Geographic Diversification and Credit Risk in Microfinance[1]

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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 by means of better governance and group lending methods.

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

JEL: G21, G23, G24, L31, O16

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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. After all, 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.

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, & Saunders, 2006; Allen N. Berger, Hasan, & Zhou, 2010; Hayden, Porath, & Westernhagen, 2007). 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 & 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 Riegel–Neal Act of 1994, banks that expanded beyond their home states benefited from a reduction in credit risk (Akhigbea & Whyte, 2003) and deposit risk (Aguirregabiria, Clark, & 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 (Bandelj, 2016; Goetz, Laeven, & Levine, 2012). Moreover, diversification increases the complexity of bank operations, thereby making it difficult for headquarters to monitor loans and control risk (Acharya et al., 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 607 MFIs in 87 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. This 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 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 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, 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 having an internal auditor report to the board and/or 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 & Morduch, 2010). Saunders and Cornett (2011, p. 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 & 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 & 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, & 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 & 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 & 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, & 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, 2000). Many MFIs are incorporated as NGOs (47 percent in our sample; see below), 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 & 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 & Lee, 2007), though they normally serve fewer clients compared to shareholder-owned MFIs, which have easier access to capital from investors and depositors (D'Espallier, Goedecke, Hudon, & Mersland, 2017; Ledgerwood, 1999). Because shareholders have rights to residuals, shareholder-owned MFIs are assumed to be better controlled (Hansmann, 2000; 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).

It is these organizational differences among MFI types as well as their dual institutional logics that make MFIs unique and different from traditional banks. 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.

Figure 1: Comparison between microfinance institutions and traditional banks

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	• Group lending • Individual lending • Small uncollateralized loans	• Mostly individual lending • Large collateralized loans
Organizational form and ownership	• Bank (shareholder-owned) • Nonbank financial institution (shareholder-owned) • Nongovernmental organization (no legal owners) • Cooperative or credit union (customer-owned)	• Bank (shareholder-owned)
Funding sources	• Donations • Subsidized debt • Commercial debt • Equity	• Commercial debt • Equity

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 (Demsetz & Strahan, 1997; Deng & Elyasiani, 2008) and credit risk (Akhigbea & Whyte, 2003). Furthermore, the risk-return tradeoff achieves a lower risk level (Acharya et al., 2006), insolvency risk declines, bank efficiency improves (Hughes, Lang, Mester, & Moon, 1996b), and deposit risk declines (Aguirregabiria et al., 2016). Goetz et al. (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 et al. (2014) find that diversification is associated with higher credit risk. Hughes, Lang, Mester, and Moon (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 & DeYoung, 1997; Fiordelisi, Marques-Ibanez, & Molyneux, 2011). Furthermore, other findings also indicate that diversification does not reduce bank risk (Demsetz & Strahan, 1997; Turkmen & 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 607 MFIs from 87 countries (see the Appendix) covering the period 1998–2015, comprising a total of 3296 MFI-year observations. The dataset is compiled based on rating assessment reports (formerly available at 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, & Mersland, 2016). 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 & Serrano-Cinca, 2007; Hudon & 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, & 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, our main metric of diversification, the variable "number of branches," has the lowest number of observations (1277), while the variable "total assets" has the highest number of observations (3219). Thus, in regressions involving the number of branches, the maximum number of observations is 1277, 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. *Loan loss provisions* (LLP) represent another common measure of credit risk (Ahlin, Lin, & Maio, 2011; Rose, 1996). It is the proportion of the loan portfolio that is reserved in anticipation of future loan losses.

As a robustness check, we use volatility of returns on assets (ROA) (e.g., Aguirregabiria et al. 2013) and a z-score, based on the sum of PaR30 and LLP, as alternative risk metrics. The z-score is defined as the number of standard deviations from the mean of composite risk (i.e., the sum of PaR30 and LLP). 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, Morgan, Samolyk, and Tarazi (2016).

Geographic diversification measure

The most common measures of geographic diversification in banking include number of branches and number of regions or states (Deng & Elyasiani, 2008; Fraser, Hooton, Kolari, & Reising, 1997). In this study, geographic diversification is measured as the number of *branches* an MFI has. This variable has also been used by Aguirregabiria et al. (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 more complex in terms of risk management and monitoring than an MFI with two branches in 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 disasters 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 & Strahan, 1997; Gulamhussen et al., 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 experience. MFI experience is measured by the number of years that the institution has been in operation as an MFI. 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 & 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 & 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 & 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, & 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, & 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.

Leverage. 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 et al. (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).

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 et al., 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. Finally, we control for time effects in two ways. First, we interact year with country to account for time effects within each country. This approach controls for differences in time effects across countries since the economic performance or policy of a country may vary from year to year. Second, 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. 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:

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

where $Risk_{it}$ represents credit risk of MFI i at time t. Credit risk is measured in terms of PaR30, LLP, volatility of ROA, 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. β_0 is the mean of unobserved heterogeneity, and β_1 and γ 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) as a robustness test. 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, & 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 & Bond, 1991). The serial correlation test considers the presence of second-order autocorrelation in the residuals from differenced equations (Arellano & 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 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.

