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Provisioning over the business cycle: Some insights from the microfinance industry☆

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ABSTRACT

This paper investigates the drivers of provisioning in MFIs and their provisioning behaviour over the business cycle. Based on an international sample of MFIs extracted from the MIX database over the 2001–2014 period, we uncover a negative relationship between MFIs' provisioning and the business cycle. Our finding corroborates the fact that MFIs do not build their loan loss provisions (LLP) during economic booms when profit and earnings are high. Since they provision more during downturns, they are more likely to suffer from unexpected losses and experience failure. This is in sharp contrast with the current Basel III countercyclical buffer requirement suggesting that financial institutions, especially banks, should build sufficient buffer in booms so that they can avoid costly capital adjustment when the economy contracts. Deeper analyses suggest however that this behaviour mainly concerns profit-oriented and deposit-taking/regulated MFIs, with business model and target close to conventional banking. This suggests that bank-like and regulated MFIs' loan loss provisions follow similar behavioral patterns to those of the conventional banking sector during the boom-and-bust cycles.

1. Introduction

The latest 2007–2009 global financial crisis has intensified the debate on effective risk management and appropriate bailout policies for stable and resilient financial systems (BCBS, 2011; 2017). 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. Less attention has been paid to microfinance institutions (MFIs). MFIs are non-negligible and specific types of financial intermediaries in the financial system of less-developed-countries (LDCs) and emerging economies.[1] They seek to earn profit, fight poverty and target poor people or reach those whose access to borrowing, savings, investment, payment services and insurance is either limited or non-existent. The services provided by MFIs are mainly in the form of uncollateralized microloans or microloans with unconventional collateral under various institutional forms, and through different types of lending methodologies. Unlike banks, MFIs are often better suited to dealing with the information asymmetries, which undermine credit markets 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

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[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, 3098 microfinance institutions (MFIs) reported reaching 211,119,547 borrowers, 114 millions of whom were living in extreme poverty (Reed, 2015). Of these poorest clients, 82.6% are women.

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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] Provisioning being a credit risk management tool used by MFIs, this paper thus aims to study provisioning behaviour of microfinance institutions (MFIs), especially its relationship with business cycles. Additionally, we examine whether the provisions set by MFIs are pro-or counter-cyclical depending on their commercial orientation.

The existing banking literature examining cyclical pattern of bank loan loss provisioning document either a countercyclical[3] provisioning behaviour (Bikker & Metzemakers, 2005; Laeven & Majnoni, 2003; Shim, 2013) or a procyclical provisioning behaviour (Caporale, Alessi, Di Colli, & Lopez, 2018; Cummings & Durrani, 2016). One assumption being that banks' borrowers are sensitive to macroeconomic conditions, and that banks' failures and economic performance are intertwined. These studies use samples of banks in developed economies and are mainly based on European and US data. What, however, about development finance organizations such as MFIs that contribute to fighting against financial exclusion in developing and emerging economies?

With respect to the link between microfinance and macroeconomic conditions, there is less consensus on how macroeconomic factors affect the MFI industry 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, Rasmussen, & Reille, 2010; Gonzalez, 2007; Lützenkirchen & Weistroffer, 2012). From these studies, we can indirectly infer that MFIs should perhaps not be required, from a regulatory perspective, to set their provision in a cyclical (pro-cyclical or counter-cyclical) manner, but instead in a way that potentially reflects their true portfolio risk. However, some other microfinance studies document strong correlation between microfinance activity and macroeconomic context (Ahlin, Lin, & Maio, 2011) and between MFI credit expansion and the 2008–2009 global financial crisis (Wagner & Winkler, 2013). These previous studies on the impact of macroeconomic conditions on MFIs' activities use either pre-crisis data or crisis data. Kar (2017) using a longer time horizon (1996–2013) shows that provisions in MFIs are cyclical. This study however does not clearly account for the uniqueness of the microfinance industry characterized by the heterogeneity of ownership type and business model. The impact of business cycle on MFIs' provisions is likely to vary across MFIs ownership type and business model. Tchakoute Tchuigoua, Soumaré, and Hessou (2020) studying the cyclical behaviour of MFIs lending over the 2001–2014 period, find borrowers' ability to repay loans during good or bad times to be a transmission channel. This work does not explicitly study the cyclical behaviour of MFIs' provisions. To the extent that the composition of MFIs client portfolio varies according to their commercial or profit orientation, we assume that MFI profit and commercial orientation can exacerbate the business cycle effect on provisions. More so, with for-profit MFIs having more wealthy clients and businesses whose activities and income are more subject to cyclical variations of the business cycle. Our study is thus, to the best of our knowledge, the first that explicitly examines the cyclical provisioning behaviour across MFIs ownership type and business model. Specifically, we investigate whether the cyclical provisioning behaviour observed in the microfinance industry varies across MFI profit status.

Investigating provisioning behaviour is of particular interest for the microfinance sector for several reasons. As mentioned above, like banks, the microfinance sector has been impacted by the recent financial crisis, but still MFIs are different from conventional financial institutions. Unlike conventional banks, MFIs are development finance organizations. Although MFIs provide loans as conventional banks, MFIs are not banks and have some distinctive features. MFIs mostly operate in developing and emerging economies and deliver financial services under different institutional forms (profit-oriented MFIs: Microfinance banks and non-bank financial institutions; and non-profit MFIs such as co-operatives/credit unions and NGOs), regulation status (regulated versus non-regulated), and business models (some MFIs gather deposits while other do not). The fact that several forms of ownership coexist within a country or within the whole microfinance sector makes microfinance a unique field to analyze the cyclicality of provision for loan losses. We therefore expect the effect of business cycle on MFIs loan loss provisioning to be heterogeneous across MFIs, depending on their ownership type and business model. Unlike non-profit MFIs, for-profit MFIs such as microfinance banks opt for more conventional risk management and governance practices (Cull, Demirgüç-Kunt, & Morduch, 2009). These microfinance banks, like some other MFIs such as cooperatives, apply deposit-taking business model, and like conventional banks, are subject to prudential regulation which include provisioning requirements (Ledgerwood, Earne, & Nelson, 2013). We can therefore expect the business cycle to impact MFIs' provisioning behaviour and the cyclical effect of prudential regulation to be much stronger in microfinance banks (for-profit MFIs).

In addition, credit risk management practices diverge from those of banks, especially because many MFIs apply joint liability contracts models which have been shown to be able to overcome problems of adverse selection, moral hazard and limited enforcement, leveraging social collateral that can substitute for the conventional collateral that the poor, by definition, lack (Armendáriz de Aghion & Morduch, 2010; Besley & Coate, 1995; Chowdhury, 2005; de Quidt, Fetzer, & Ghatak, 2018; Griffin & Husted, 2015; Stiglitz, 1990). As recommended by the BCBS (2010) and Christen, Lauer, Lyman, and Rosenberg (2012), the provisioning schedule for delinquent microloans should be even more aggressive than the schedule for delinquent secured bank loans to reflect the lack of collateral requirements. Unlike banks, many MFIs have fewer resources to invest in risk management, and in this regard, loan loss provisioning is another key credit-risk management tool they can rely on. In fact, loan loss provisioning is set to absorb expected losses (Bikker & Metzemakers, 2005), while capital is mostly designed for unexpected credit risk. Since MFIs have short-term loans and are subject to less information asymmetry given that they serve well known clientele, provisioning for the expected losses is likely one of their best practice in terms of risk-management. Then, 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.

Furthermore, the microfinance sector in many countries experienced a trend toward commercialization over the past three decades. Large multinational banks and greenfield MFIs have entered the microfinance business through downscaling strategies (Bruton, Khavul, & Chavez, 2011; Cull, Harten, Nishida, Rusu, & Greta, 2015). Some MFIs experienced an institutional transformation from NGO to a privately-owned status. Some other MFIs are listed in stock markets and are well entrenched in the financial sector (Brière & Szafarz, 2015). Commercialized MFIs such as profit-oriented MFIs now compete fiercely with conventional banks in micro, small and medium sized enterprises (MSMEs) lending segments through upscaling strategies (Cull, Demirgüç-Kunt, & Morduch, 2014; Vanroose & d'Espallier, 2013). They are likely to suffer from macro-economic shocks coming either from international financial capital markets or from the demand side (their target clientele which are more connected to domestic economic conditions). This means that some of their clientele is likely to have the same profile

[2] Indeed, the CSFI ranks risk management as number two among the risks faced by MFIs, and concerns about the quality of risk management among service providers continue 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.

[3] Pro-cyclicality here refers to positive co-movement between loan loss provisions and business cycles, whereas counter-cyclical provisioning refers to a negative relationship between loan loss provisions and the business cycle.

as banks' clients. As the composition of MFIs' client portfolios evolved as a result of commercialization, it is likely that those among their clients who are wealthier will be affected by macroeconomic shocks and disruptions with implications for their activities. The cyclical pattern of loan loss provision is likely to vary according to whether the MFI is a for-profit MFI or not. From the above arguments, we thus expect microfinance banks (for-profit MFIs), to have negative co-movement between their loan loss provision and the business cycle. For these MFIs, exogenous increase in risk during cyclical downswing may result in a decline in borrowers repayment capacity. Hence, as nonperforming loans increase, loan loss provisions increase.

