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**Article — Accepted Manuscript (Postprint)**

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Journal of Banking & Finance

*Suggested Citation:* Zamore, Stephen; Beisland, Leif Atle; Mersland, Roy (2019) : Geographic diversification and credit risk in microfinance, Journal of Banking & Finance, ISSN 1872-6372, Elsevier, Amsterdam, Vol. 109, pp. 1-13, <https://doi.org/10.1016/j.jbankfin.2019.105665>

This Version is available at:

<https://hdl.handle.net/10419/323833>

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Published in Journal of Banking and Finance. Vol. 109. December 2019, 105665.

<https://doi.org/10.1016/j.jbankfin.2019.105665>

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## **Geographic Diversification and Credit Risk in Microfinance**

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### **Abstract**

This paper examines the relation between geographic diversification and credit risk in microfinance. The empirical findings from the banking industry are mixed and inconclusive. This study extends the discussion into a new international setting: the global microfinance industry with lenders having both social and financial objectives. Using a large global sample of microfinance institutions (MFIs), we find that geographic diversification comes with more credit risks. However, this finding is more pronounced among non-shareholder MFIs like NGOs and cooperatives, compared to shareholder-owned MFIs. Moreover, the results show that MFIs can mitigate the effect of geographic diversification on risk with group lending methodology.

*Keywords:* microfinance, geographic diversification, credit risk, portfolio at risk, loan-loss provisions, nonperforming loans.

*JEL:* G21, G23, G24, L31, O16

## **1. Introduction**

This study examines the relationship between geographic diversification and credit risk in microfinance institutions (MFIs). The long-standing question of whether financial institutions and banks should diversify their operations has yet to be answered clearly. There is a growing body of scholarly literature on whether geographic diversification (or “diversification” for short) increases or decreases bank risk, but there is no consensus to date in the banking industry. Despite the importance of the debate, it appears that the issue has never been tested in the microfinance industry. This is unfortunate because industry insiders often recommend that MFIs diversify geographically as a means of reducing loan portfolio risk (Steinwand 2000). For example, in reports from specialized external microfinance rating agencies, the source of data used in this study, it is frequently recommended that MFIs should diversify geographically as a means of reducing risk. Moreover, the findings from the banking industry may or may not be applicable to the microfinance industry since MFIs are different from commercial banks.

First, MFIs pursue the double bottom-line objectives of financial sustainability and social outreach and hence differ from commercial banks. Credit risk and diversification potentially affect both financial performance and MFIs’ ability to fulfil their social objective of reaching out to more low-income customers. Second, MFIs’ customers (low-income people and microenterprises) are normally excluded by traditional commercial banks because they are considered risky (due to factors like where they live and what they do), yet such customers are the focus of MFIs. Third, the loans MFIs give to their customers are smaller and without collateral security while commercial banks’ loans are larger and collateralized. Fourth, most MFIs (e.g., 62 percent of MFIs in our sample) are non-shareholder organizations (NGOs and cooperatives/credit unions) (Misra and Lee 2007) which compared to shareholder owned organizations have slacker governance and allow more risk-taking by CEOs (Galema, Lensink, and Mersland 2012).

Increasingly, MFIs face banking regulation and oversight, similar to mainstream banks (Ledgerwood 1999). Such regulation and supervision may create incentives for either diversification or specialization (Acharya, Hasan, and Saunders 2006, Hayden, Porath, and Westernhagen 2007, Berger, Hasan, and Zhou 2010). Thus, the present study is of potential interest to policymakers who are concerned whether diversification is beneficial to financial institutions such as MFIs (Bandelj 2016).

Credit risk can also be related to the recent criticism of the microfinance industry for its high interest rates and heavy-handed collection methods (Bateman 2010). A particularly dramatic incident was the suicide crisis that occurred in India in 2010 (Bandyopadhyay and Shankar 2014). This suicide crisis was attributed to the heavy-handed collection of defaulted microcredit and showed that a good credit risk strategy is fundamental for MFI managers. Thus, the present study is of potential interest also to microfinance practitioners and stakeholders, particularly managers, donors, investors, and regulators.

Although there are empirical studies on the effect of diversification on bank risk, scholars have yet to arrive at a consensus (Bandelj 2016). Empirical findings consistent with modern portfolio theory suggest that banks should diversify across regions to eliminate region-specific credit risk and thereby reduce their overall risk level. For instance, Fang and Lelyveld (2014) find that international diversification is beneficial to banks because their credit risk level is reduced. Similarly, following the introduction of the US Riegle–Neal Act of 1994, banks that expanded beyond their home states benefited from a reduction in credit risk (Akhigbea and Whyte 2003) and deposit risk (Aguirregabiria, Clark, and Wang 2016). Deng and Elyasiani (2008) also find that diversification is associated with a reduction in bank risk. Their findings suggest that banks can increase their customer portfolios through diversification to reduce bank failure.

By contrast, studies based on agency theory suggest that banks should avoid diversification because it is difficult to monitor remote operations. As a result of poor monitoring, branch managers of banks may pursue their personal goals at the expense of the bank's goals (Goetz, Laeven, and Levine 2012, Bandelj 2016). Moreover, diversification increases the complexity of bank operations, thereby making it difficult for headquarters to monitor loans and control risk (Acharya, Hasan, and Saunders 2006, Winton 1999). Gulamhussen, Pinheiro, and Pozzolo (2014) find that, contrary to the above-mentioned results of Fang and Lelyveld (2014), international diversification increases bank risk.

To date, scholars have paid little attention to the issue of diversification versus focus (i.e., non-diversification) in the rapidly growing microfinance industry. This lack of research is unfortunate in a banking industry where, for instance, MFIs provided a total of US\$102 billion in loans to 132 million poor borrowers worldwide in 2016 (Convergences 2017). Our novel research applies a sample of 657 MFIs in 88 countries over the period 1998–2015 to provide initial international evidence on the issue of diversification in the microfinance industry.

The findings suggest that diversification and credit risk are positively related: geographic diversification comes with more credit risks. The higher risk can be attributed to the difficulty of monitoring remote operations. It can also be attributed to the fact that institutions tend to expand into similar economic areas (e.g., rural areas) with the same underlying systematic factors and therefore gain few diversification benefits. For these reasons, the net effect of geographic diversification in microfinance is higher credit risk.

The results further show that the positive relation is more pronounced among MFIs without owners (i.e., non-governmental organizations (NGOs) and member-based cooperatives) compared to shareholder-owned MFIs (i.e., banks and non-bank financial institutions). Because shareholder entities in general are expected to have governance structures superior to those of non-shareholder entities (Hansmann 1996), this finding strengthens the claim that the

increased risk is driven primarily by monitoring challenges. In line with this monitoring argument, the results further indicate that the positive effect of diversification on risk can be mitigated by practicing group lending rather than individual lending. Overall, the findings should encourage further research and guide microfinance practitioners and policymakers about which type of MFI might potentially benefit from diversification.

The rest of the paper is organized as follows. Section 2 presents the theory and reviews the literature. Section 3 describes the data and variables. Section 4 describes the econometric model. Section 5 presents and discusses the empirical findings, and Section 6 concludes.

## **2. Theory and Related Literature**

### *2.1 Theory of risk diversification*

MFIs, like other financial institutions, are exposed to different types of risk, including credit, interest rate, market, currency, liquidity, operational, and country risks. Among these risks, credit risk is typically the most important for MFIs because their main service is the provision of microcredit (Armendáriz and Morduch 2010). Saunders and Cornett (2011, 186) define credit risk as the “risk that the promised cash flows from loans and securities held by financial institutions may not be paid in full.” Credit risk has great implications for the survival of banks. This was dramatically illustrated by the global financial crisis. Thus, credit risk causes bank failure (Fang and Lelyveld 2014), and MFIs are not immune to its effects because microfinance is simply banking in small quantities. Moreover, credit risk in microfinance is normally higher than that in regular banking because of the shorter repayment periods that are typically around 12 months. Hence, MFIs may face serious problems within a few weeks if loan repayments are delayed. Moreover, repayment problems among a few microfinance clients may rapidly spread to many clients (Bond and Rai 2009). This may lead to serious problems for the MFIs as well as the overall microfinance sector in a country. For instance, between 1996 and 2000, Bolivian

MFIs faced many repayment problems, which precipitated an economic crisis (Vogelgesang 2003).

Diversification in finance involves holding many different investments to reduce the risk of financial loss. The concept of diversification is fundamental to the portfolio theory developed by Markowitz (1952). The theory assumes imperfect correlations between asset returns. This allows for lower portfolio risk compared to the sum of individual investment risks. Through diversification, a bank can reduce default risk on the loan portfolio without decreasing the expected returns (Emmons, Gilbert, and Yeager 2004). Geographic diversification is one type of diversification where a bank's activities are dispersed in different locations (within/across cities, regions, and countries).

Therefore, drawing on portfolio theory, MFIs can potentially reduce risk by geographic diversification. Specifically, the diversification strategy can limit MFIs' likelihood of insolvency by reducing credit and liquidity risk (Liang and Rhoades 1988). Applying portfolio theory to the credit risk of MFIs, one can assume that this type of risk is reduced when loans are spread among many borrowers in different geographic locations. The logic of this line of reasoning is straightforward: a farming-related crisis such as a drought might be limited to a specific geographic area, a factory closure might hit borrowers in a certain locale, a natural disaster might befall cities and villages in a limited region, and so on. With regard to liquidity risk, diversification can be particularly important for deposit-taking MFIs because it reduces the standard deviation of deposit flows (Liang and Rhoades 1988).

Agency theory, by contrast, suggests that diversification may not be beneficial to a firm because managers may have improved opportunities to extract private benefits at the expense of owners' value (Goetz, Laeven, and Levine 2016). More diversified entities are potentially more complex than other entities, which can reduce monitoring effectiveness. Empire building by managers is one possible consequence of reduced monitoring (Jensen 1986). Effective

monitoring may be particularly challenging in non-governmental organizations (NGOs) because these organizations do not have owners with pecuniary incentives (Hansmann 1996). Many MFIs are incorporated as NGOs or cooperatives, thus potentially making the predictions of agency theory more relevant in microfinance than in traditional banking.

If we disentangle the discussion from both portfolio theory and agency theory and apply a more practical lens to the issue, we are left with little doubt that the increased complexity diversification brings can pose a challenge to MFIs. For instance, according to Winton (1999), diversification complicates client monitoring. Thus, diversification can lead to an increase in MFIs' credit risk due to an inability to monitor multiple branches and distant borrowers.