5. Results and Discussion

5.1 Descriptive Statistics and Correlations

Table 1 presents the descriptive statistics of the variables. On average, 6 percent of the total loan portfolio is in arrears for longer than 30 days and 4 percent is reserved in anticipation of future loan losses. The sum of the two indicators is used to produce a mean z-score of 5. The mean volatility of ROA is 6 percent. The average MFI is 11 years old, has 18 branches, and holds US$15 million in total assets, of which 38 percent is financed by equity capital. Regarding lending methodology, 42 percent of the MFIs give group loans and the rest offer individual loans.

Table 1: Descriptive statistics

	Mean	Std. Dev.	Min.	Max.	Obs.
Portfolio at risk (%)	6.06	7.50	0.10	48.90	2777
Loan loss provisions (%)	3.61	4.64	0.10	56.60	2561
Z-score	4.57	0.89	-2.01	3.45	2261
Volatility of ROA (%)	5.98	7.73	0.05	75.66	3208
Number of branches	18.11	32.70	1.00	376.00	1277
MFI age	10.76	6.34	2.00	33.00	3078
Assets (US$000)	14944.97	33153.55	50.00	365256.99	3219
Leverage (equity/assets)	0.38	0.24	0.01	1.00	3101
Shareholder firm	0.37	0.48	0.00	1.00	3049
NGO	0.47	0.49	0.00	1.00	3096
Coop	0.15	0.36	0.00	1.00	3096
Bank	0.05	0.21	0.00	1.00	3096
Nonbank	0.32	0.46	0.00	1.00	3096
Group	0.42	0.49	0.00	1.00	2842
GDP per capita (US$)	6533.41	5007.46	703.39	26429.35	3244
Governance index	-2.95	2.22	-10.47	8.63	3082
Rural and urban	0.55	0.49	0.00	1.00	2641

Concerning ownership structure, 37 percent of the MFIs are shareholder-owned (consisting of 5 percent banks and 32 percent nonbank financial institutions) and the rest are non-shareholder-owned MFIs (comprising 47 percent non-governmental organizations and 15 percent cooperatives and member-owned organizations). In terms of geographical focus, about 55 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, GDP per capita has a mean value of US$6,533 and the mean governance index is -2.95. A higher governance index means a higher quality of governance structure in the country.

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 but all of them are below 0.50. That is, all of the correlations are below the suggested rule of thumb of 0.80 (Studenmund, 2011). Similarly, all of the VIF scores are below 5 (Studenmund, 2011). This indicates that multicollinearity is not a significant problem in this study.

Table 2: Pairwise correlation matrix and variance inflation factor

	VIF	1	2	3	4	5	6	7	8
1. Branches	1.65	1.0000							
2. MFI age	1.39	0.2034*	1.0000						
3. ln assets	1.38	0.4362*	0.3182*	1.0000					
4. Leverage	1.32	-0.0669	-0.0985*	-0.2221*	1.0000				
5. SHF	1.2	-0.0886	-0.1855*	0.1451*	-0.1035*	1.0000			
6. Group	1.18	0.0978*	-0.1068*	-0.2449*	0.1102*	-0.0751*	1.0000		
7. GDP/cap.	1.14	0.0029	0.0472	0.1657*	0.0148	-0.0576	-0.2173*	1.0000	
8. Gov. ind.	1.07	-0.0240	-0.0025	0.0560	0.0149	-0.0220	-0.0837*	0.4376*	1.0000
9. Crisis	1.02	-0.0246	0.0724*	0.1214*	-0.0877*	0.0454	0.0229	0.0194	-0.0413

Notes: The table reports pairwise correlations among explanatory variables. ln = natural logarithm, SHF = shareholder firm, VIF = variance inflation factor.
* Denotes statistical significance at the 5 percent level or lower.

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, as well as OLS[2] estimates for the volatility of earnings since the variable is computed per MFI. We control for country and time effects in two ways. First, we interact country with year in models (1–4). This strategy results in higher explanatory power (22–29% R-square) compared to that of the other models (6–11% R-square). Second, in models (5–8), we replace the country and year interaction term with two country-level variables, namely, GDP per capita and the governance index, and a time indicator (crisis).

The results of models (2–8) 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 may 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.

Concerning the control variables, we get some indications that larger MFIs have lower nonperforming loans – significant in models (4), (5), and (8) but showing a negative coefficient in 6 out of 8 models – suggesting that larger MFIs may have a greater ability to monitor loans (Baele, De Jonghe, & Vennet, 2007). However, it is interesting to note that number of branches is a much more significant variable in the regressions than MFI size. 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 far more important than the mere size effect for the level of credit risk.

[2] Since the volatility of returns on assets is computed per MFI, it is not logical to use a panel estimator. Accordingly, an OLS estimator is used to estimate the volatility of the ROA model.