Based on an international sample of MFIs extracted from the MIX database over the 2001–2014 period, we uncover a negative relationship between MFIs' provisioning and the business cycle. This finding suggests that unconditional to their loan loss reserve, MFIs provision more expenses to back their foreseen portfolio risk in recession compared to expansion. During good economic times, MFIs borrowers have better investments opportunities, face less liquidity constraints and can easily repay loans leading MFIs to anticipate less loan losses. We also underscore that this negative provisioning relationship with the business cycle is mostly observed among for-profit and deposit-taking (that are more likely to be regulated) MFIs. This may suggest that profit-oriented and regulated MFIs' loan loss provisions follow similar behavioral patterns to those of the conventional banking sector during the boom and bust cycles. Non-regulated and not-for-profit MFIs' loan loss provisioning are mainly idiosyncratic, making these MFI types less vulnerable to business cycles. This is because their clients are resilient to economic fluctuations Gonzalez (2007). These findings allow us to contribute to the debate related to the cyclical pattern of provisioning in at least two ways. First, we add to the existing literature on cyclicality of provisioning in financial organizations by focusing on a large international sample of firms operating in the field of development finance, especially double bottom-lines institutions such as MFIs that mainly operate in developing economies. Second, by linking MFIs' loan loss provisioning to the business cycle, we also add to the general literature on risk management in microfinance institutions. MFIs provisioning behaviour, especially for-profit and deposit-taking MFIs provisioning behaviour over the cycle is less in line with the ongoing Basel III reform in banks. In fact, it should be expected that MFIs accumulate more provisions during periods of economic booms to be used to sustain their lending activities during recessions. We thus call upon regulatory authorities and policy makers to design tailored macroprudential tools such as specific countercyclical buffer for regulated MFIs and microfinance banks. Given the fact that MFIs banks can be considered as development banks in developing economies, our study also contributes to the literature on the cyclical behaviour of bank capital with a focus on organizations belonging to the field of development finance.

The remainder of the paper is organized as follows. Section 2 presents the research methodology, the data and the description of the variables. Section 3 discusses the empirical results. We conclude in Section 4.

2. Research methodology

2.1. Data

The data used in this study come from various sources. Data for MFI-level variables come from the Microfinance Information eXchange (The MIX) database, which is growing in use in the microfinance empirical literature (e.g., Bogan, 2012; Servin, Lensink, & Van den Berg, 2012; Tchakoute Tchuigoua, 2016; Vanroose & 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 2000 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 auditors, and for some of them, by the big four accounting firms. In addition to the fact that their financial statements are audited, those at level five are rated by ratings 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. Table 1 below gives a summary of the sample distribution by year. The sample countries can be found in Appendix 2, where the number of observations per country is provided. The data are unevenly distributed across the years, i.e. the panel sample is unbalanced. 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).

We have three important types of MFIs in our database as shown in Table 2: for-profit MFIs (51.5%), cooperatives and credit unions (12.3%) and NGOs (36.2%). For-profit MFIs include microfinance banks and NBFIs (non-bank financial institutions). In terms of their regulatory status, we have 67.6% of MFIs being subject to prudential regulation as opposed to 32.4% of non-regulated MFIs in the sample. Of MFIs in the sample, 83.05% are deposit-taking institutions, and the remaining 16.95% are non-deposit-taking organizations.

Country-level GDP data come from the World Bank's World Development Indicators database (WDI), whereas data on credit-to-GDP ratios come from the website of the Bank for International Settlements (BIS).

2.2. Variables

2.2.1. Dependent variable

Following previous banking and microfinance literature that study banks' provisioning behaviour (e.g., Ahmed, Takeda, & Thomas, 1999; Bouvatier, Lepetit, & Strobel, 2014; Bushman & Williams, 2012; Kanagaretnam, Krishnan, & Lobo, 2010; Kanagaretnam, Lim, & Lobo, 2010; Kanagaretnam, Lim, & Lobo, 2014; Tchakoute Tchuigoua, 2018), we use

Table 1
Sample distribution by year.

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	6148	100

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.

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

MFI type (%)			Regulatory status (%)	
For-profit	Coop/Credit unions	NGOs	Regulated	Non-regulated
51.51	12.27	36.22	67.58	32.42
For-profit status (%)		Deposit-taking status (%)		
For-profit	Not-for-profit	Deposit-taking	Non-deposit-taking	
51.51	48.49	83.05	16.95	

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

provisions for loan losses (loan loss provisions) as the dependant variable. Indeed, since we are interested in how MFIs provision for their Loan Loss Reserve (LLR) (a balance sheet item) through the business cycle, we consider the LLP as a valid measure since it signals whether MFIs perceive any additional risk in their portfolio to provision to. As a matter of fact, amid the COVID 19, many large US banks provision heavily for the LLR despite having adequate loan loss reserves. Credit loss provisions made to absorb expected credit losses, been added to capital and reserves at the end of the fiscal year, instead of using LLR as our left-hand side variable (dependent variable), we instead prefer to use the flow variable, i.e. the LLP, as the above cited papers. For robustness check, we run additional regressions to control for the beginning period loan loss reserve. These additional regression results are reported in the Online Appendix Table 1A.[4]

LLP measures loan loss provisions as a percentage of the total outstanding loan portfolio. This gives an indication of the expense incurred by the institution to anticipate future loan losses. In this study, loan loss provisions[5] refer to an income statement account reflecting the cost of anticipated failure to collect loan principal. In terms of provisioning practice, Kumar and Paul (2009) suggest that two approaches are adopted by MFIs in India: The blanket approach and the ageing approach. The blanket approach suggests that MFIs provision to maintain a specific ratio of loan loss reserve to the outstanding loan portfolio. This specific ratio can be conservative (2–3%) or varies with the behaviour of the historical loan loss. The ageing approach is however more related to the portfolio quality since it tracks the ageing of past due loans and assign weights for provisioning based on the age of the loan past due. 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. In this case, MFIs can follow self-regulatory provisioning requirements or comply with the Consultative Group to Assist the Poor (Rosenberg, Nasr, Peck Christen, & Mwangi, 2003) and Microrate (2014) guidelines (see Appendix 1). As we can read above, provisioning practices are not homogenous among MFIs, and differ across country, region and MFIs' type.

2.2.2. Variables of interest

To investigate the cyclical behaviour of MFIs' provisioning, we use real GDP growth to capture countries' economic performance, hence our main business cycle proxy is the real GDP growth (GDPGrowth). For robustness check, we complement this business cycle variable with a 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, Borio, & Tsatsaronis, 2011; Gourinchas & Obstfeld, 2012; Jordà, Schularick, & Taylor, 2011; Schularick & 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, Gambacorta, Lombardo, and Pereira da Silva (2017) and Murcia and Kohlscheen (2016)). Therefore, it is desirable for MFIs to enter a recession with sufficient provisions to maintain the level of their lending activities. This is possible only if MFIs increase their provisions during booms so that they have sufficient loss absorption capacity during the subsequent bust. 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 the credit-to-GDP gap. This indicator is expected to provide an early warning signal for an upcoming crisis. Credit-to-GDP growth (CGDPG) is used to capture the credit cycle.

2.2.3. MFI-level control variables

Below are the control variables we judge relevant for our study. These variables have been used in other microfinance studies (e.g., Cull, Demirgüç-Kunt, & Morduch, 2011; Cull et al., 2014; Galema, Lensink, & Spierdijk, 2011; d'Espallier, Goedecke, Hudon, & Mersland, 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 financial institutions that extensively use soft information and engage in relationship lending. Small financial institutions 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, Miller, Petersen, Rajan, & Stein, 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 expenses. *Size* is measured by the natural logarithm of the book value of assets.

Capital ratio: In the existing banking literature, the link between loan loss provisions and regulatory capital has been investigated but findings are mixed. Some studies find no evidence indicating that provisions are used for capital management (Collins, Shackelford, & Wahlen, 1995; Leventis, Dimitropoulos, & Anandarajan, 2011), while others using data on US banks find support for a negative relationship between loan loss provision and 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, Chamberlain, & Magliolo, 1995; Beatty & Liao, 2014). We thus control for regulatory capital requirements and measure MFI capitalization by the equity-to-assets ratio, our so-called capital ratio (CAR). For MFIs that are subject to the regulation and supervision of banking authorities, provisions may be used to manipulate their capital ratio in order to comply with regulatory requirements and prudential rules. 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

[4] Our findings do not change after controlling for the first lag of loan loss reserve (LLR).

[5] Loan loss provision differs from loan loss reserve which refers to a balance sheet account that compensates for expected losses in the value of the portfolio due to non-collection.

Table 3
Variable definitions and descriptions.

	Variable	Description
Loan loss provision ratio	LLP	*Net loan loss provision /average gross outstanding portfolio* Net loan loss provision = Loan loss provision and write-offs minus Recovery from Loans written off Source: MIX
Assets	SIZE	*Log of total assets* Source: MIX
Equity	CAR	*Capital ratio = Equity divided by 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 which indicates 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
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
Economic Growth	GDPGrowth	*Real gross domestic product (GDP) growth* Source: WDI

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

donations to charitable organizations. MFIs, whether they are subject to prudential regulation or not, may have incentives to engage in capital management.