## *2.2 Institutional background of MFIs*

Microfinance institutions are hybrid organizations with two competing logics, namely, social and financial logics (Battilana and Dorado 2010). The first logic relates to the provision of financial services to the unbanked populations in the world. MFIs aim at providing uncollateralized microcredit to economically poor people, who have little or no collateral to qualify for loans from commercial banks. Social logic refers to the social outreach goal of MFIs.

The second logic concerns the financial sustainability of the MFIs themselves. Thus, in providing financial services to poor people and microenterprises, the institutions aim to be profitable or at least break even. To achieve this goal, MFIs charge interest on microcredit and fees for other financial services much as commercial banks do. Hence, MFIs follow a financial logic. Morduch (1999) describes this combination of social and financial logics as the “win-win “promise” of microfinance.

MFIs are normally registered either as shareholder firms (banks and non-bank financial institutions) or as non-profit organizations (cooperatives and non-governmental organizations



or NGOs) (Mersland 2009). Cooperatives (and so-called “credit unions,” which are similar to cooperatives) are member-based organizations and are therefore funded by the members. That is, cooperatives are controlled by the members, who are at once the customers and the recipients of any profits generated from the operations of the organization. NGOs are organizations without legally recognized owners (Mersland 2009). They are mostly financed by international impact investors as well as benevolent donors like the World Bank, the Inter-American Development Bank, government agencies, and private individuals. Since NGOs do not have owners, they are exposed to diverse influences from many stakeholders.

NGOs and cooperatives make up the vast majority of MFIs (Misra and Lee 2007), though they normally serve fewer clients compared to shareholder-owned MFIs, which have easier access to capital from investors and depositors (Ledgerwood 1999, D’Espallier et al. 2017). Because shareholders have rights to residuals, shareholder-owned MFIs are assumed to be better controlled (Hansmann 1996, Mersland 2009) and this suggests that credit risk may be lower in shareholder-owned MFIs than in NGOs and cooperatives. For instance, stricter monitoring of shareholder-owned MFIs can prevent CEOs from engaging in extreme risk-taking behavior to achieve private benefits or build an “empire,” whereas such risk-taking behavior can easily go unchecked in NGOs (Galema et al. 2012).

Figure 1 summarizes the main differences between MFIs and traditional banks. First, MFIs are double bottom-line achievers, whereas banks are single bottom-line achievers. Second, the main customers of MFIs are the customers excluded by traditional banks. Third, MFIs offer smaller, uncollateralized loans guaranteed by groups or individuals, whereas banks provide larger, collateralized loans to (mostly) individual borrowers and firms. Fourth, MFIs are registered as either shareholder firms or non-profit organizations like NGOs and cooperatives, whereas banks are mainly incorporated as shareholder firms. Finally, MFIs are financed by donors, social investors, and commercial investors, whereas banks are financed by commercial

investors. These differences show that MFIs are indeed unique; hence, an investigation into the link between diversification and risk in MFIs is warranted.

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### *2.3 Empirical literature and hypothesis development*

Empirical studies on diversification and bank risk report mixed results. For instance, Rose (1996), Levonian (1994), and Liang and Rhoades (1988) find that diversification reduces bank risk. According to Rose (1996), there is a threshold of diversification (e.g., more than 50 percent of bank-held assets outside the home state) above which risk declines.

Other studies show that diversification reduces bank failure (Deng and Elyasiani 2008, Demsetz and Strahan 1997) and credit risk (Akhigbea and Whyte 2003). Furthermore, diversification leads to higher performance for low-risk banks (Acharya, Hasan, and Saunders 2006), lower insolvency risk (Hughes et al. 1996b) and lower deposit risk (Aguirregabiria, Clark, and Wang 2016). Goetz, Laeven, and Levine (2016) add that diversification lowers risk to a greater extent when banks expand into different economic areas. These findings are consistent with modern portfolio theory. Accordingly, this paper's first hypothesis (stated as an alternative to the null hypothesis of no relationship) is formulated as follows:

*H1: There is a negative relationship between geographic diversification and credit risk in microfinance institutions.*

Contrary to the predictions based on portfolio theory, some empirical findings suggest that diversification not only does not reduce bank risk but in fact increases it. For instance,

Gulamhussen, Pinheiro, and Pozzolo (2014) find that diversification is associated with higher credit risk. Hughes et al. (1996a) also find that when an efficient bank is more geographically diversified, it reports higher returns, but also higher levels of risk. This finding is consistent with risk-return tradeoff, given that higher returns come with higher risks.

Similarly, Chong (1991) reports that diversification presents an opportunity for banks to take on more risk. Banks increase their leverage to diversify, which can lead to higher bankruptcy risk and market risk. Goetz, Laeven, and Levine (2012) find that diversification increases the complexity of the bank and that this makes monitoring difficult. Complexity enables corporate insiders to extract larger private benefits, which has an adverse effect on firm value. Additionally, Cerasi and Daltung (2000) note that it is costly to monitor multiple operations resulting from diversification. On the other hand, poor monitoring of borrowers due to dispersed operations can result in higher loan defaults.

The findings of Deng and Elyasiani (2008) suggest that as the distance between the bank headquarters and its branches increases, so does risk. This finding is consistent with Winton's (1999) argument linking higher complexity and weaker monitoring, which may lead to higher nonperforming loans. Similarly, Berger and DeYoung (2001) show that diversification increases bank inefficiency since monitoring gets weaker as the distance between the head office and a branch office increases. The increased inefficiency can lead to higher credit risk (Berger and DeYoung 1997, Fiordelisi, Marques-Ibanez, and Molyneux 2011). Furthermore, other findings also indicate that diversification does not reduce bank risk (Demsetz and Strahan 1997, Turkmen and Yigit 2012). Thus, a second, alternative hypothesis is proposed as follows:

*H2: There is a positive relationship between geographic diversification and credit risk in microfinance institutions.*

In light of these conflicting theoretical predictions (i.e., portfolio theory versus agency theory), it may come as no surprise that the empirical findings on the relationship between diversification and risk are also mixed. Overall, traditional banking studies do not offer an unambiguous expectation for the microfinance industry. We have therefore proposed the two alternative hypotheses. Moreover, conflicting research in other settings suggests that the effect of diversification is context-dependent and that it is an empirical question whether diversification has a positive or negative relationship to microfinance risk. Due to this ambiguity, all empirical tests conducted in this paper will be two-sided.

### **3. Data and Variable Definitions**

#### *3.1 Data*

Our dataset is an unbalanced panel sample of 657 MFIs from 88 countries (see the Appendix) covering the period 1998–2015, comprising a total of 3756 MFI-year observations. The dataset is compiled based on rating assessment reports (formerly available at [www.ratingfund2.org](http://www.ratingfund2.org) and the rating agencies' websites). The reports are produced by five specialized rating agencies (MicroRate, Microfinanza, Planet Rating, Crisil, and M-Cril). All of them have been approved and supported by the Rating Fund of the Consultative Group to Assist the Poor (C-GAP), a microfinance branch of the World Bank. Each of the rating reports contains data for the current rating year and previous years. It is worth noting that there is no perfect dataset to accurately represent the microfinance industry (Strøm, D'Espallier, and Mersland 2014, Hartarska, Shen, and Mersland 2013). However, we believe that our dataset is particularly suited to this study because it excludes small MFIs or development programs that do not seek to apply microfinance in a business-like manner.

In the microfinance industry, rating reports are one of the most reliable and representative sources of available data (Gutiérrez-Nieto and Serrano-Cinca 2007, Hudon and Traca 2011).

The rating of MFIs, with support from donors such as the Inter-American Development Bank and the European Union, has been key to achieving transparency in the industry (Beisland, Mersland, and Randøy 2014). Notably, the microfinance ratings provided by the five agencies are much wider in scope than traditional credit ratings are. They cover a wide range of categories, including financial information, outreach, ownership, regulation, governance, clients, and financial products.

The variables applied in this study are identically defined across rating agencies; however, the specific information published varies across agencies and reports, causing a different number of observations for different variables. That is, as an unbalanced panel dataset, not all MFIs have the same number of observations for some variables. For instance, the variable “write-off” (one of our dependent variables) has the lowest number of observations (2083), while the variable “crisis” has the highest number of observations (3756). Thus, in regressions involving the write-off, the maximum number of observations is 2083, whereas in regressions without this variable the number of observations is higher. Finally, we use country-level data from the World Bank’s World Development and Worldwide Governance databases.

### *3.2 Variables definitions*

#### *Credit risk measures*

A common measure of credit risk in banking is the *nonperforming loans rate* (e.g., Kwan and Eisenbeis (1997)), defined as the proportion of a loan portfolio that is in arrears for longer than 90 days. In microfinance, a shorter period (30 days) is often used because loans are mostly short-term in nature. Loan terms are typically around 12 months. Thus, nonperforming loans are commonly referred to as the *30-day Portfolio at Risk* (PaR30). PaR30 has been used in other studies such as Caudill, Gropper, and Hartarska (2009) and Mersland and Strøm (2009). An increase in PaR30 indicates that more borrowers of MFIs are unable to repay their loans

within 30 days, resulting in higher credit risk for the MFI. Another metric that measures actual credit risk in the microfinance industry is write-off (Randøy, Strøm, and Mersland 2015, Caudill, Gropper, and Hartarska 2009). Write-off is the proportion of the loan portfolio that is written off and accounted as a loss for the MFI. *Loan loss provisions* (LLP) represent another common measure of credit risk (Rose 1996, Ahlin, Lin, and Maio 2011). It is the proportion of the loan portfolio that is reserved in anticipation of future loan losses.

As a robustness check, we use the sum of PaR30 and write-off as another credit risk metric. This composite metric reflects the total actual credit risk for the MFI. We also construct a z-score using this composite risk measure and use it as alternative risk metric. The z-score is defined as the number of standard deviations from the mean of composite risk. It is calculated as *composite risk* minus its mean divided by its standard deviation per MFI. The z-score has been used in prior studies, e.g., Meslier et al. (2016). Finally, we use volatility of returns on assets (ROA) (e.g., Aguirregabiria et al. 2016) as another risk metric.

#### *Geographic diversification measure*

The most common measures of geographic diversification in banking studies include number of branches and number of regions or states (Deng and Elyasiani 2008, Fraser et al. 1997). In this study, geographic diversification is measured as the number of *branches* an MFI has. This variable has, for example, been used by Aguirregabiria, Clark, and Wang (2016) and Hughes et al. (1996a).

