.26
Zimbabwe	7	0.11
Total	**6,148**	**100**