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 MFI loan portfolio risk and loan loss provision.

Profitability: Provisions are now recognized as a tool for earnings management in banks (Ahmed et al., 1999; Kanagaretnam et al., 2014; Kanagaretnam, Lim, & Lobo, 2010; 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 to hide profit, and that to seek more funding from donors. This earnings management behaviour has been studied in the non-profit organization literature, e.g. Chen (2016) and Verbruggen and Christiaens (2012), among others. We may thus expect a negative relationship between profitability and loan loss provisions. Profitability is measured by the *return on assets* (ROA), an indicator widely used in many microfinance studies (e.g., Bogan, 2012; Galema, Lensink, & Mersland, 2012).[6]

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 terms of loan allocation that are likely to affect loan repayment performance and provisioning. In addition to MFI-specific financial characteristics given above, 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 non-availability 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, loans to village banks) or the distribution of loans by type (i.e., household financing, enterprise finance, education, loans to SMEs, loans to microenterprises).

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

2.3. Baseline econometric model

To investigate the cyclical behaviour of loan loss provisions, we estimate the following baseline model:

$$LLP_{it} = \alpha_0 + \beta X_{it-1} + \gamma W_{jt} + \delta_i + \varepsilon_{it}, \tag{1}$$

where X_{it-1} is a vector of MFI-level variables; W_{jt} is a vector of country-level non-discretionary components and includes the growth rates of both real GDP and credit-to-GDP ratios, our main test variables. δ_i is the MFI's individual unobserved effect. We assume these unobserved individual effects to be correlated with MFI-level variables. ε_{it} is the idiosyncratic error which captures the discretionary component of loan loss provisioning (Kanagaretnam et al., 2014; Kanagaretnam, Lim, & Lobo, 2010; Tchakoute Tchuigoua, 2018). We estimate eq. (1) with the vector W_{jt} composed of our main test variables (real GDP and credit-to-GDP ratios) and control for MFI-level variables (vector X_{it-1}) such as *MFI* size (SIZE), the percentage of female borrowers (FEMALE), depth of outreach (DEPTH), profitability (ROA), loan portfolio quality (PAR30),

[6] Another accounting measure of profitability is the return on equity (ROE), commonly used in banking studies. This measure is dependent on firm capital structure, specifically equity. Our sample includes different types of MFIs with different profit orientation (profit-oriented vs. non-profit-oriented), different ownership structure (for-profit MFIs, cooperatives and credit unions, NGOs), and different business models (deposit-taking and non-deposit-taking). Not-for-profit MFIs do not have equity capital for earnings purposes. Here, we thus do not use ROE as a profitability indicator. We found it appropriate to use ROA as our profitability indicator given that it is common to all MFIs, and may have the same interpretation in all categories of MFIs, and also for ease of comparison.

Table 4
Summary statistics.

Panel A. Sample statistics for the full sample

Variable	Obs	Mean	SD	Min	Max
LLP	5525	0.019	0.014	0.000	0.060
SIZE	6096	16.017	1.969	6.359	22.446
CAR	6088	0.320	0.414	−18.353	17.753
PAR30	5606	0.044	0.045	0.000	0.1673
ROA	5569	0.018	0.111	−3.453	0.728
LO	4905	337	1036	0	67,418
DEPTH	5999	0.759	2.508	0.000	112.768
FEMALE	5418	0.654	0.265	0.000	1.272
GDPGrowth	3555	0.052	0.040	−0.193	0.339
CGDPG	3530	0.056	0.125	−1.152	1.194

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

Variable	MFI regulatory status		MFI type		
	Non-regulated	Regulated	For-profit	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	0.044	0.043	0.042	0.056	0.042
ROA	0.015	0.020	0.019	0.019	0.018
LO	321.817	345.108	329.459	417.583	326.344
DEPTH	0.343	0.959	1.034	0.858	0.324
FEMALE	0.715	0.623	0.612	0.504	0.760

Panel C. Sample statistics by MFI profit orientation and MFI deposit-taking status

Variable	MFI deposit-taking status		Profit orientation	
	Deposit-taking	Non-deposit-taking	For-profit	Not-for-profit
LLP	0.019	0.020	0.019	0.018
SIZE	16.160	15.321	16.591	15.423
CAR	0.306	0.387	0.299	0.341
PAR30	0.047	0.040	0.046	0.042
ROA	0.018	0.019	0.019	0.018
LO	346.890	298.233	329.459	344.764
DEPTH	0.812	0.502	1.034	0.476
FEMALE	0.661	0.623	0.612	0.695

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). 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 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 *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 growth* (GDPGrowth) and the *credit-to-GDP growth* (CGDPG).

loan monitoring (LO) and capital ratio (CAR). We include the lag of these MFI-level variables in order to reduce the endogeneity concern.

We are mostly interested in the vector of coefficients (β, γ) which capture respectively the effects of the MFIs' idiosyncratic characteristics (X_{it-1}) and macroeconomic variables (W_{jt}) on the level of loan loss provision (LLP_{it}) of MFI i in year t. We estimate models using pooled OLS, fixed effects (FE) and random effects (RE) panel regression, and test for the best specification among the three estimation techniques (OLS, FE and RE). Note that fixed effects panel estimation has the additional advantage of controlling for selection on time-invariant unobservable (fixed effects).

To test whether the effect of business cycle on MFIs provisions varies across MFIs profit status and business model, we split the sample of MFIs into subgroups based on their profit status (for-profit MFIs versus not-for-profit MFIs), their regulation status (regulated MFIs versus non-regulated MFIs; deposit-taking MFIs versus non-deposit-taking MFIs) and re-estimate our model.

Later we use alternative econometric specifications, such as dynamic panel system-GMM and seemingly unrelated regression (SUREG) estimations, for further robustness checks of our results. Regarding the dynamic GMM, we estimate eq. (1) augmented with the lag of the LLP as covariate. By estimating the SUREG, we try to account for possible simultaneity between covariates. More formally, we assume that MFIs have goals related to outreach, profitability, and stability which imply that they try to reach several goals at the same time. More specifically, we assume that MFIs try to set loan loss provisions (LLP) simultaneously with the depth of outreach (DEPTH), financial performance (ROA), loan portfolio quality (PAR30), loan monitoring (LO) and capital ratio (CAR).

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% 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 from 0.5 to 2.7% depending on geographical location of the MFIs; the loan loss provision ratio is lower in South Asia and 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, consistent with 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.

When we further investigate the LLP rates by MFI type and MFI regulatory status, we find that, although the average LLP rates are similar across sub-groups of MFIs (as shown in Table 4), there is however a difference in the LLP distribution depending on MFI regulatory status and type. The tail of the distribution is relatively heavier for regulated MFIs than among their non-regulated peers, which seems to indicate different behaviour in their provisioning. We also observe a heavy tail for profit-oriented MFIs compared to non-profit-oriented MFIs (cooperatives and credit unions, and NGOs). Note, however, that most regulated MFIs are profit-oriented MFIs in the majority of the countries.

In terms of the control variables, the differences observed for LLP in terms of the distributions of the sub-groups of MFIs subsist. For instance, regulated and for-profit MFIs are larger in size 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 profit-oriented MFIs, 42.2 million USD for cooperatives and credit unions and 19.2 million USD for NGOs.

The average capital-to-asset ratio of MFIs is 32%; 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 profit-oriented MFIs (29.9%) and cooperatives and credit unions (26.3%). On average, portfolio at risk (30 days) is equivalent to 4.4% 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 profit-oriented 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 entire sample is 0.759. 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 profit-oriented MFIs, implying that these groups of MFIs are likely to 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. For-profit MFIs and NGO MFIs have fewer borrowers per loan officer (326 and 329 respectively) than 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 (76.0%), followed by profit-oriented MFIs (61.2%), and then cooperatives and credit unions (50.4%).

Table 5 presents the Pearson correlation matrix between the variables. We focus our analysis mainly on the relationship between the dependent variable (LLP) and the control variables. MFIs' size and portfolio at risk (30 days) are positively related to LLP at the 5% confidence level, while MFIs' profitability (ROA), number of borrowers per loan officer (LO) and proportion of female borrowers (FEMALE) have a negative correlation with it (significant at 5%). More importantly, the business cycle indicator, real GDP growth, is negatively related to LLP. GDP growth and credit-to-GDP growth are positively correlated with a correlation coefficient of 13.2%, which is not too high. Therefore, the two indicators are useful as they each capture different dimensions of business cycles. As we claim above, our main indicator for the business cycle is the real GDP growth, the variable credit-to-GDP is used as alternative measure of business cycle for further robustness check.

The negative relationship between the real GDP growth (business cycle) and LLP can be observed in Fig. 1 and seems to indicate that the two variables move in opposite directions to each other. 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.