However, Deng and Elyasiani (2008) argue that number of branches does not capture the distance between the head office and a branch office; hence, it is not a perfect measure of geographic diversification. However, to us it is not only the geographic distance per se that matters. The mere fact that a bank has branches, whether in the same city/region or different cities/regions, increases the complexity of the bank. That is, even within the same location,

having a large number of branches affects credit risk since it is difficult to monitor many branch-level loans at the same time (Winton 1999). For instance, an MFI with five branches in Mexico City is probably more complex in terms of risk management and monitoring than an MFI with two branches in two different cities in Mexico.

To increase the robustness of our results, we also analyze the MFIs' *market focus* to account for the geographic distance concerns. MFIs that target both urban and rural clients are likely to be more geographically diversified than MFIs that operate in either exclusively urban areas or exclusively rural areas. Moreover, diversification into rural areas exposes the MFI to greater credit risk since the productivity of most farming-related borrowers is influenced by unexpected natural challenges like floods, droughts, and plant and animal diseases. Such exogenous factors affect the ability of the borrowers to repay loans and hence lead to higher defaults. In our sample, some MFIs target urban clients only, others focus on rural areas only, while some focus on both urban and rural areas. In our robustness test, we use the urban-rural dimension as a direct measure of diversification.

#### *Firm-level control variables*

*MFI size.* The size of the MFI has an influence on diversification. Due to their capacity base, larger firms are more diversified than smaller ones (Demsetz and Strahan 1997, Gulamhussen, Pinheiro, and Pozzolo 2014). Thus, additional diversification requires additional size (Winton 1999), making it necessary to control for size in our analysis. Moreover, size and number of branches can be expected to be correlated. Thus, to isolate the geography and complexity components of the branch variable it is important to capture the size component in a separate control variable. To measure MFI size, we use *total assets* (natural logarithm), which is a common measure of firm size (e.g., Deng and Elyasiani 2008).

*MFI age.* MFI age is the number of years the institution has been in operation as an MFI and it is a proxy for experience. Older MFIs are likely to control credit risk better than younger ones do. Learning curve theory suggests that firms become more efficient over time because they learn their business better through the constant repetition of their operations. Caudill et al. (2009) show that over time, some MFIs become cost-efficient. Improved efficiency should result in lower numbers of nonperforming loans (Berger and DeYoung 1997). Thus, inexperienced MFIs are more likely to have higher credit risks than experienced ones are.

*Lending methods.* MFIs use different lending methodologies (group and individual), which may influence credit risk. Group lending is an important innovation of microfinance (Hulme and Mosley 1996). It enhances the repayment of credit by enlisting peer pressure from other group members. This pressure is due to the fact that group members are jointly liable for the default of one member. Overall, group loans are less risky than individual loans because of better screening, monitoring, auditing, and enforcement (Ghatak and Guinnane 1999). Moreover, it is easier to monitor groups than individuals because it is more cost-efficient. Thus, we expect MFIs that offer group loans to have lower credit risk than those that offer individual loans.

*MFI type.* According to agency theory, microfinance NGOs may have higher risk levels compared to other types of MFIs because the absence of owners may lead to less monitoring of the CEO, which in turn may lead to excessive risk-taking by the CEO (Galema, Lensink, and Mersland 2012). However, because NGOs tend to have broader objectives toward helping the poor than do other types of MFIs, they may monitor credit clients more closely (D'Espallier, Guerin, and Mersland 2011). This monitoring may result in a lower credit risk for NGOs. Likewise, clients in member-based MFIs like credit cooperatives have strong incentives to repay their loans since a saving instalment is part of the business model of cooperatives (Ledgerwood 1999). Overall, credit risk may vary between shareholder-owned and non-



shareholder-owned MFIs. In our sample, we have four types of MFIs: non-governmental organizations (NGO), cooperatives (coop), banks (bank) and non-bank financial institutions (nonbank). We categorize bank and nonbank MFIs as shareholder-owned MFIs, and NGO and coop MFIs as non-shareholder-owned MFIs, and we use this categorization to control for MFI type.

*Equity capital.* We control for the risk-taking behavior of MFIs by including the equity-to-total-assets ratio. MFIs with different capital structures may also have different credit risk levels. Similar to the previous argument, shareholders may monitor the institution to ensure that excessive risks are not taken. Debtholders, on the other hand, do not have residual rights and hence they do not exhibit the same motivations to monitor a firm as long as contract terms are followed.

#### *Country-level and time control variables*

*Macroeconomy.* We control for the influence of systematic factors on credit risk, following other scholars such as Ahlin, Lin, and Maio (2011) and Louzis, Vouldis, and Metaxas (2012). Accordingly, we include in our estimations *GDP per capita* from the World Bank, adjusted for international purchasing power parity (constant 2011) and *GDP growth*.

*Governance.* We also control for the quality of the governance structure in each country since it may influence credit risk at the MFI level (Ahlin, Lin, and Maio 2011). Thus, we construct a governance index from six of the Word Bank's Worldwide Governance Indicators, namely: voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption. A similar construction has been used in Mia and Lee (2017).

*Time effect control.* We control for the global financial crisis by constructing a binary variable (*Crisis*) based on the sample period (1998–2015). *Crisis* takes the value of 1 for the

period 2007–2009 following Geiger et al.’s (2013) cut-off points, and 0 otherwise. We assume that the credit risk of MFIs in the crisis period is higher than in normal periods. In further analysis, we control for all years not only the financial crisis period.

*Regional effect.* Finally, we control for differences among MFIs due to their geographical locations. MFIs in our sample are located in six regions: East Asia and Pacific, Eastern Europe and Central Asia, Latin America and Caribbean, Sub-Saharan Africa, South Asia, and Middle East and North Africa. A list of all the variables is provided in Table A2 of the Appendix.

#### 4. Methodology

This study employs panel-data regressions to examine the influence of diversification on credit risk. According to Baltagi (2013), the use of panel data has several advantages over cross-sectional data. One advantage is that panel data helps control for individual heterogeneity. Additionally, panel data provides more information, variability, degrees of freedom, and efficiency, while mitigating the effects of multicollinearity. Furthermore, panel data helps account for unobserved effects that are not detectable in cross-sectional models (Wooldridge 2011). Based on Wooldridge (2011), our empirical model is expressed as follows:

$$Risk_{it} = \beta_0 + \beta_1 branch_{it} + \gamma X_{it} + c_i + u_{it} \quad (1)$$

where  $Risk_{it}$  represents credit risk of MFI  $i$  at time  $t$ . Credit risk is measured in terms of PaR30, write-off, composite risk (sum of PaR30 and write-off), LLP, and z-score, as discussed above.  $Branch_{it}$  is number of branch offices of the  $i^{th}$  MFI at time  $t$  and  $X_{it}$  is a vector of control variables, namely, MFI size, MFI experience, lending method, organizational form of MFI, and macroeconomic and macroinstitutional factors.  $\beta_0$  is the mean of unobserved heterogeneity, and  $\beta_1$  and  $\gamma$  are coefficients.  $c_i$  is the firm-specific unobserved effect and  $u_{it}$  is the remaining error term that varies across both  $t$  and  $i$ .

We start the empirical analysis by first checking whether panel techniques are indeed more appropriate than ordinary least squares (OLS) by applying the Breusch–Pagan test (Greene

2003). If the test rejects the null hypothesis, then the panel-data model is preferable. The test results (unreported) show that panel-data techniques are appropriate. Next, to decide whether the fixed effects (FE) estimator or the random effects (RE) estimator is suitable for the data, we use Hausman (1978) specification test. The FE estimator assumes that  $C_i$  is correlated with all of the explanatory variables, whereas the RE estimator assumes that  $C_i$  is uncorrelated with the explanatory variables. A rejection of the null hypothesis of Hausman's test suggests that FE is preferable. In the empirical section, we let the Hausman test decide whether the RE or FE estimator is appropriate for each regression.

To control for possible endogeneity bias, we use the generalized method of moments (GMM) model. It is possible that the decision to diversify geographically is an endogenous choice. That is, the number of branches variable can be influenced by the previous period's credit risk. While it is often difficult to get relevant instruments to remove endogeneity bias statistically, panel data offers more opportunities to do so than cross-sectional data (Deaton 1995). In this regard, the GMM estimator is appropriate (Wintoki, Linck, and Netter 2012) because it generates instruments using both lagged dependent and explanatory variables. Specifically, we use Blundell and Bond's (1998) system GMM model, where lagged differences of the dependent variables are used as instruments in level equations in addition to lagged levels of dependent variables for equations in the first differences (Baltagi 2013).

The GMM model requires two specification tests: the serial correlation test and the test for over-identification restrictions (Arellano and Bond 1991). The serial correlation test considers the presence of second-order autocorrelation in the residuals from differenced equations (Arellano and Bond 1991). If the p-value is larger than 0.05, it means that there is no second-order autocorrelation – which is the case in this study. The null hypothesis for the over-identification restrictions test (the Hansen J test) is that the instrument set is valid. If this test result does not reject the null hypothesis, then the instruments are valid – as they are in our

case. The difference-in-Hansen test of exogeneity (Eichenbaum, Hansen, and Singleton 1988) is used to test the null hypothesis that the subset of instruments used in the levels equations are exogenous. In this study, this null hypothesis is not rejected indicating exogeneity of subsets of instruments used in the system GMM estimates. In sum, the null of hypotheses of second-order autocorrelation test, Hansen J test and the difference-in-Hansen test cannot be rejected in this study, suggesting that our GMM estimates are valid.

We use the “forward” orthogonal deviations transformation (Arellano and Bover 1995) in the system GMM estimation because it is suitable for our unbalanced panel. The regular first-difference transformation magnifies gaps in unbalanced panels because this transformation subtracts the “previous observation from the contemporaneous one” (Roodman 2009, 104). To overcome this weakness, the forward orthogonal deviations transformation subtracts the “average of all future available observations of a variable” (Roodman 2009, 104, Wintoki, Linck, and Netter 2012). Thus, this approach minimizes data loss.

## 5. Results and Discussion

### 5.1 Descriptive statistics and correlations

Table 1 presents the descriptive statistics of the variables. On average, 8 percent of the total loan portfolio is in arrears for more than 30 days, 3 percent of the portfolio has been written off as irrecoverable and 4 percent is reserved in anticipation of future loan losses. Summing PaR30 and Write-off, the total actual credit risk is about 11 percent of the loan portfolio. The average MFI is 11 years old, has 14 branches, and holds US\$16 million in total assets, of which 38 percent is financed by equity capital. Regarding lending methodology, 39 percent of the MFIs practice group lending and the rest practice individual lending.