3.2. Multivariate analysis

3.2.1. Baseline regressions (static model)

Table 6 presents the regression results of eq. (1) with the lag of all covariates using the three estimation techniques: panel fixed effects, panel random effects and pooled OLS. We implement two tests (Fisher test and Hausman test) to decide between the pooled OLS, the fixed effects and the random effects models. The Fisher test allows us to assess the joint significance of the individual effects (random and fixed) against the pooled OLS. Specifically, it tests the distance between a model without the individual effects and a model with those effects. As an illustration, for the regression model presented in columns 1 to 3, we obtained a Fisher F-statistic of 2.86 with a p-value of 0% confirming the need to include the individual effects. Since our Fisher test rejects the null hypothesis, we move to the Hausman (1978) specification test. The Hausman statistic is distributed as a chi-square and tests for the distance between the fixed effects and the random effects. A higher distance favours the fixed effects over the random effects. Regarding the Hausman test, we obtain a chi^2-statistic of 22.40 with a p-value of 0.42% confirming the superiority of the fixed effects model over the random effects model. These tests pave the way toward the choice of the fixed effects method as the core regression strategy for our panel static modelling.

Recall that our initial sample is comprised of 6148 firm-year observations from 1474 MFIs worldwide over 2001–2014. However, the number of observations reported in our regression tables can be expected to vary from one table to another. This is explained by the fact that when using lags, we lose MFIs with data from only one year. In addition, some MFIs have missing data for some variables. Also, some countries have missing data for GDP. This shrinks the sample size.

Columns 1 to 3 of Table 6 report the regression results, respectively, for the pooled OLS, the fixed effects (FE) and the random effects (RE) estimations with the real GDP growth (GDPGrowth). Our analysis suggests that the growth in real GDP are negatively associated with the MFIs' LLP target. This negative co-movement between MFIs' LLP and the GDP growth is in line with the literature suggesting that macroeconomic

Table 5
Correlation matrix.

	LLP	L.LLP	L.SIZE	L.CAR	L.PAR30	L.ROA	L.LO	L.FEMALE	L.DEPTH	GDPGrowth	CGDPG
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.LO	−0.0866*	−0.1211*	0.0811*	−0.0787*	−0.0042	0.0567*	1.0000				
L.FEMALE	−0.0769*	−0.1020*	−0.1860*	0.0033	−0.0547*	−0.0046	0.1011*	1			
L.DEPTH	0.0139	0.0541*	0.1552*	−0.066	−0.004	−0.0092	−0.1197*	−0.2292*	1		
GDPGrowth	−0.1160*	−0.0855*	−0.0294	0.0421*	−0.0307	0.0121	0.0239	0.0145	0.0469*	1	
CGDPG	−0.0252	−0.0106	0.0228	0.0668*	−0.0714*	0.0308	0.0239	−0.1030*	−0.0054	0.1321*	1

This table presents the Pearson correlation matrix of our variables. 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 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 *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 growth* (GDPGrowth) and the credit-to-GDP growth (CGDPG). The prefix "L." in front of a variable designates the lag of the variable.
* $p < 0.05$.

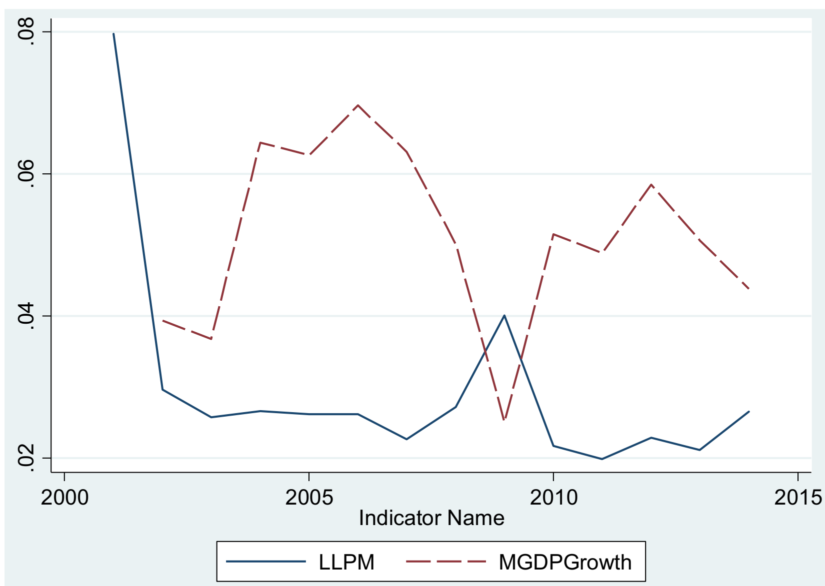

Fig. 1. Dynamic of the sample average LLP and average GDP growth.
This graph plots the dynamic of the sample average of loan loss provisions (LLPM) and GDP growth (MGDPGrowth) over time.

variables influence MFIs' credit growth (Wagner & Winkler, 2013) and performance (Ahlin et al., 2011). Our finding corroborates the fact that MFIs do not build their LLP in booms when profit and earnings are high. Therefore, if their provisions are very low when they enter a recession, they are more likely to suffer from unexpected losses and experience failure. This is in sharp contrast with the current Basel III contracyclical buffer requirement suggesting that banks should build sufficient buffer in booms so that they can avoid costly capital adjustment when the economy contracts. Note that there is no such counter-cyclical capital requirement for MFIs.

Concerning the economic magnitude of our finding, let's assume that a typical MFI is operating around the sample average LLP of 2% during a normal time, with an average GDP growth of 5.2% (see Panel A of Table 4). A decrease in the GDP growth by one standard deviation, corresponding to 4% drop, will increase the LLP required by approximately 12 basis points ($= -0.029 \times -0.04$) using the fixed effects regression coefficient. This corresponds to a loan loss provision increase from 2% to 2.12%, or a 6% increase in the LLP. When considering the worst-case economic downturn from the average GDP path, i.e., the GDP growth drops from +5.2% to −19.3% (the lowest GDP growth rate observed in the sample), corresponding to a sharp 24.5% (19.3% + 5.2%) decrease in GDP, it increases the average required LLP by 71 basis points ($= -0.029 \times -0.245$) to 2.71% compared to an average PAR30 of 4.42%.

Moreover, we find that idiosyncratic factors such as the MFIs' size and their portfolio risk (PAR30) have positive effects on the level of their loan loss provisions. 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,

Table 6
Baseline regressions results.

Variables	Macro variable = Real GDP growth		
	(1) OLS	(2) Fixed Effects	(3) Random Effects
L.SIZE	**0.0010*****	**0.0011*****	**0.0010*****
	(0.0002)	(0.0004)	(0.0002)
L.FEMALE	−0.0016	0.0052	−0.0005
	(0.0011)	(0.0034)	(0.0015)
L.CAR	**0.0053*****	−0.0013	**0.0036**$^{** *}$
	(0.0013)	(0.0026)	(0.0016)
L.PAR30	**0.0251*****	**0.0176*****	**0.0185*****
	(0.0042)	(0.0061)	(0.0043)
L.ROA	**−0.0085*****	−0.0007	**−0.0088*****
	(0.0024)	(0.0056)	(0.0028)
L.DEPTH	−0.0003	−0.0004	−0.0002
	(0.0002)	(0.0005)	(0.0003)
L.LO	**−2.58e-6*****	2.61e-7	**−1.69e-6*****
	(6.14e-7)	(1.09e-6)	(6.56e-7)
GDPGrowth	**−0.0481*****	**−0.0291*****	**−0.0370*****
	(0.0070)	(0.0073)	(0.0065)
Constant	0.0045	−0.0022	0.0024
	(0.0032)	(0.0074)	(0.0041)
Number of Obs.	2.495	2.495	2.495
R^2	0.0594	0.0236	0.0565
Number of MFIs	755	755	755

This table presents the regression model of Eq. 1 with all covariates. The model is estimated using three methodologies: pooled ordinary least squares (OLS), fixed effects (FE) and random effects (RE). 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 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 *borrowers per loan officer* (LO) measured by the ratio of the number of active borrowers to the number of loan officers; 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 share of the poorest clients among the MFI's clientele. The **macroeconomic variable** is the *real GDP growth* (GDPGrowth). The prefix "L." in front of a variable designates the lag of the variable. Robust standard errors are in parentheses.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

which generates better repayment performance and therefore requires lower provision expenses. Our descriptive analysis in subsection 3.1 supports this finding, as smaller-sized NGOs are the most capitalized type of MFIs. The positive relationship between LLP and PAR30 suggests alignment between their portfolio quality and their provisions.

The above analysis on the relationship between MFIs' loan loss provisioning and the business cycle is only valid if we can provide evidence on MFIs' asset deterioration in recession, which is not necessarily the case for all MFIs as evidenced by some previous studies. Indeed, 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 & 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 of 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 operating mainly in the informal sector and whose activities are less affected by the boom-bust cycle. This leads to us investigating whether the cyclicality of MFIs' provisioning is a function of their ownership status and/or business model.

3.2.2. For-profit MFIs versus not-for-profit MFIs

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 negative co-movement between their LLP and the business cycle, and that there is no need to require them to adjust their capital positively with the business cycle. This argument is only valid for smaller MFIs as they target a clientele that is very concentrated and that they know well. It may, however, not be true for all types of MFIs, especially for for-profit MFIs. We suspect that for for-profit MFIs whose portfolios are more or less similar to banks, their portfolio risk will look different from other MFIs and correspondingly deteriorate in periods of recession. For this type of MFIs, it may be important to implement a counter-cyclical buffer.

To investigate whether the relationship between the business cycle and provisioning behaviour varies according to MFI profit status, we re-estimate our baseline models after including the cross-product *GDP Growth*Profit status*. We also run separate tests after dividing the MFIs sample into two subgroups based on their profit orientation (for-profit MFIs versus not-for-profit MFIs). We combine NGO MFIs and cooperative and credit union MFIs under the umbrella of not-for-profit MFIs. From the results presented in columns 1, 2 and 3 of Panel A of Table 7 below, we find that the negative co-movement between the business cycle and loan loss provision is mainly driven by the behaviour of profit-oriented microfinance organizations, for which this relationship holds and is significant. This is not the case for the not-for-profit MFIs subgroup. The coefficient of real GDP growth, our main indicator of business cycles, is not significant in this subgroup. The rationale is that profit-oriented MFIs nowadays compete with banks by targeting clients who are also more exposed to economic fluctuations (Baraton & Léon, 2019; Cull et al., 2014; Vanroose & d'Espallier, 2013). Our finding is also in line with Wagner and Winkler (2013), who find microfinance institutions to follow similar cyclical patterns as conventional banks. Their study, however, is on lending behaviour of MFIs during the 2007–2009 financial crisis. Furthermore, we re-run the regressions and interact MFI type (for-profit, NGO, cooperative and credit union) with the business cycle variable (see Table 7, Panel B). It comes out that only for-profit MFIs exhibit a negative co-movement with the business cycle variable. We also run the regressions on the subgroups of not-for-profit MFIs, namely NGO MFIs and cooperatives and credit unions MFIs,

Table 7
Baseline regressions results with decomposition by MFIs profit status and business model.

Panel A: Baseline regression results by MFI subgroup

Variables	Profit orientation			Regulatory status			Deposit-taking status		
	(1) Whole sample	(2) For-profit	(3) Not-for-profit	(4) Whole sample	(5) Regulated	(6) Non-regulated	(7) Whole sample	(8) Deposit-taking	(9) Non-deposit-taking
L.SIZE	0.0010*	0.0010***	0.0001	0.0010*	0.0009**	0.0015*	0.0011**	0.0011***	0.0006
	(0.0005)	(0.0002)	(0.0007)	(0.0005)	(0.0005)	(0.0008)	(0.0005)	(0.0004)	(0.0013)
L.FEMALE	0.0054*	−0.0016	−0.0018	0.0053	0.0056	0.0050	0.0054*	0.0050	0.0101
	(0.0032)	(0.0011)	(0.0055)	(0.0032)	(0.0039)	(0.0073)	(0.0033)	(0.0036)	(0.0105)
L.CAR	−0.0013	0.0053***	−0.0038	−0.0013	0.0005	−0.0050	−0.0016	−0.0025	−0.0002
	(0.0031)	(0.0013)	(0.0038)	(0.0031)	(0.0030)	(0.0050)	(0.0031)	(0.0029)	(0.0062)
L.PAR30	0.0187**	0.0251***	0.0169**	0.0184**	0.0170**	0.0230*	0.0181**	0.0153**	0.0658**
	(0.0090)	(0.0042)	(0.0084)	(0.0091)	(0.0071)	(0.0118)	(0.0091)	(0.0061)	(0.0294)
L.ROA	−0.0004	−0.0085***	0.0021	−0.0002	−0.0052	0.0040	−0.0005	0.0000	−0.0065
	(0.0050)	(0.0024)	(0.0082)	(0.0050)	(0.0079)	(0.0081)	(0.0050)	(0.0060)	(0.0155)
L.DEPTH	−0.0005	−0.0003	−0.0004	−0.0005	−0.0006	0.0035	−0.0005	−0.0007	0.0041*
	(0.0005)	(0.0002)	(0.0018)	(0.0005)	(0.0006)	(0.0024)	(0.0004)	(0.0006)	(0.0022)
L.LO	0.0000	−2.58e-6***	4.62e-7	0.0000	6.80e-7	−3.60e-6	0.0000	−2.76e-7	9.48e-6**
	(0.0000)	(6.14e-7)	(1.18e-6)	(0.0000)	(1.13e-07)	(3.79e-6)	(0.0000)	(1.10e-6)	(4.78e-6)
GDPGrowth		**−0.0481** ***	−0.0114		**−0.0400** ***	0.0004		**−0.0309** ***	−0.0239
		(0.0070)	(0.0118)		(0.0085)	(0.0146)		(0.0080)	(0.0180)
Not-for-profit ×GDPGrowth	−0.0114								
	(0.0111)								
For-profit × GDPGrowth	**−0.0404** ***								
	(0.0122)								
Non-regulated × GDPGrowth				−0.0012					
				(0.0136)					
Regulated × GDPGrowth				**−0.0381** ***					
				(0.0105)					
Non-deposit-taking × GDPGrowth							−0.0206		
							(0.0142)		
Deposit-taking × GDPGrowth							**−0.0349** ***		
							(0.0106)		
Constant	−0.0008	0.0045	0.0176	−0.0013	0.0001	−0.0073	−0.0017	−0.0017	−0.0038
	(0.0099)	(0.0032)	(0.0122)	(0.0098)	(0.0084)	(0.0153)	(0.0099)	(0.0077)	(0.0238)
Number of Obs.	2478	1236	1242	2478	1643	852	2478	2035	460
R^2	0.0258	0.0594	0.0083	0.0264	0.0350	0.0218	0.0242	0.0270	0.0450
Number of MFIs	751	366	388	751	500	255	751	596	159

Panel B: Baseline regressions results by MFI type

Variables	Profit orientation	For-profit MFIs	CU/COOP MFIs	NGO MFIs
L.SIZE	0.0010*	0.0016***	−0.0039***	0.0009
	(0.0005)	(0.0005)	(0.0015)	(0.0008)
L.FEMALE	0.0051	0.0099**	−0.0162	0.0018
	(0.0033)	(0.0046)	(0.0119)	(0.0061)
L.CAR	−0.0010	0.0011	−0.0491***	−0.0015
	(0.0031)	(0.0036)	(0.0173)	(0.0040)
L.PAR30	0.0181**	0.0197**	0.0825**	0.0152*
	(0.0090)	(0.0088)	(0.0324)	(0.0089)
L.ROA	−0.0004	−0.0030	0.1407**	−0.0017
	(0.0054)	(0.0084)	(0.0548)	(0.0085)
L.DEPTH	−0.0006	−0.0006	−0.0015	0.0017
	(0.0004)	(0.0006)	(0.0027)	(0.0023)
L.LO	0.0000	−0.0000	0.0000	−0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GDPGrowth		**−0.0400** ***	0.0135	−0.0160
		(0.0096)	(0.0225)	(0.0136)
MFI type				
For-profit × GDPGrowth	**−0.0410** ***			
	(0.0122)			
CU/COOP × GDPGrowth	0.0049			
	(0.0239)			
NGO × GDPGrowth	−0.0160			
	(0.0132)			
Constant	−0.0012	−0.0123	0.0927***	0.0032
	(0.0100)	(0.0095)	(0.0267)	(0.0141)
Observations	2476	1.250	276	950
R-squared	0.0262	0.0478	0.1158	0.0109
Number of mfiid	746	366	93	284

This table presents the regression model of Eq. 1 with all covariates. Only the fixed effects estimation results are provided. The superiority of the fixed effects is based on the results from the Fisher and Hausman tests. **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 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 *borrowers per loan officer* (LO) measured by the ratio of the number of active borrowers to the number of loan officers; 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 share of the poorest clients among the MFI's clientele. The **macroeconomic variable** is the *real GDP growth* (GDPGrowth). The prefix "L." in front of a variable designates the lag of the variable. Robust standard errors are in parentheses.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 8
First difference regression results of the baseline equation with decomposition by MFIs profit status and business model.