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**Insert Table 1 about here**  
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Concerning ownership structure, 38 percent of the MFIs are shareholder-owned (consisting of banks and nonbank financial institutions) and the rest are non-shareholder-owned MFIs (comprising non-governmental organizations and cooperatives and member-owned organizations). In terms of geographical focus, about 54 percent of the MFIs serve both rural and urban clients and the rest focus on either rural or urban clients only. With respect to macroeconomic and macroinstitutional indicators, the annual GDP growth is about 4 percent on average and the mean governance index is 0.82. A higher governance index means a higher quality of governance structure in the country. The financial crisis period accounts for about 28 percent of the observations. Finally, 14 percent of the MFIs are located in East Asia and Pacific, 28 percent in Eastern Europe and Central Asia, 31 percent in Latin America and Caribbean, 18 percent in Sub-Saharan Africa, 4 percent in South Asia, and the rest in Middle East and North Africa.

Next, we present pairwise correlations and variance inflation factor (VIF) scores between the independent variables (Table 2). Most of the correlations are significant at the 5 percent level or lower and most of them are below 0.50. Only the correlation (0.84) between *GDP per capita* and *Governance Index* is greater than 0.50 but it is within the 0.90 threshold suggested by Hair et al. (2010). That is, all of the correlations are below suggested rules of thumb (Studenmund 2011, Hair et al. 2010, Kennedy 2008). Similarly, all of the VIF scores are below 5 (Studenmund 2011). This indicates that multicollinearity is not a significant problem in this study.

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**Insert Table 2 about here**

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## 5.2 *The relation between geographic diversification and credit risk*

Table 3 presents estimates of both random and fixed effects models based on Hausman's (1978) test. The results of models (1, 3 & 5) show that number of MFI branches (*Branches*) has a

significant positive relationship with risk. This clearly suggests that MFIs with a larger number of branches also have higher default rates and vice versa for those with fewer branches. The finding implies that the disadvantages of diversification (typically arising from agency costs and increased complexity) outweigh the advantages (as suggested by modern portfolio theory). Thus, the net effect of diversification in this study is higher loan defaults.

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**Insert Table 3 about here**  
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Concerning the control variables, we get strong indications that larger MFIs have lower nonperforming loans – significant in models (1–4) and showing a negative coefficient in all the 5 models – suggesting that larger MFIs may have a greater ability to monitor loans (Baele, De Jonghe, and Vennet 2007). In principle, the number of branches variable could also have been used as a size indicator. However, we control for size through assets to separate the size effect and leave branches as a more clear-cut indicator of geographic diversification. This methodological choice allows us to suggest that the diversification effect is important for the level of credit risk.

Surprisingly, older MFIs are not efficient in controlling defaults because they have higher nonperforming loans (significant in 3 models). The finding concurs with that of Caudill et al. (2009) who document evidence of MFIs not becoming efficient over time. In their study, inefficient MFIs are those that rely more on subsidies and less on deposits. In all the 5 models, group lending is negatively associated with risk (significant in 4 models), consistent with microfinance literature (Ghatak and Guinnane 1999). Group lending is an important initiative of microfinance introduced to solve repayment problems (Hulme and Mosley 1996, Armendáriz and Morduch 2010).

Furthermore, in model (5), *equity capital* is significantly associated with lower risk, suggesting that an increase in equity financing in microfinance can lead to lower credit risk.

The finding that MFIs with higher financing risk take on less credit risk is reasonable and expected. However, the results further show that shareholder-owned MFIs carry higher risk than non-shareholder-owned MFIs. This departs from expectation and we will return to this later.

As expected, economic development tends to reduce credit risk, as is evident in the significant negative coefficient of *GDP growth*, consistent with the literature (Louzis, Vouldis, and Metaxas 2012, Carey 1998). That is, in growing economies, borrowers are able to generate income to repay debts. Also, the *GDP per capita* has negative and insignificant coefficients in most models. As expected, high-quality governance structures in a country reduce risk. This is evident in the negative coefficients in models (1–3) with model (3) being statistically significant. Finally, we find that credit risk is not necessarily time-invariant: as expected, credit risk was higher during the global financial crisis as more clients struggled to repay their debts during this economic downturn.

As a robustness check, we repeat models (1–5) using the rural-urban dummy (1 = an MFI serves both rural and urban clients, and 0 = otherwise). This is to account for the geographic distance concerns of Deng and Elyasiani (2008), i.e., whether number of branches actually measures geographic diversification. The (untabulated) results reveal that the *rural-urban* variable is positively related to risk in all five models, but with fewer significant coefficients. This implies that MFIs extending their services to clients in many geographic areas end up incurring more loan defaults. Overall, the results of this additional test lend support to our main conclusions.

Table 4 presents the results of the dynamic panel model (system GMM). The results generally mirror those presented in Table 3 (static model). In particular, the positive relationship between geographic diversification and credit risk is more pronounced in the

GMM estimation<sup>1</sup>. The number of branches variable has more (significant in 4 models) significant coefficients than in Table 3 (significant in 3 models). Thus, after addressing possible endogeneity concern, the results still suggest a positive relationship between geographic diversification and credit risk. The results relating to the control variables are also more pronounced in the dynamic model with similar relationships with credit risk as reported in Table 3. For instance, MFI size is now significant in all the five models compared to being significant in four models in Table 3.

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**Insert Table 4 about here**  
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### *5.3 Other findings: Trend analysis, organizational type and lending method*

In this section, we further explore the positive relationship between geographic diversification and credit risk with respect to different times, organizational forms and lending methods. In Table 5, we present results based on trend analysis, continuing with the number of branches as our main explanatory variable. We are interested in knowing whether the positive relationship between number of branches and credit risk is the same before, during, and after the global financial crisis (2007–2009). In other words, in which part of the sample period (1998–2015) does the positive effect of branches on risk set in? To answer this, we regress PaR30 on number of branches and all the controls except the financial *crisis* dummy. The results indicate that the positive effect is the same before, during and after the financial crisis but became significant after this period (crisis). We stress that the numbers of observations are smaller in the subperiods, but we report these results to show that diversification indeed comes with higher credit risk in microfinance.

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<sup>1</sup> First-difference transformation in the system GMM estimation yields similar estimates (untabulated).



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**Insert Table 5 about here**  
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In Table 6, we compare the diversification-risk link across ownership/organizational structures of MFIs. As mentioned before, MFIs without owners may carry higher risk due to slacker monitoring compared to MFIs with owners (Galema et al. 2012). Because shareholders have rights to residuals, they have incentives to monitor a firm more closely than other stakeholders. As the results in Table 6 show, this is indeed the case. It is clearly seen that there is a strong positive relationship between number of branches and risk (significant in 3 models out of 5 models) in the non-shareholder group. In fact, number of branches is positively related to risk in all the models in this group.

Regarding the controls, it is interesting to note that the effect of group lending is more pronounced among the non-shareholder-owned MFIs compared to the shareholder-owned MFIs. This is not surprising because microfinance emerged with group lending initiative (Armendáriz and Morduch 2010) by non-profit organizations and today these organizations dominate the microfinance market (Misra and Lee 2007). Shareholder-owned MFIs tend to operate like commercial banks where individual lending is the norm. On the other hand, the effect of equity capital is more pronounced among the shareholder-owned group compared to the non-shareholder-owned group. This finding is expected because most non-shareholder organizations (especially NGOs) are financed by donations and subsidized debt (Hudon and Traca 2011).

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**Insert Table 6 about here**  
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In other tests, we check how the positive effect of diversification on risk might be mitigated. First, we repeat models (1–5) in Table 3, excluding the group lending control and compare the

results between group and individual lending methods. The (untabulated) results reveal that the positive influence of number of branches is more pronounced among MFIs offering individual loans. This suggests that the difficulty in monitoring individual borrowers becomes worse when an MFI diversifies geographically. Second, we interact number of branches with group lending (1 = group loan, 0 = individual loan) and run 10 models. The results (Table 7) indicate that the main effect of number of branches is stronger and the effect of group lending remains the same as in the main results in Tables 3 and 4, but that the interaction term between branches and group lending is negatively (in 9 models) and significantly (in 4 out of 10 models) related to risk. This suggests that MFIs may mitigate the effect of diversification on risk by employing a group lending methodology, which is self-monitoring. Overall, the results illustrate the importance of the group lending methodology in microfinance (Ghatak and Guinnane 1999, Armendáriz and Morduch 2010).

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**Insert Table 7 about here**  
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We further check whether stricter governance can mitigate the negative effect of diversification in terms of higher risk. To do so, we interact internal audit (1 = an MFI has an internal audit function reporting to the board, and 0 = otherwise) with number of branches and rerun the models. The results (untabulated) show that number of branches is no longer significantly correlated with risk and that internal audit is negatively related with risk but is significant in only one model. The interaction term between the two variables has no strong statistical influence on risk. Overall, there is no strong evidence to suggest that internal audit function can be a control mechanism that MFIs may use to mitigate the effect of diversification on risk.

To further check the robustness of the general positive relationship between diversification and risk, we rerun models (1–5) using a standard OLS estimator, first using number of branches

as the test variable and, second, replacing the branches with the *rural-urban* dummy. In both robustness tests, the (untabulated) results show that the positive relationship between diversification and risk remains unchanged.

Overall, the results of the four estimators (random effects, fixed effects, OLS, and GMM) indicate that geographic diversification of microfinance institutions may result in higher risk in terms of higher nonperforming loans, higher write-offs and higher loan-loss provisions as well as higher volatility of earnings<sup>2</sup>. Our findings further highlight that the positive relationship is more pronounced among non-shareholder-owned MFIs (like NGOs) compared to shareholder-owned MFIs. Finally, the positive effect of diversification on risk can be mitigated with monitoring mechanisms like group lending.

Theoretically, the findings are generally in line with agency theory arguments. Branch managers of microfinance institutions may tend to use diversification to extract private benefits at the expense of the MFI (Goetz, Laeven, and Levine 2012, Bandelj 2016). This is possible because diversification increases the complexity of an institution (Winton 1999), thus making it difficult for owners and headquarters to monitor remote operations (Acharya, Hasan, and Saunders 2006). In microfinance, monitoring by owners may be weaker than in regular banking because a majority of the MFIs are NGOs, which do not have owners. Thus, higher agency costs may offset any diversification premium, which seems to be the case in this study. The findings may also be attributed to increased complexity, which may diminish the monitoring of clients. To conclude, the findings provide support for the second hypothesis that there is a positive relationship between geographic diversification and credit risk in microfinance institutions.