Variables	Profit orientation			Regulatory status		Deposit-taking status	
	(1) Whole sample	(2) For-profit	(3) Non-for-profit	(4) Regulated	(5) Non-regulated	(6) Deposit-taking	(7) Non-deposit-taking
L.SIZE	**0.0028****	0.0021	0.0030	0.0026	0.0027	**0.0035****	−0.0000
	(0.0013)	(0.0017)	(0.0023)	(0.0016)	(0.0025)	(0.0015)	(0.0032)
L.FEMALE	0.0053	**0.0111***	−0.0006	0.0062	−0.0002	0.0043	0.0086
	(0.0043)	(0.0062)	(0.0059)	(0.0048)	(0.0092)	(0.0045)	(0.0118)
L.CAR	0.0003	0.0020	−0.0028	0.0026	−0.0061	−0.0015	0.0028
	(0.0039)	(0.0052)	(0.0061)	(0.0046)	(0.0074)	(0.0045)	(0.0084)
L.PAR30	0.0050	0.0055	0.0053	0.0056	0.0068	0.0053	0.0055
	(0.0064)	(0.0091)	(0.0092)	(0.0076)	(0.0123)	(0.0064)	(0.0346)
L.ROA	0.0077	0.0125	0.0045	0.0158	0.0019	0.0087	0.0002
	(0.0066)	(0.0116)	(0.0081)	(0.0102)	(0.0088)	(0.0072)	(0.0179)
L.DEPTH	0.0001	−0.0001	−0.0012	0.0000	0.0007	−0.0001	0.0013
	(0.0007)	(0.0008)	(0.0022)	(0.0008)	(0.0023)	(0.0007)	(0.0024)
L.LO	8.14e-7	8.60e-7	1.61e-7	8.51e-7	1.09e-7	7.52e-7	9.79e-7
	(1.01e-6)	(1.06e-6)	(3.18e-6)	(1.05e-6)	(4.03e-6)	(1.00e-6)	(6.51e-6)
GDPGrowth	**−0.0253*****	**−0.0430*****	−0.0023	**−0.0355*****	0.0029	**−0.0331*****	0.0053
	(0.0071)	(0.0096)	(0.0107)	(0.0083)	(0.0134)	(0.0077)	(0.0179)
Constant	−0.0003	0.0003	−0.0007	−0.0001	−0.0005	−0.0005	0.0007
	(0.0005)	(0.0007)	(0.0007)	(0.0006)	(0.0008)	(0.0005)	(0.0012)
No. of Obs.	1557	775	773	1015	542	1.292	265
R^2	0.0165	0.0399	0.0053	0.0300	0.0054	0.0266	0.0045
No. of MFIs	516	266	380	334	182	596	159

This table presents the model of Eq. 1 with all covariates. Only the fixed effects estimation results are provided. The superiority of the fixed effects is based on the results from the Fisher and Hausman tests. **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 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 *borrowers per loan officer* (LO) measured by the ratio of the number of active borrowers to the number of loan officers; 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 share of the poorest clients among the MFI's clientele. **The macroeconomic variable** is the *real GDP growth* (GDPGrowth). The prefix "L." in front of a variable designates the lag of the variable. Robust standard errors are in parentheses.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

separately. The results given in Panel B of Table 7 show non-significant coefficients for the business cycle indicator as in the case of not-for-profit MFIs as a whole.

Moreover, in all the regressions, we find a significant positive relationship between MFIs' portfolio at risk (PAR30) and their LLP level, consistent with the finding of the full sample above. We also find confirmation of the positive relationship between loan loss provisioning and the size of for-profit MFIs. This can be contrasted with cooperatives and credit union MFIs, whose LLP is negatively related to their size and capital ratio. The fact that cooperative and credit union MFIs with higher capital-to-asset ratios hold less LLP, this may suggest that cooperative and credit unions use loan loss provisions to manage capital.

3.2.3. MFIs business model effect

Within the microfinance industry, MFIs apply different business models to deliver the microfinance promise. Some MFIs gather deposits while other do not. Deposit-taking MFIs are bank-like MFIs, and therefore may be under regulatory pressure. According to the banking literature (e.g., Drehmann et al., 2011; Murcia & Kohlscheen, 2016; Schularick & Taylor, 2012), the pro-cyclical behaviour of provisions may be due to regulatory pressure. It is expected that they adopt a prudential loan loss provisioning behaviour. We thus assess whether deposit-taking and regulated MFIs' loan loss provisions behaviour during the boom-and-bust cycles follow similar patterns to that of the conventional banking sector. To test whether regulation can partly explain our findings, we conduct further analyses by including the cross-products *GDP Growth*Regulatory status* and *GDP Growth*Deposit-taking status* in our baseline model. We then divided the sample into regulated MFIs (those that are subject to prudential regulation) and non-regulated MFIs and re-estimate our baseline models using those sub-samples. The results are presented in columns 4, 5 and 6 of Panel A of Table 7. As in the cases of the full sample and the subgroup of for-profit MFIs, regulated MFIs' loan loss provisions co-move negatively with the business cycle indicator. This is consistent with our premise that regulated MFIs are more likely to be large profit-oriented MFIs, subject to stringent or similar regulation like banks in some countries. We also find that size and portfolio-at-risk are positively correlated with LLP. We also distinguish between deposit-taking MFIs and non-deposit-taking ones. Our main motivation being that deposit-taking institutions are more likely to be regulated. Our results provided in columns 7, 8 and 9 of Panel A of Table 7 suggest that only deposit-taking MFIs have an LLP that varies negatively with the business cycle.

Table 9
Dynamic panel estimation results of the LLP.

Variables	Profit orientation			Deposit-taking status		Regulatory status		Regressions for control	
	(1) Whole sample	(2) For-profit	(3) Not-for-profit	(4) Deposit-taking	(5) Non-deposit-taking	(6) Regulated	(7) Non-regulated	(8) FE	(9) OLS
L.LLP	**0.1849****	**0.2066****	**0.3009****	**0.2954****	**0.2274****	**0.2155****	**0.3023****	**0.1035****	**0.4839****
	(0.0648)	(0.0447)	(0.0566)	(0.0406)	(0.0649)	(0.0443)	(0.0709)	(0.0237)	(0.0173)
L.SIZE	0.0003	**0.0009****	0.0003	**0.0008****	0.0002	**0.0006****	**0.0014****	**0.0011****	**0.0007****
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0006)	(0.0003)	(0.0006)	(0.0004)	(0.0001)
L.FEMALE	−0.0004	−0.0006	0.0003	−0.0002	−0.0013	−0.0020	0.0041	0.0056	−0.0001
	(0.0016)	(0.0018)	(0.0019)	(0.0014)	(0.0039)	(0.0016)	(0.0029)	(0.0034)	(0.0010)
L.CAR	−0.0006	0.0044	−0.0038	0.0051	−0.0070	0.0046	−0.0003	−0.0013	**0.0038****
	(0.0055)	(0.0046)	(0.0050)	(0.0036)	(0.0051)	(0.0034)	(0.0053)	(0.0026)	(0.0011)
L.PAR30	−0.0079	0.0101	0.0096	0.0043	0.0356	0.0112	0.0214	**0.0131****	**0.0087****
	(0.0099)	(0.0133)	(0.0128)	(0.0103)	(0.0321)	(0.0122)	(0.0131)	(0.0061)	(0.0037)
L.ROA	0.0202	0.0107	0.0063	−0.0025	0.0140	0.0112	−0.0117	0.0024	−0.0030
	(0.0162)	(0.0073)	(0.0145)	(0.0034)	(0.0121)	(0.0083)	(0.0112)	(0.0056)	(0.0021)
L.DEPTH	**0.0006****	0.0001	0.0006	**0.0003***	0.0006	0.0003	**0.0015****	−0.0003	−0.0000
	(0.0002)	(0.0002)	(0.0008)	(0.0002)	(0.0007)	(0.0002)	(0.0005)	(0.0005)	(0.0002)
L.LO	−6.10e-6	−2.55e-6	−9.79e-6	−1.40e-7	−1.11e-6	−4.19e-7	−1.05e-5	−3.99e-7	−1.22e-6
	2.71e-6	3.25e-6	4.06e-6	3.57e-7	3.10e-6	4.38e-7	3.72e-6	1.08e-6	5.37e-7
GDPGrowth	**−0.0649****	**−0.0608****	0.0101	**−0.0582****	−0.0075	**−0.0523****	−0.0027	**−0.0281****	**−0.0339****
	(0.0180)	(0.0154)	(0.0246)	(0.0162)	(0.0248)	(0.0133)	(0.0257)	(0.0073)	(0.0061)
Constant	0.0148*	0.0027	0.0110	0.0012	0.0127	0.0063	−0.0098	−0.0039	−0.0017
	(0.0077)	(0.0070)	(0.0078)	(0.0055)	(0.0102)	(0.0054)	(0.0114)	(0.0073)	(0.0028)
Number of Obs.	2493	1250	1243	2033	460	1642	851	2493	2493
AR(1) test	0.000	0.000	0.000	0.000	0.002	0.000	0.000		
AR(2) test	0.004	0.182	0.009	0.066	0.071	0.117	0.009		
AR(3) test	0.752	0.238	0.920	0.425	0.072	0.306	0.949		
Hansen J test	0.173	0.586	0.712	0.135	0.999	0.276	0.999		
R^2								0.285	0.103
Number of MFIs	754	366	388	595	159	499	255	754	754

This table presents the dynamic panel adjustment estimates of the LLP using the Arellano and Bond (1998) two-step GMM estimator. The last two columns with FE and OLS refer, respectively, to fixed effects and pooled OLS estimates. ***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 ratio* (CAR) measured by the equity-to-assets ratio; the *portfolio at risk at 30 days* (PAR30) which is the share of the portfolio with outstanding payments; the *return on assets* (ROA) which is the profitability measure; 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. The *real GDP growth* (GDPGrowth) is used as the **macroeconomic variable**. The prefix "L." in front of a variable designates the lag of the variable. Robust standard errors are in parentheses.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

3.3. Robustness checks[7]

3.3.1. First difference regression

The fixed effects estimators, used above as our first best estimation method, would give unbiased coefficients if the assumption of strict exogeneity of MFIs characteristics holds. Our main variable of interest that is the economic cycle is less likely to be affected by MFIs provisioning since MFIs are barely dominant players that can influence the business cycle. There is however some risk that other covariates related to MFIs characteristics, even taken in lags have important correlation with the contemporaneous errors since there are function of unobservable fixed effect contained in the residual. To address this issue, we estimate our baseline model in difference form instead. By comparing fixed effects estimation results and the first difference estimates, we implicitly test whether this strict exogeneity assumption holds in our case. The previous results are confirmed by the estimation results given in Table 8, i.e. negative relationships between MFIs' LLP and the business cycle mainly observed among the for-profit MFIs, regulated MFIs and deposit-taking MFIs subsamples.

3.3.2. Dynamic panel estimation

In our baseline regressions, we exclude the lag of the LLP as a potential right-hand side variable as some previous studies in the banking sector have done (e.g., Bikker & Metzemakers, 2005). However, to analyze the determinants of loan loss provisioning in the banking sector, some other studies specify a dynamic adjustment framework model for at least two reasons: first, to capture the speed of adjustment of loan loss provisions by assuming that banks progressively adjust their level of provisions toward a target level of provisions; and second, to account for the time dependency of provisions (Bouvatier et al., 2014; Bouvatier & Lepetit, 2012; Caporale et al., 2018; Laeven & Majnoni, 2003). However, no such evidence exists in the microfinance literature. Our study relies on a large international sample of MFIs, and there is no clear evidence that the time dependency of provisions materializes, and even when it exists, it is less likely to be consistent across MFIs and across countries. In addition, due to the non-availability of quarterly data, we use annual data, which does not allow us to capture the dynamic and the speed of adjustment over quarters. In practice, some MFIs proceed to a yearly adjustment of their provisions. Examples of MFIs practicing this

[7] We supplement these robustness checks with further robustness analyses, which results are reported in the Online Appendix. We first include loan loss reserve (LLR) in our baseline model (Online Appendix Table 1A). We then estimate a model in which we simultaneously include GDP growth and credit-to-GDP (Online Appendix Table 2A). The results reported in the Online Appendix tables show that the inclusion of additional control variables does not change our story.

yearly provisioning adjustment behaviour are Advans Yaoundé Cameroon and PAMECAS in Senegal.[8]

In absence of a clear theory on the MFIs' LLP practice, we rely on the correlation structure of the LLP time series to identify potential persistence. The correlation between LLP and its lag is 50%, an indication of possible persistence in loan loss provisioning. To account for potential persistence in the LLP formation, we further investigate the provisioning behaviour of MFIs in a dynamic framework. For that, we model MFIs' loan loss provisioning in a dynamic partial adjustment framework. In particular, 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 postpone some of their expenses' adjustment to their LLP. Following the banking literature on partial adjustment (see for instance: Bouvatier et al., 2014; Guidara, Lai, Soumaré, & Tchana, 2013; Hessou & Lai, 2017, 2018; Jacques & Nigro, 1997; Kanga, Murinde, & Soumaré, 2020; Shrieves & Dahl, 1992; among many others), this dynamic adjustment behaviour is described as follows:

$$\Delta \mathrm{LLP}_{\mathrm{it}} = \lambda \left(\mathrm{LLP}^{*}_{\mathrm{it}} - \mathrm{LLP}_{\mathrm{it-1}}\right) + \eta_{\mathrm{it}}, \tag{2}$$

where i indexes MFIs, and t indexes year. Eq. (2) reads as follows: Each year, MFIs adjust a proportion λ of the difference between their *desired* (or long-term) loan loss provision level LLP_{it}^* and their actual loan loss provision LLP_{it-1}. We assume that the long-term target LLP_{it}^* is a function of MFIs' characteristics (both aggregate and idiosyncratic factors) and external factors, and is expressed as follows:

$$\mathrm{LLP}^{*}_{\mathrm{it}} = \alpha_0 + \beta^{*} X_{\mathrm{it-1}} + \gamma^{*} W_{\mathrm{jt}}, \tag{3}$$

where α_0 is a constant, β^* and γ^* are vectors of coefficients of the control variables X and W. i indexes MFIs, j indexes countries and t indexes years. X_{it-1} is a vector of MFI-level variables which include *MFI size*, the percentage of *female borrowers,* MFI loan portfolio quality or risk (PAR30), the depth of outreach (DEPTH), MFI financial performance (ROA), loan monitoring (LO) and MFI capital ratio (CAR). W_{jt} is a vector of country-level non-discretionary components and includes the growth rates of both real GDP and credit-to-GDP ratios. Plugging (3) into (2) yields:

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

where η_{it} is the idiosyncratic error. One may argue that partial adjustment does not apply to microfinance institutions in general since they are not bound by regulation as banks are, and therefore there is no need for MFIs to partially adjust their provisions toward a given target. Nevertheless, eq. (4) can still hold if we observe persistence in the provisioning data, which seems to be the case based on the graphical analysis and the descriptive statistics.

To estimate eq. (4), we apply the generalized method of moments (GMM) estimator developed for dynamic panel data by Arellano and Bond (1991), extended by Arellano and Bover (1995) and Blundell and Bond (1998) and implemented using Roodman's (2009) procedure. The method is suitable for the structure of our dataset which has a large N (1474 MFIs) and small T (14-year period).[9] Under the system-GMM approach, we can address many forms of endogeneity using deeper lags of the endogenous variable and the exogenous variables. As is typical, the lag of the dependent variable (L.LLP) is assumed endogenous in the difference system-GMM framework. In addition to the lag of the LLP, other variables such as PAR30, DEPTH, ROA, LO and CAR are also likely endogenous. Therefore, as suggested by Roodman (2009), we instrument them with deeper lags of the exogenous and endogenous variables. We collapse instruments to limit the number of instruments that have to be included. We provide the number of instruments used in each regression. The Hansen test is used to validate the instruments. Since the small size of our sample is likely to affect the strength of the standard error estimation, we implement and report the robust Windmeijer's (2005) bias-corrected standard deviation in our tables.

Note that the fixed effects and the OLS estimates of eq. (4) provide mutually consistent intervals for the true value of λ.[10] In fact, the estimation of λ via fixed effects 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 effects estimations to be valid.

Table 9 presents the regression results of our system-GMM. The main results confirm our previous finding regarding the negative comovement between LLP and the real GDP growth. While the results confirm our priors, the regression on the whole sample failed the AR (2) test. Therefore, we use longer lags of the endogenous variables as instruments. More importantly, the Hansen J test confirms that our instruments are valid and robust (p-value greater than 10%). 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 81.7%. This finding is supported by the high correlation reported in the correlation table (Table 5), where we report a 50% positive correlation between previous year's LLP and current LLP, an indication of persistence in LLP. The value of λ lies between the OLS and the fixed effects estimates (see first line of Table 9, columns 1, 8 and 9).

All our main previous findings are confirmed. In particular, the negative relation between the LLP and the macroeconomic performance is confirmed both for the whole sample and in the subsamples of profit-oriented MFIs, regulated MFIs and deposit-taking MFIs. For non-regulated MFIs, not-for-profit MFIs and non-deposit-taking MFIs, the relationship is not significant.

3.3.3. System of equations regression

Using eq. (1) as we did above may raise some criticisms as to whether the simultaneity between the LLP and the other covariates (namely: outreach; risk; profitability; monitoring and capital) could affect the main finding regarding the significance of the business cycle variable. This might be justified since, in a joint estimation, the variance-covariance matrix depends on the structure of error of the other equations in the system. Eq. (1) is therefore estimated via a seemingly unrelated regression (SUREG) model (see Zellner, 1962, 1963 and Zellner & Huang, 1962) based on a Feasible Generalized Least Squares approach. The SUREG iterates over the estimated disturbance covariance matrix of the joint system and parameter estimates until the parameter estimates converge.[11] Therefore, LLP is determined as part of a system of equations, specified as follows:

[8] We thank Gafe Bobda Appolin (former CEO of Advans Yaoundé Cameroon) and Abdoulaye Wane (Chief Compliance Officer at PAMECAS Senegal) for sharing with us insights on the provisioning practices of these two institutions.

[9] Many MFIs have limited data, i.e. 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.

[10] Following the existing literature (see Lemmon, Roberts, & Zender, 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).

[11] See Stata manual on the subject at: https://www.stata.com/manuals13/rsureg.pdf

Table 10
The system of equations approach (SUREG) estimation results.