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<sup>2</sup> In untabulated regressions, we used the volatility of earnings (ROA) as an alternative risk metric and found significant positive relationship between number of branches and this dependent variable.

## 6. Conclusion

This study investigates the relation between geographic diversification and credit risk in microfinance. The existing empirical studies are inconclusive as to whether banks should diversify. We extend the scope of the literature to include hybrid banking organizations (organizations with both social and financial logics; Battilana and Dorado 2010) and analyze from a risk perspective whether MFIs should diversify geographically. Number of branches and rural-urban focus are used as proxies for geographic diversification, and credit risk is measured in terms of portfolio at risk, write-off, composite risk (sum of PaR30 and write-off), loan loss provisions, z-score, and volatility of returns on assets.

The findings suggest that there is a significant positive relationship between geographic diversification and credit risk in microfinance. In particular, diversification seems to lead to higher share of nonperforming loans, higher write-offs, and higher loan loss provisions. From a risk perspective, this finding suggests that diversification is not beneficial to MFIs, especially non-shareholder-owned MFIs. Operating with many branches makes the institution more complex and probably weakens the monitoring ability of both the owners and the head office. In view of the monitoring argument, the findings further suggest that the effect of diversification on risk can be mitigated by implementing a group lending methodology.

The results have important practical implications for both the microfinance industry and banking authorities. For practitioners in general, it is important that they consider their management and monitoring capabilities before making geographic diversification decisions. That is, diversification is not bad in and of itself as long as there are enhanced monitoring and control mechanisms in place. Otherwise, an MFI is better off focusing geographically as far as credit risk is concerned. In the absence of such internal controls, NGOs, in particular, would do well to remain focused on a few geographic areas. Regulatory authorities, rating agencies and other policymakers should avoid issuing general recommendations that MFIs reduce their

risk by diversifying geographically. After all, microfinance is a relational transaction requiring close contact between the lender and the borrower. MFIs thus need proper governance and management structures before venturing into new geographic areas.

We conclude by noting that this study is limited to risk. From a risk-return perspective, higher credit risk may improve the financial performance of MFIs if the MFIs reach out to new customers. Even if these customers increase the loan losses, the net effect on bottom-line earnings can still be positive. In future research, it would be interesting to expand the diversification universe and study the effects of product diversification on risk. An additional aspect that should be researched is the relationship between diversification and social performance. Many MFIs have clear objectives of fighting poverty. An important dimension of social performance is outreach to new and more remote clients. Socially concerned MFIs could be willing to increase their risk if the outcome is that more poor people have access to microfinance services.

Notably, it is possible that the number of branches can be influenced by the previous period's credit risk, making the decision to diversify geographically an endogenous choice. We have used a standard statistical approach to handle possible endogeneity, but we cannot completely rule out the possibility that we are observing an association rather than causation. This issue should be further addressed in future research, and a survey study among managers is needed to shed light on the relation between geographic diversification and credit risk. Future research could also use an alternative proxy for geographical diversification like distance from head office or a measure for economic areas.

## **Research Funding**

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

## Declaration of Competing Interests

There are no competing interest.

## References

- Acharya, Viral V., Iftekhhar Hasan, and Anthony Saunders. 2006. "Should banks be diversified? Evidence from individual bank loan portfolios." *Journal of Business* 79 (3):1355-1412.
- Aguirregabiria, Victor, Robert Clark, and Hui Wang. 2016. "Diversification of geographic risk in retail bank networks: Evidence from bank expansion after the Riegle-Neal Act." *RAND Journal of Economics* 47 (3):529 - 572.
- Ahlin, Christian, Jocelyn Lin, and Michael Maio. 2011. "Where does microfinance flourish? Microfinance institution performance in macroeconomic context." *Journal of Development Economics* 95 (2):105-120.
- Akhigbea, Aigbe, and Ann A. Whyte. 2003. "Changes in market assessments of bank risk following the Riegle-Neal Act of 1994." *Journal of Banking & Finance* 27 (1):87-102.
- Arellano, Manuel, and Stephen Bond. 1991. "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations." *Review of Economic Studies* 58 (2):277-297.
- Arellano, Manuel, and Olympia Bover. 1995. "Another look at the instrumental variable estimation of error-components models." *Journal of econometrics* 68 (1):29-51.
- Armendáriz, Beatriz, and Jonathan Morduch. 2010. *The Economics of Microfinance*. 2 ed. Cambridge, MA: The MIT Press.
- Baele, L., O. De Jonghe, and R. V. Vennet. 2007. "Does the stock market value bank diversification?" *Journal of Banking & Finance* 31 (7):1999-2023.
- Baltagi, Badi H. 2013. *Econometric Analysis of Panel data* 4ed. Chichester, England: John Wiley & Sons.
- Bandelj, A. 2016. "Should banks be geographically diversified? Empirical evidence from cross-country diversification of European banks." *European Journal of Finance* 22 (2):143-166.
- Bandyopadhyay, Trishit, and Savita Shankar. 2014. "The impact of the 2010 Andhra Pradesh crisis on the operational efficiency of Indian microfinance institutions." In *Microfinance Institutions: Financial and Social Performance*., edited by Roy Mersland and Øystein R. Strøm. Hampshire, UK: Palgrave Macmillan.
- Bateman, M. 2010. *Why Doesn't Microfinance Work? The Destructive Rise of Local Neoliberalism*. London: Zed Books.
- Battilana, Julie, and Silvia Dorado. 2010. "Building sustainable hybrid organizations: The case of commercial microfinance organizations." *Academy of Management Journal* 53 (6):1419-1440.
- Beisland, Leif A., Roy Mersland, and Trond Randøy. 2014. "Transparency and disclosure in the global microfinance industry: Implications for practice and policy makers." In *Oxford Handbook of Political, Institutional and Corporate Transparency*, edited by J. Forssbaeck and Lars Oxelheim. New York: Oxford University Press.
- Berger, Allen N, and Robert DeYoung. 2001. "The effects of geographic expansion on bank efficiency." *Journal of Financial Services Research* 19 (2-3):163-184.
- Berger, Allen N., and Robert DeYoung. 1997. "Problem loans and cost efficiency in commercial banks." *Journal of Banking & Finance* 21:849-870.

- Berger, Allen N., Iftekhhar Hasan, and Mingming Zhou. 2010. "The effects of focus versus diversification on bank performance: Evidence from Chinese banks." *Journal of Banking & Finance* 34 (7):1417-1435.
- Blundell, Richard, and Stephen Bond. 1998. "Initial conditions and moment restrictions in dynamic panel data models." *Journal of Econometrics* 87 (1):115-143.
- Bond, P., and A. S. Rai. 2009. "Borrower runs." *Journal of Development Economics* 88 (2):185-191.
- Carey, M. 1998. "Credit risk in private debt portfolios." *Journal of Finance* 53 (4):1363-1387.
- Caudill, Steven B., Daniel M. Gropper, and Valentina Hartarska. 2009. "Which microfinance institutions are becoming more cost effective with time? Evidence from a mixture model." *Journal of Money, Credit & Banking* 41 (4):651 - 672.
- Cerasi, Vittoria, and Sonja Daltung. 2000. "The optimal size of a bank: Costs and benefits of diversification." *European Economic Review* 44:1701-1726.
- Chong, Beng Soon. 1991. "The effects of interstate banking on commercial banks' risk and profitability." *Review of Economics and Statistics* 73 (1):78 - 84.
- Convergences. 2017. Is Microfinance Still Working. In *Microfinance Barometer*, edited by Jean-Luc Perron. Paris, France: Convergences.
- D'Espallier, Bert, Isabelle Guerin, and Roy Mersland. 2011. "Women and repayment in Microfinance." *World Development* 39 (5):758-772.
- D'Espallier, Bert, Jann Goedecke, Marek Hudon, and Roy Mersland. 2017. "From NGOs to banks: Does institutional transformation alter the business model of microfinance institutions?" *World Development* 89:19-33.
- Deaton, Angus. 1995. "Data and econometric tools for development analysis." In *Handbook of Development Economics*, edited by J. Behrman and T. Srinivasan, 1785-1882. Amsterdam: Elsevier.
- Demsetz, Rebecca S., and Philip E. Strahan. 1997. "Diversification, size, and risk at bank holding companies." *Journal of Money, Credit and Banking* 29 (3):300 - 313.
- Deng, Saiying E., and Elyas Elyasiani. 2008. "Geographic diversification, bank holding company value, and risk." *Journal of Money, Credit and Banking*, 40 (6):1217-1238.
- Eichenbaum, Martin S, Lars Peter Hansen, and Kenneth J Singleton. 1988. "A time series analysis of representative agent models of consumption and leisure choice under uncertainty." *The Quarterly Journal of Economics* 103 (1):51-78.
- Emmons, William R., Alton R. Gilbert, and Timothy J. Yeager. 2004. "Reducing the risk at small community banks: Is it size or geographic diversification that matters? ." *Journal of Financial Services Research* 25 (2-3):259 - 281.
- Fang, Yiwei, and Iman v. Lelyveld. 2014. "Geographic diversification in banking." *Journal of Financial Stability* 15:172-181.
- Fiordelisi, Franco, David Marques-Ibanez, and Phil Molyneux. 2011. "Efficiency and risk in European banking." *Journal of Banking & Finance* 35:1315-1326.
- Fraser, Donald R, Jerry L Hooton, James W Kolari, and Joseph J Reising. 1997. "The wealth effects of interstate branching." *Journal of Banking & Finance* 21 (5):589-611.
- Galema, Rients, Robert Lensink, and Roy Mersland. 2012. "Do powerful CEOs determine microfinance performance?" *Journal of Management Studies* 49 (4):718-742.
- Geiger, Marshall A, K Raghunandan, and William Riccardi. 2013. "The global financial crisis: US bankruptcies and going-concern audit opinions." *Accounting Horizons* 28 (1):59-75.
- Ghatak, Maitreesh, and Timothy W Guinnane. 1999. "The economics of lending with joint liability: Theory and practice." *Journal of Development Economics* 60 (1):195-228.
- Goetz, Martin, Luc Laeven, and Ross Levine. 2016. "Does the geographic expansion of bank assets reduce risk?" *Journal of Financial Economics* 120 (2):346 - 362.

- Goetz, Martin, Luc Laeven, and Ross Levine. 2012. "The Valuation Effects of Geographic Diversification: Evidence from U.S. Banks." *IMF Working Paper* 12/50.
- Greene, William H. 2003. *Econometric Analysis*. 5th ed. Upper Saddle River, New Jersey: Prentice Hall.
- Gulamhussen, Mohamed A., Carlos Pinheiro, and Alberto F. Pozzolo. 2014. "International diversification and risk of multinational banks: Evidence from the pre-crisis period." *Journal of Financial Stability* 13:30-43.
- Gutiérrez-Nieto, Begoña, and Carlos Serrano-Cinca. 2007. "Factors explaining the rating of microfinance institutions." *Nonprofit and Voluntary Sector Quarterly* 36 (3):439-464.
- Hair, Joseph F., William C. Black, Barry J. Babin, and Rolph E. Anderson. 2010. *Multivariate Data Analysis* 7th ed. Upper Saddle River, New Jersey: Pearson Education.
- Hansmann, Henry. 1996. *The Ownership of Enterprise*. Cambridge, Massachusetts: Belknap Press of Harvard University Press.
- Hartarska, Valentina, Xuan Shen, and Roy Mersland. 2013. "Scale economies and input price elasticities in microfinance institutions." *Journal of Banking & Finance* 37:118-131.
- Hausman, Jerry A. 1978. "Specification tests in econometrics." *Econometrica*:1251-1271.
- Hayden, Evelyn, Daniel Porath, and Natalja v. Westernhagen. 2007. "Does diversification improve the performance of German banks? Evidence from individual bank loan portfolios." *Journal of Financial Services Research* 32:123 - 140.
- Hudon, Marek, and Daniel Traca. 2011. "On the efficiency effects of subsidies in microfinance: An empirical inquiry." *World development* 39 (6):966-973.
- Hughes, Joseph P., William Lang, Loretta J. Mester, and Choon-Geol Moon. 1996a. "Efficient banking under interstate branching." *Journal of Money Credit and Banking* 28 (4):1045 - 1071.
- Hughes, Joseph P., William Lang, Loretta J. Mester, and Choon-Geol Moon. 1996b. "Safety in numbers? Geographic diversification and bank insolvency risk." *Working Paper no.* 96-14.
- Hulme, David, and Paul Mosley. 1996. *Finance against Poverty* Vol. 1. London: Routledge
- Jensen, Michael C. 1986. "Agency costs of free cash flow, corporate finance and takeovers." *American Economic Review* 76 (2):323 – 329.
- Kennedy, P. 2008. *A Guide to Econometrics*. 6 ed. Malden, MA: Blackwell Publishing.
- Kwan, Simon H., and Robert A. Eisenbeis. 1997. "Bank risk, capitalization, and operating efficiency." *Journal of Financial Services Research* 12 (2/3):117-131.
- Ledgerwood, Joana. 1999. *Microfinance Handbook: An Institutional and Financial Perspective*. Washington, D. C.: World Bank.
- Levonian, Mark E. 1994. "Interstate banking and risk." *Federal Reserve Bank of San Francisco Weekly Letter* No. 94-26.
- Liang, Nellie , and Stephen A. Rhoades. 1988. "Geographic diversification and risk in banking." *Journal of Economics and Business* 40 (4):271–284.
- Louzis, Dimitrios P., Angelos T. Vouldis, and Vasilios L. Metaxas. 2012. "Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios." *Journal of Banking & Finance* 36 (4):1012-1027.
- Mersland, Roy. 2009. "The cost of ownership in microfinance organizations." *World Development* 37 (2):469-478.
- Mersland, Roy, and Øystein R. Strøm. 2009. "Performance and governance in microfinance institutions." *Journal of Banking & Finance* 33 (4):662–669.
- Meslier, Céline, Donald P. Morgan, Katherine Samolyk, and Amine Tarazi. 2016. "The benefits and costs of geographic diversification in banking." *Journal of International Money and Finance* 69:287-317.



- Mia, Md Aslam, and Hwok-Aun Lee. 2017. "Mission drift and ethical crisis in microfinance institutions: What matters?" *Journal of Cleaner Production* 164:102-114.
- Misra, Rewa, and Nanci Lee. 2007. "Primary agricultural society linkage: The best remote self-help groups in India can do?" *Small Enterprise Development* 18 (1):25 - 36.
- Morduch, Jonathan. 1999. "The microfinance promise." *Journal of Economic Literature* XXXVII:1569–1614.
- Randøy, Trond, R Øystein Strøm, and Roy Mersland. 2015. "The Impact of Entrepreneur-CEOs in Microfinance Institutions: A Global Survey." *Entrepreneurship Theory and Practice* 39 (4):927-953.
- Roodman, David. 2009. "How to do xtabond2: An introduction to difference and system GMM in Stata." *Stata Journal* 9 (1):86-136.
- Rose, Peter S. 1996. "The diversification and cost effects of interstate banking." *Financial Review* 31 (2):431- 452.
- Saunders, A. , and Marcia M. Cornett. 2011. *Financial Institutions Management: A Risk Management Approach*. 7 ed. New York: McGraw Hill.
- Steinwand, Dirk 2000. *A Risk Management Framework for Microfinance Institutions*. Eschborn, Germany: GTZ, Financial Systems Development.
- Strøm, Reidar Øystein, Bert D’Espallier, and Roy Mersland. 2014. "Female leadership, performance, and governance in microfinance institutions." *Journal of Banking & Finance* 42:60-75.
- Studenmund, A. H. . 2011. *Using Econometrics: A Practical Guide* 6th International ed. Upper Saddle River: Pearson Education.
- Turkmen, Sibel Y., and Ihsan Yigit. 2012. "Diversification in banking and its effect on banks’ performance: Evidence from Turkey." *American International Journal of Contemporary Research* 2 (12):111-119.
- Vogelgesang, Ulrike. 2003. "Microfinance in times of crisis: The effects of competition, rising indebtedness, and economic crisis on repayment behavior." *World Development* 31 (12):2085-2114.
- Wintoki, M Babajide, James S Linck, and Jeffry M Netter. 2012. "Endogeneity and the dynamics of internal corporate governance." *Journal of Financial Economics* 105 (3):581-606.
- Winton, Andrew. 1999. *Don’t Put All Your Eggs in One Basket? Diversification and Specialization in Lending*. . Mimeo: University of Minnesota.

Table 1: Descriptive statistics

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Portfolio at risk (%)	7.7642	9.4606	1.0000	97.3000	2616
Write-offs (%)	3.3935	6.3584	0.1100	92.8000	2083
Loan loss provisions (%)	4.4037	4.9551	1.0000	63.3000	2326
Combined credit risk (%)	9.5551	10.8108	1.0000	98.2000	2651
Z-score	0.0000	0.8965	-2.2166	3.4693	2620
Number of branches	13.5850	16.8478	1.0000	120.0000	3511
Assets (US\$ million)	16.1365	35.7133	0.0500	339.540	3587
MFI size (log assets)	15.3586	1.5796	10.8198	19.6431	3587
Equity capital	0.3796	0.2445	0.0022	1.0000	3512
Group lending	0.3946	0.4888	0.0000	1.0000	3563
Shareholder-owned firm	0.3846	0.4866	0.0000	1.0000	3604
MFI age	11.0975	7.8947	0.0000	79.0000	3653
Governance index	0.8211	6.0292	-11.8867	11.3382	3007
GDP per capita (log)	9.1724	1.2213	6.3020	11.3554	3087
GDP growth (%)	4.3951	4.6495	-14.7244	37.9987	3339
Rural-urban	0.5446	0.4980	0.0000	1.0000	2956
Financial crisis	0.2753	0.4467	0.0000	1.0000	3756
East Asia & Pacific	0.1404	0.3474	0.0000	1.0000	3156
Europe & Central Asia	0.2763	0.4472	0.0000	1.0000	3156
Latin America & Caribbean	0.3131	0.4638	0.0000	1.0000	3156
South Asia	0.0361	0.1866	0.0000	1.0000	3156
Sub-Saharan Africa	0.1755	0.3805	0.0000	1.0000	3156

Table 2: Pairwise correlation matrix and variance inflation factor

	VIF	1	2	3	4	5	6	7	8	9
1. Branches	1.48									
2. MFI size	2.02	0.4486*								
3. Equity	1.13	-0.1266*	-0.2337*							
4. Group	1.22	0.0718*	-0.2330*	0.1146*						
5. SHF	1.30	-0.0215	0.1432*	-0.0937*	-0.0917*					
6. MFI age	1.35	0.1695*	0.3757*	-0.1076*	-0.1302*	-0.2230*				
7. Gov. ind	4.25	-0.0044	0.0706*	0.0261	-0.0495	-0.1740*	0.1842*			
8. GDP/cap	3.98	0.0055	0.0253	0.0638*	0.0046	-0.0465	0.1370*	0.8457*		
9. GDP gro	1.39	-0.045	-0.0581*	0.0301	0.0089	0.0403	-0.1177*	-0.4388*	-0.3966*	
10. Crisis	1.09	0.029	0.1156*	-0.0824*	-0.0172	0.0457	0.0677*	0.0471	0.0781*	-0.2132*

*Notes:* The table reports pairwise correlations among explanatory variables. MFI size is the natural logarithm of total assets, SHF = shareholder firm, Gov. ind= Governance Index, GDP/cap = GDP per capita (log), GDP gro = GDP growth, Crisis = global financial crisis period and VIF = variance inflation factor. \* Denotes statistical significance at the 5 percent level or lower.