Variables	Static structural model with the lags of the endogenous covariates					
	(1) LLP	(2) CAR	(3) PAR30	(4) ROA	(5) DEPTH	(6) LO
L.LLP		**0.7747*****	**0.2846****	**−0.4427*****	**−3.3682****	**−564.2637****
		(0.2817)	(0.1412)	(0.1238)	(1.3338)	(268.7613)
L.CAR	**0.0053*****		**−0.0347*****	**0.0781*****	**−0.1529***	−29.9842
	(0.0014)		(0.0097)	(0.0084)	(0.0906)	(18.2945)
L.PAR30	**0.0217*****	**−0.1311****		−0.0147	0.2895	−72.3175
	(0.0042)	(0.0595)		(0.0263)	(0.2825)	(56.9489)
L.ROA	**−0.0072*****	**0.2977*****	0.0137		**−0.2893***	37.4303
	(0.0025)	(0.0341)	(0.0174)		(0.1626)	(32.8426)
L.DEPTH	**−0.0004***	**−0.0071****	0.0004	**−0.0034****		**−7.7596****
	(0.0002)	(0.0033)	(0.0017)	(0.0015)		(3.1493)
L.LO	**−0.0000*****	0.0000	**0.0000*****	0.0000	**−0.0002*****	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
GDPGrowth	**−0.0502*****	−0.0992	**−0.1349*****	0.0108	**1.7991*****	139.0315
	(0.0073)	(0.1015)	(0.0515)	(0.0448)	(0.4796)	(97.0859)
L.SIZE	**0.0010*****	**−0.0392*****	−0.0010	**0.0086*****	**0.0680*****	**9.6649*****
	(0.0002)	(0.0024)	(0.0013)	(0.0011)	(0.0121)	(2.4442)
L.FEMALE	**−0.0026****	**−0.0692*****	**−0.0276*****	0.0019	**−1.2187*****	**93.3466*****
	(0.0012)	(0.0167)	(0.0085)	(0.0074)	(0.0766)	(16.0517)
Constant	0.0053	0.9629***	0.0848***	−0.1279***	0.3566	−20.3263
	(0.0035)	(0.0441)	(0.0244)	(0.0212)	(0.2295)	(46.3517)
Control for MFI type	Yes	Yes	Yes	Yes	Yes	Yes
No. Of Obs.	2374	2374	2374	2374	2374	2374
R^2	0.0612	0.1341	0.0173	0.0336	0.1659	0.5532

This table presents the outcome of the system of equations approach (SUREG). **The dependent variable** of interest is the *loan loss provision ratio* (LLP) measured as a percentage of the outstanding loan portfolio. The result for this variable is given in columns 1. **MFI-level variables** include: the *Size* measured by the natural logarithm of the book value of assets; the *capital 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 *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. The **macroeconomic variable** is the real GDP growth (GDPGrowth). The prefix "L." in front of a variable designates the lag of the variable. Robust standard errors are in parentheses.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

$$\boldsymbol{Y}_{it} = A_0 + A_1 \boldsymbol{Y}_{it-1} + BX_{it-1} + CW_{jt} + \boldsymbol{\delta}_i + \boldsymbol{\varepsilon}_{it}, \quad (5)$$

where **Y** is a 6 × 1 vector of loan loss provisions (LLP), MFI capital ratio (CAR), MFI loan portfolio quality or risk (PAR30), MFI depth of outreach (DEPTH), MFI financial performance (ROA) and MFI loan monitoring (LO). A_0 is a vector of constant. A_1 is a 6 × 6 matrix with zero on its diagonal. B and C are matrixes with values of the coefficients of the control variables *X* and *W*. i indexes MFIs, j indexes countries, and t indexes years. X_{it-1} is a vector of other MFI-level variables which include *MFI size* and the percentage of *female borrowers* and lags of the dependant variables of other equations of the system. W_{jt} is a vector of country-level non-discretionary components and includes the growth rate of real GDP. δ_i is the MFI's individual unobserved effect. We assume that the error term vector ε_{it} covariance matrix is non-diagonal suggesting that shocks to LLP are likely related to shocks in other equations of the system. The estimation results reported in Table 10 confirm our main findings, i.e. negative co-movement between growth of real GDP and LLP for the whole sample.

3.3.4. Credit-to-GDP as alternative proxy for business cycles

As discussed above in the variables' description sub-section, *credit-to-GDP* has been suggested as a warning signal for credit build-up in the economy. This variable can be used to proxy business cycle as well. For this reason, we run our regressions using this indicator instead of the real GDP growth. The regression results are presented in Table 11. As in the GDP growth case, we focus on the fixed effects regressions. The results confirm our finding that the business cycle, proxied by *credit-to-GDP*, is negatively associated with MFIs LLP.

4. Conclusion and policy implications

The current debate on macroprudential regulation for financial stability is more directed toward banks, and less attention is being paid to microfinance institutions. Provisions for credit losses constitute one important tool to protect MFIs 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 provisions, and if those provisions are made in consideration of macroeconomic and idiosyncratic business risks. For that purpose, we use an international sample of MFIs from the MIX database over 2001–2014, and uncover a negative relationship between MFIs' provisioning and the business cycle. In other words, MFIs accumulate less provisions during periods of economic booms to be potentially used to sustain their lending activities during recessions. This provisioning behaviour mainly concerns bank-like and deposit-taking/regulated MFIs. 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 provisions are positively correlated with the portfolio quality.

While our main results are robust across a series of regression methods, we are aware that none of our identification strategies fully control for potential sample selection or endogeneity biases, mainly due to the absence of valid external instruments in our dataset. We therefore stress that our results should be interpreted with caution. The subject of our study, however, is crucial, as it will contribute to the debate on how to design appropriate macro-prudential regulation for all segments of the financial system, in particular regulations targeting microfinance institutions, without altering their double-bottom-line orientation. Accordingly, we encourage further research on loan provisioning

Table 11
Regression results with *Credit-to-GDP* as the business cycle indicator.

Variables	Full sample	Profit orientation		Regulatory status		Deposit-taking status	
	Full sample	(1) For-profit	(2) Not-for-profit	(3) Regulated	(4) Non-regulated	(5) Deposit-taking	(6) Non-deposit-taking
L.SIZE	**0.0012*****	**0.0019*****	0.0001	**0.0011****	**0.0015***	**0.0012*****	0.0007
	(0.0004)	(0.0005)	(0.0007)	(0.0005)	(0.0008)	(0.0004)	(0.0013)
L.FEMALE	0.0050	**0.0099****	−0.0013	0.0056	0.0058	0.0048	0.0096
	(0.0035)	(0.0046)	(0.0054)	(0.0040)	(0.0075)	(0.0037)	(0.0105)
L.CAR	−0.0018	−0.0004	−0.0044	−0.0006	−0.0050	−0.0030	−0.0009
	(0.0026)	(0.0036)	(0.0037)	(0.0031)	(0.0050)	(0.0029)	(0.0062)
L.PAR30	**0.0174*****	**0.0178****	**0.0178****	**0.0163****	**0.0228***	**0.0152****	**0.0650****
	(0.0061)	(0.0089)	(0.0084)	(0.0072)	(0.0118)	(0.0062)	(0.0295)
L.ROA	0.0004	−0.0028	0.0028	−0.0048	0.0059	0.0010	−0.0050
	(0.0059)	(0.0086)	(0.0081)	(0.0081)	(0.0086)	(0.0063)	(0.0156)
L.DEPTH	−0.0005	−0.0007	0.0006	−0.0007	0.0033	−0.0008	**0.0039***
	(0.0006)	(0.0006)	(0.0015)	(0.0006)	(0.0025)	(0.0006)	(0.0022)
L.LO	2.19e−7	-7.54e-7	4.20e-7	6.25e-7	−3.80e-7	−3.02e-7	**9.22e-6***
	(1.09e-6)	(2.85e-6)	(1.18e-6)	(1.14e-6)	(3.79e-6)	(1.11e-6)	(4.76e-6)
CGDPG	**−0.0056****	−0.0038	**−0.0087****	**−0.0054***	−0.0068	**−0.0057****	−0.0053
	(0.0025)	(0.0030)	(0.0044)	(0.0028)	(0.0053)	(0.0028)	(0.0054)
Constant	−0.0049	−0.0186*	0.0173	−0.0044	−0.0088	−0.0048	−0.0045
	(0.0074)	(0.0096)	(0.0121)	(0.0085)	(0.0155)	(0.0078)	(0.0239)
Number of Obs.	2.482	1.241	1241	1.633	849	2022	460
R^2	0.0178	0.0314	0.0125	0.0195	0.0250	0.0200	0.0424
Number of MFIs	751	366	386	498	253	592	159

This table presents the regression model of Eq. 1 with all covariates. Only the fixed effects estimation results are provided. The superiority of the fixed effects is based on the results from the Fisher and Hausman tests. **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 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 *borrowers per loan officer* (LO) measured by the ratio of the number of active borrowers to the number of loan officers; 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 share of the poorest clients among the MFI's clientele. The **macroeconomic variable** is the *credit-to-GDP growth* (CGDPG). The prefix "L." in front of a variable designates the lag of the variable. Robust standard errors are in parentheses.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

practices of MFIs, possibly with newly available richer data sets that enable to resolve some of the problems we are unable to avoid with presently available data.

Authors' contributions

All authors have contributed equally to: Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Software; Supervision; Validation; Visualization; Writing - original draft; Writing - review & editing.

Appendix A. 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 B. 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

(*continued on next page*)

(*continued*)

Country	Nb. obs.	Percent
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

(*continued on next page*)

(*continued*)

Country	Nb. obs.	Percent
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	6148	100

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