Table 3: The link between geographic diversification and credit risk: static models

	(1) PaR30	(2) Write-off	(3) Composite	(4) Z-score	(5) LLP
Branches	0.0518** (0.0230)	0.0304 (0.0213)	0.0624* (0.0322)	0.0017 (0.0079)	0.0400** (0.0163)
MFI size	-1.7980*** (0.2995)	-0.9598*** (0.2254)	-2.0851*** (0.3981)	-0.2538** (0.1187)	-0.5040 (0.3584)
Equity capital	-1.1744 (1.7918)	-1.0143 (1.2091)	-1.3083 (2.1067)	-0.4148 (0.3346)	-2.2957** (1.0565)
Group lending	-3.0394*** (0.6902)	-1.1996** (0.5428)	-3.8878*** (0.8856)	-0.4035 (0.3141)	-1.0434** (0.5296)
Shareholder firm	1.3074** (0.6099)	-0.0523 (0.6700)	1.0138 (0.8414)	0.3554 (0.2845)	-0.5141 (0.8250)
MFI age	0.1090** (0.0450)	0.0916** (0.0464)	0.1467** (0.0642)	0.0211 (0.0362)	-0.1121 (0.1085)
Governance index	-0.1691 (0.1551)	-0.2853 (0.1839)	-0.3528* (0.2133)	0.0807 (0.0778)	0.4219 (0.3425)
GDP per capita	-0.6161 (0.8434)	0.5569 (0.6850)	-0.5942 (0.9986)	-0.5151 (0.6378)	0.9394 (1.5816)
GDP growth	-0.0701* (0.0407)	0.0777 (0.1252)	-0.1205** (0.0472)	-0.0148 (0.0097)	-0.0253 (0.0449)
Crisis	-0.1371 (0.4009)	0.1669 (0.3372)	-0.0562 (0.4470)	0.0050 (0.0787)	0.6944*** (0.2651)
Regional dummies	Yes	Yes	Yes	Yes	Yes
Constant	39.3885*** (8.4119)	12.2168* (6.6227)	45.2310*** (9.9308)	8.5083 (5.5912)	5.5391 (13.5141)
Observations	1,632	1,273	1,653	1,638	1,486
Number of MFIs	382	316	358	343	369
Chi2/F test (p-value)	0.0000	0.0007	0.0000	0.0153	0.0008
Hausman test (p-value)	0.5594	0.3077	0.8011	0.0054	0.0106
Estimator	Random	Random	Random	Fixed	Fixed

*Notes:* This table lists fixed and random effects estimates on the link between geographic diversification and credit risk. *PaR30* is nonperforming loans over 30 days, *Write-off* is the proportion of the loan portfolio written off, *Composite* means composite credit risk which is the sum of *PaR30* and *Write-off*, *Z-score* is computed based on the sum of *PaR30* and *Write-off*, and *LLP* is loan loss provisions. *Branches* represents number of branches, *MFI size* is the natural logarithm of total assets, *MFI age* is number of years of the institution, and *Equity capital* is calculated as equity divided by total assets. *Group lending* = 1 if group loans and = 0 if individual loans, *Shareholder firm* = 1 if shareholder-owned firm and = 0 if non-shareholder-owned firm, *Governance index* capture macro-institutional differences, *GDP per capita* is the natural logarithm of gross domestic product per capita adjusted for purchasing power parity, and *Crisis* = 1 if global financial crisis period and = 0 otherwise. The regional dummies included are East Asia & Pacific, Eastern Europe & Central Asia, Latin America & Caribbean, South Asia and Sub-Saharan Africa while Middle East & North Africa is the based category. Robust standard errors are in parentheses.

\* Denotes statistical significance at the 10% level.

\*\* Denotes statistical significance at the 5% level.

\*\*\* Denotes statistical significance at the 1% level.

Table 4: The link between geographic diversification and credit risk: dynamic model

	(6)	(7)	(8)	(9)	(10)
	PaR30	Write-off	Composite	Z-score	LLP
Lagged dependent ( $y_{t-1}$ )	-0.0260 (0.0496)	0.0755 (0.1128)	0.1733*** (0.0433)	0.1974 (0.1339)	0.9181*** (0.0800)
Branches	0.0751** (0.0297)	0.0159 (0.0183)	0.0672** (0.0338)	0.0112* (0.0063)	0.1143*** (0.0306)
MFI size	-3.0854*** (0.5932)	-1.3227*** (0.5000)	-2.5547*** (0.6212)	-0.2573** (0.1284)	-0.7535*** (0.2655)
Equity capital	-0.0791 (2.2630)	-0.3250 (0.8601)	0.2605 (1.9480)	0.0610 (0.2103)	-0.1412 (0.8186)
Group lending	-15.1141*** (5.3768)	-6.9219* (3.6901)	-11.8000** (5.7406)	-2.1259* (1.2161)	-0.6297 (0.5223)
Shareholder firm	1.2792 (1.2875)	-0.4114 (0.5644)	0.6015 (1.2826)	0.0397 (0.1834)	0.6276 (0.4359)
MFI age	0.1802*** (0.0594)	0.0896*** (0.0301)	0.1136** (0.0502)	0.0006 (0.0063)	0.0243 (0.0172)
Governance index	0.1377 (0.4987)	-0.5658** (0.2525)	0.3119 (0.4932)	0.1538** (0.0777)	-0.1742 (0.2556)
GDP per capita	-2.3904 (2.0140)	1.5907 (1.0536)	-2.6597 (1.9622)	-0.6940** (0.3220)	0.6488 (1.0485)
GDP growth	-0.1186 (0.1051)	-0.2017*** (0.0587)	-0.0500 (0.0948)	0.0215 (0.0155)	-0.0429 (0.0704)
Crisis	0.6505 (0.5791)	0.2071 (0.3086)	1.1415* (0.6166)	0.2190*** (0.0802)	0.8911*** (0.3372)
Regional dummies	Yes	Yes	Yes	Yes	Yes
Constant	81.2445*** (16.4917)	11.0541 (8.0060)	74.6984*** (15.6262)	11.4820*** (2.7201)	3.3609 (8.7311)
Observations	1,250	903	1,298	1,298	1,046
Number of MFIs	337	262	336	336	314
Number of instruments	37	39	37	39	24
AR(1) test (p-value)	0.006	0.062	0.000	0.007	0.001
AR(2) test (p-value)	0.604	0.895	0.850	0.129	0.139
Hansen test (p-value)	0.680	0.505	0.774	0.631	0.604
Difference-in-Hansen (p-val.)	0.506	0.416	0.860	0.675	0.817
Wald Chi2 (p-value)	0.000	0.000	0.000	0.037	0.000

Notes: This table reports results of two-step system GMM. AR (1) and AR (2) are tests for first- and second-order serial correlation in the first-differenced residuals, under the null hypothesis of no serial correlation. The Hansen test of over-identification is under the null hypothesis that the instrument set is valid, as is the case here. The Difference-in-Hansen test is under the null hypothesis that the subset of instruments used in the levels equations are exogenous. In the system GMM specification, we used the “forward” orthogonal deviations transformation instead of first-differencing because our data is unbalanced panel. We also used the “collapse” option to prevent instrument proliferation. Standard errors are in parentheses. See notes in Table 3 and Table A2 (in Appendix) for definitions of the variables.

\* Denotes statistical significance at the 10% level.

\*\* Denotes statistical significance at the 5% level.

\*\*\* Denotes statistical significance at the 1% level.

Table 5: Geographic diversification and credit risk: A trend analysis

	(11) Pre-crisis	(12) Crisis	(13) Post-crisis	(14) Full period
Branches	0.0442 (0.0322)	0.0003 (0.0256)	0.0607* (0.0365)	0.0519** (0.0230)
MFI size	-1.8403*** (0.4210)	-1.5539*** (0.3930)	-2.1336*** (0.5099)	-1.8082*** (0.2958)
Equity capital	-1.8328 (1.6757)	1.1793 (3.5980)	3.0213 (5.3571)	-1.1330 (1.7799)
Group lending	-3.8861*** (1.0656)	-2.9319*** (0.9305)	-0.5536 (1.2854)	-3.0456*** (0.6878)
Shareholder firm	0.4396 (0.9827)	1.1835 (0.9753)	2.7875** (1.3000)	1.3181** (0.6137)
MFI age	0.0677 (0.0537)	0.1777*** (0.0565)	0.0704 (0.0689)	0.1100** (0.0444)
Governance index	-0.0922 (0.1992)	-0.2366 (0.1540)	0.1708 (0.2202)	-0.1659 (0.1569)
GDP per capita	-1.4190 (1.0916)	-0.1141 (0.6392)	-2.3791* (1.2724)	-0.6391 (0.8553)
GDP growth	-0.0309 (0.0785)	-0.0860* (0.0502)	-0.2294* (0.1389)	-0.0661* (0.0391)
Regional dummies	Yes	Yes	Yes	Yes
Constant	49.1835*** (10.5931)	29.2547*** (8.1288)	59.4412*** (15.3685)	39.6787*** (8.5239)
Observations	743	509	380	1,632
Number of MFIs	277	243	168	382
Wald Chi2 (p-value)	0.0000	0.0000	0.0094	0.0000

Notes: This table lists random effects estimates across different periods of the sample. The dependent variable is PAR30. *Pre-crisis* refers to the portion (1998–2006) of the sample period (1998–2015) before the global financial crisis (2007–2009) and *post-crisis* to 2010–2015. Robust standard errors are in parentheses.

\* Denotes statistical significance at the 10% level.

\*\* Denotes statistical significance at the 5% level.

\*\*\* Denotes statistical significance at the 1% level

Table 6: Geographic diversification and credit risk: An organizational comparative analysis

	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
	Shareholder-owned Firm					Non-shareholder-owned Firm				
	PaR30	Write-off	Composite	Z-score	LLP	PaR30	Write-off	Composite	Z-score	LLP
Branches	0.0641 (0.0438)	-0.0101 (0.0151)	0.0322 (0.0449)	-0.0023 (0.0105)	0.0762 (0.0522)	0.0387 (0.0278)	0.0598* (0.0330)	0.0728* (0.0442)	0.0014 (0.0102)	0.0408** (0.0177)
MFI size	-1.4326*** (0.4413)	-0.7021*** (0.2572)	-1.6567*** (0.5171)	-0.3680** (0.1671)	-0.8290*** (0.2679)	-2.1559*** (0.4091)	-1.1942*** (0.3557)	-2.5599*** (0.5621)	-0.2284 (0.1722)	-0.4699 (0.5044)
Equity capital	-6.4948* (3.4818)	-2.4546* (1.3759)	-8.0972** (3.5193)	-1.1994** (0.5671)	-1.3346 (1.2776)	2.6162 (2.1239)	-0.0449 (1.7743)	3.1980 (2.7247)	0.1433 (0.3991)	-1.5007 (1.3423)
Group lending	-2.1238** (1.0664)	-0.5810 (0.5513)	-1.5905 (1.1908)	0.6977*** (0.1041)	-1.4069** (0.5638)	-3.6400*** (0.9266)	-2.0077*** (0.7588)	-5.9770*** (1.2267)	-1.3270*** (0.3688)	-2.0613*** (0.4425)
MFI age	0.1166 (0.0805)	0.0861 (0.0532)	0.2009* (0.1174)	0.1027** (0.0456)	-0.0259 (0.0439)	0.0936 (0.0583)	0.0984 (0.0616)	0.1095 (0.0845)	-0.0188 (0.0513)	-0.0613 (0.1461)
Governance index	-0.0167 (0.1968)	-0.2328 (0.1839)	-0.3346 (0.2452)	0.0263 (0.1274)	-0.0383 (0.1199)	-0.2834 (0.2062)	-0.3259 (0.2733)	-0.4420 (0.3036)	0.1144 (0.1024)	0.4574 (0.3394)
GDP per capita	-1.6555* (0.9042)	0.2726 (0.7344)	-1.2519 (1.1083)	-1.1358 (1.0575)	-0.8512 (0.7044)	0.0926 (1.2048)	0.4747 (0.8075)	-0.2016 (1.4050)	-0.3139 (0.7047)	-1.1714 (2.0109)
GDP growth	-0.1244** (0.0570)	-0.0422 (0.0381)	-0.1786*** (0.0673)	-0.0279** (0.0141)	-0.0676 (0.0471)	-0.0447 (0.0571)	0.1646 (0.2079)	-0.1091 (0.0666)	-0.0071 (0.0120)	0.0116 (0.0681)
Crisis	-0.8353 (0.6328)	-0.2803 (0.3488)	-0.9098 (0.6736)	-0.1233 (0.1240)	0.8391** (0.4008)	0.5148 (0.5047)	0.4447 (0.4855)	0.7253 (0.5746)	0.1363 (0.0945)	0.7052** (0.3421)
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	47.5778*** (10.5218)	12.9460 (8.0956)	49.5620*** (12.8171)	15.4993* (8.4781)	26.2045*** (8.9676)	38.6261*** (12.1235)	12.8999* (6.7115)	43.5385*** (13.4455)	6.9486 (6.6130)	22.9847 (18.1185)
Observations	692	539	698	689	649	940	734	955	949	837
Number of MFIs	173	151	165	156	172	227	183	211	205	216
Chi/F test (p-val)	0.0029	0.0421	0.0004	0.0000	0.0006	0.0000	0.0024	0.0000	0.0016	0.0001

Robust standard errors in parentheses

\*\*\* p-value&lt;0.01, \*\* p-value&lt;0.05, \* p-value&lt;0.10

Table 7: Geographic diversification and credit risk: Interaction between branches and group lending

	(25) PaR30	(26) Write-off	(27) Composite	(28) Z-score	(29) LLP	(30) PaR30	(31) Write-off	(32) Composite	(33) Z-score	(34) LLP
Branches	0.0611* (0.0340)	0.0279 (0.0212)	0.0707* (0.0428)	0.0088 (0.0095)	0.0720** (0.0359)	0.0711** (0.0324)	0.0378** (0.0165)	0.0870** (0.0369)	0.0024 (0.0019)	0.0688*** (0.0193)
Group lending	-2.8444*** (0.8913)	-1.2736* (0.6663)	-3.6904*** (1.0938)	-0.2050 (0.3674)	-0.3921 (0.4807)	-1.7423 (1.1237)	0.0245 (0.6008)	-1.6607 (1.5259)	0.0055 (0.0398)	0.3811 (0.4687)
Branch x group	-0.0160 (0.0429)	0.0055 (0.0318)	-0.0156 (0.0509)	-0.0157 (0.0115)	-0.0584* (0.0349)	-0.0834* (0.0496)	-0.0151 (0.0293)	-0.0954* (0.0520)	-0.0033 (0.0024)	-0.0766*** (0.0223)
MFI size	-1.8168*** (0.3070)	-0.9548*** (0.2263)	-2.0990*** (0.4020)	-0.2585** (0.1205)	-0.7906*** (0.1726)	-1.2071*** (0.3549)	-0.9683*** (0.2273)	-1.6783*** (0.4652)	-0.0553*** (0.0176)	-0.7788*** (0.1783)
Equity capital	-1.2040 (1.7943)	-1.0058 (1.2061)	-1.3242 (2.1081)	-0.4307 (0.3337)	-0.5957 (0.8755)	1.2484** (0.6101)	0.1430 (0.5830)	1.3059 (0.8460)	0.0335 (0.0391)	0.3850 (0.3960)
Shareholder firm	1.2975** (0.6098)	-0.0496 (0.6673)	1.0035 (0.8407)	0.3269 (0.2877)	0.3171 (0.4212)	-3.7702** (1.7629)	-2.0461* (1.0676)	-5.3928** (2.1100)	-0.1264 (0.0959)	-1.2363 (0.8596)
MFI age	0.1085** (0.0450)	0.0916** (0.0464)	0.1457** (0.0644)	0.0231 (0.0362)	0.0179 (0.0261)	0.0843* (0.0430)	0.0734* (0.0376)	0.1192** (0.0584)	0.0019 (0.0014)	0.0369 (0.0271)
Governance index	-0.1719 (0.1558)	-0.2842 (0.1833)	-0.3553* (0.2138)	0.0681 (0.0779)	-0.1423** (0.0720)	No No	No No	No No	No No	No No
GDP per capita	-0.6155 (0.8443)	0.5577 (0.6857)	-0.5967 (1.0005)	-0.6543 (0.6434)	-0.1920 (0.3895)	No No	No No	No No	No No	No No
GDP growth	-0.0704* (0.0409)	0.0780 (0.1254)	-0.1206** (0.0473)	-0.0138 (0.0098)	-0.0292 (0.0399)	No No	No No	No No	No No	No No
Crisis	-0.1381 (0.4013)	0.1689 (0.3395)	-0.0558 (0.4469)	0.0094 (0.0783)	0.7590*** (0.2367)	No No	No No	No No	No No	No No
Country dummies	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Time dummies	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	39.6078*** (8.4567)	12.1490* (6.6723)	45.4200*** (9.9409)	9.7603* (5.6512)	17.7911*** (4.8361)	21.1325*** (5.5641)	11.2340*** (3.1811)	27.0495*** (7.0602)	0.8249** (0.3919)	15.3287*** (2.4337)
Observations	1,632	1,273	1,653	1,638	1,486	1,948	1,552	1,990	1,972	1,750
Number of MFIs	382	316	358	343	369	434	360	405	387	414



Chi2/F(p-value)	0.0000	0.0012	0.0000	0.0104	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
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Robust standard errors in parentheses  
 \*\*\* p-value<0.01, \*\* p-values<0.05, \* p-value<0.10

Basis of comparison	Microfinance Institutions	Traditional Banks
Goal	Social and financial orientations	Profit-oriented
Customer type	Low-income people (poor families and microenterprises). This is the group not served by traditional banks	High-income people (wealthy individuals, SMEs, large enterprises).
Lending model	<ul style="list-style-type: none"> <li>• Group lending</li> <li>• Individual lending</li> <li>• Small uncollateralized loans</li> </ul>	<ul style="list-style-type: none"> <li>• Mostly individual lending</li> <li>• Large collateralized loans</li> </ul>
Organizational form and ownership	<ul style="list-style-type: none"> <li>• Bank (shareholder-owned)</li> <li>• Nonbank financial institution (shareholder-owned)</li> <li>• Nongovernmental organization (no legal owners)</li> <li>• Cooperative or credit union (customer-owned)</li> </ul>	<ul style="list-style-type: none"> <li>• Bank (shareholder-owned)</li> </ul>
Funding sources	<ul style="list-style-type: none"> <li>• Donations</li> <li>• Subsidized debt</li> <li>• Commercial debt</li> <li>• Equity</li> </ul>	<ul style="list-style-type: none"> <li>• Commercial debt</li> <li>• Equity</li> </ul>

Figure 1: Comparison between microfinance institutions and traditional banks

## Appendix

Table A1: Distribution of number of microfinance institutions by country

Country	No. of MFIs	Country	No. of MFIs	Country	No. of MFIs
Albania	3	Moldova	2	Chad	3
Argentina	2	Morocco	8	Rwanda	13
Armenia	6	Nicaragua	19	Zambia	3
Benin	8	Pakistan	2	China	6
Bolivia	18	Paraguay	2	Serbia	2
Bosnia and Herzegovina	12	Peru	47	Ghana	6
Brazil	25	Philippines	22	Malawi	3
Bulgaria	3	Romania	7	Gambia	1
Burkina Faso	9	Russia	17	kosovo	5
Cambodia	14	Senegal	12	Congo	1
Chile	2	South Africa	4	Burundi	6
Colombia	14	Sri Lanka	2	Niger	9
Dominican Republic	8	Tanzania	9	Democratic Republic	2
Ecuador	24	Togo	5	Afghanistan	2
Egypt	6	Trinidad and Tobago	1	Costa Rica	3
El Salvador	8	Tunisia	1	Lebanon	2
Ethiopia	10	Uganda	25	Turkey	1
Georgia	8	Montenegro	2	Palestine	3
Guatemala	10	Cameroon	6	Comoros	1
Haiti	3	Guinea	3	Italy	3
Honduras	18	Timor	1	Samoa	1
India	32	Bangladesh	2	Sierra Leone	2
Indonesia	4	Nepal	5	South Sudan	1
Jordan	3	Vietnam	4	United Kingdom	1
Kazakhstan	8	Azerbaijan	9	Yemen	1
Kenya	18	Mongolia	4	Angola	1
Kyrgyz Republic	9	Nigeria	7	Macedonia	1
Madagascar	4	Mozambique	1	Jamaica	1
Mali	11	Tajikistan	11	<b>Total</b>	<b>657</b>
Mexico	32	Croatia	1		

Table A2: Definitions of variables

Variable	Definition
Portfolio at Risk	Fraction of loan portfolio in arrears for more than 30 days.
Write-off	Fraction of loan portfolio written off and accounted as loss.
Loan loss provisions	Fraction of loan portfolio reserved for future loan losses.
z-score	Calculated as the difference between composite risk (sum of portfolio at risk and loan loss provisions) and its mean divided by its standard deviation.
Volatility of ROA	The standard deviation of returns on assets per MFI.
Branch	The number of branch offices an MFI has.
MFI age	Number of years in operation as a microfinance institution.
MFI size	Total assets (log values used in estimations).
Equity capital	Equity divided by total assets.
Group	1 = if loans are made mainly to groups, 0 = individuals.
Shareholder firm (SHF)	1 = shareholder owned firm, 0 = non-shareholder-owned firm.
Governance index	This is the sum of six global governance scores on voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption. Data are taken from the World Bank database.
GDP per capita	Gross domestic product per capita, converted to international dollars using purchasing power parity rates (constant 2011).
GDP growth	Annual percentage growth rate of GDP
Crisis	1 = global financial crisis period (2007–2009), 0 = otherwise.
Rural and urban	1 = if an MFI serves both rural and urban clients, 0 = MFIs serving only urban clients or only rural clients.