Table 3: The link between geographic diversification and credit risk

	(1) PAR30	(2) LLP	(3) Z-score	(4) StdROA	(5) PAR30	(6) LLP	(7) Z-score	(8) StdROA
Branches	0.0119	0.0242***	0.0091***	0.0205***	0.0097*	0.0223***	0.0075***	0.0150*
	(0.0117)	(0.0068)	(0.0029)	(0.0076)	(0.0049)	(0.0036)	(0.0020)	(0.0079)
Group	-0.3010	0.3523	0.2478	2.0686***	-2.3293***	0.3724	0.0229	1.8415***
	(0.9342)	(0.5860)	(0.3144)	(0.5347)	(0.4989)	(0.5166)	(0.2294)	(0.4177)
MFI size	0.1764	0.1749	-0.1988	-0.9388***	-1.0215***	-0.1379	-0.1729	-0.7961***
	(0.7551)	(0.6856)	(0.1884)	(0.2092)	(0.1897)	(0.5629)	(0.1806)	(0.1895)
Leverage	-0.6278	-2.0749	-0.1396	1.3087	-1.6566	-4.5316***	-0.6512	0.3077
	(1.9158)	(1.6706)	(0.6194)	(0.9825)	(1.1769)	(1.6407)	(0.5400)	(0.9769)
MFI experience	-0.0290	0.2710***	0.2457***	-0.0429	0.2074***	0.1432	0.1507***	-0.0391
	(0.3384)	(0.0466)	(0.0139)	(0.0447)	(0.0491)	(0.1520)	(0.0515)	(0.0346)
SHF	1.3395	0.0298	0.1674	1.2583**	1.0331**	0.5051	0.2382	0.9842**
	(0.9038)	(1.0379)	(0.4624)	(0.5320)	(0.4367)	(0.7220)	(0.2980)	(0.3986)
Country*year	Yes	Yes	Yes	Yes	No	No	No	No
Gov. index					0.3105***	0.2753	0.1430	0.2200*
					(0.1201)	(0.2768)	(0.1315)	(0.1195)
GDP per capita					-1.2542***	-6.1204**	-2.7995***	0.1891
					(0.3040)	(2.5362)	(0.8578)	(0.3038)
Crisis					0.0955	0.5796*	0.2478**	-0.0555
					(0.3309)	(0.3170)	(0.1102)	(0.4325)
Constant	75.2915	854.8619***	332.9617***	-448.7531***	31.3904***	57.0262***	25.0795***	16.3197***
	(682.9691)	(295.3657)	(89.2207)	(157.9873)	(4.3037)	(19.5171)	(6.6189)	(4.0423)
Observations	1,013	915	847	1,046	982	888	824	1,018
R-squared	0.229	0.235	0.218	0.294	0.108	0.066	0.075	0.061
Number of MFIs	477	443	390	-	460	428	379	-
F/Chi2-test (p-value)	0.0000	0.0000	0.0009	0.0000	0.0000	0.0000	0.0000	0.0000
Hausman (p-value)	0.0000	0.0000	0.0021	-	0.1793	0.0000	0.0009	-
Estimator	Fixed	Fixed	Fixed	OLS	Random	Fixed	Fixed	OLS

Notes: This table lists fixed, random effects and OLS estimates on the link between geographic diversification and credit risk. *PaR30* is nonperforming loans over 30 days, *LLP* is loan loss provisions, *z-score* is computed based on the sum of PaR30 and LLP, and StdROA is volatility of returns on assets. *Branches* represents number of branches, *MFI size* is the natural logarithm of total assets, *MFI experience* is the age (years) of the institution, and *Leverage* is calculated as equity divided by total assets. *Group* = 1 if group loans and = 0 if individual loans, *SHF* = 1 if shareholder-owned firm and = 0 if non-shareholder-owned firm, *Gov. index* represents governance index capturing macroinstitutional 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. Robust standard errors are in parentheses.
*** denotes statistical significance at the 10 percent, 5 percent and 1 percent level respectively

Surprisingly, older MFIs are not efficient in controlling defaults because they have higher nonperforming loans (evident in four 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 model (5), group lending is negatively associated with lower risk, consistent with microfinance literature (Ghatak & Guinnane, 1999). However, the coefficient is positive and significant in the two OLS models, suggesting higher risk and hence a mixed effect of group lending on risk. The mixed results render this variable far less important than our test variable of diversification.

Furthermore, in model (6), financial leverage 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 per capita*, consistent with the literature (Carey, 1998; Louzis et al., 2012). That is, in more developed economies, borrowers have more income to repay debts. However, high-quality governance structure in a country does not necessarily reduce risk. This finding departs from expectation, though it is not necessarily surprising since MFIs serve clients operating in the informal economy where a country's formal governance structure does not often have much influence. 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 (1–8) 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 eight 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.

In Table 4, 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 the z-score on number of branches and all the controls except the financial crisis dummy. The results indicate that the positive effect started during the financial crisis but became significant after this period. We stress that the numbers of observations are smaller in the subperiods, but we report the additional test to suggest that our findings of increased credit risk following increased diversification are relevant.

Table 4: Geographic diversification and credit risk: A trend analysis

	(17) Pre-crisis	(18) Crisis	(19) Post-crisis	(20) Full period
Branches	-0.0001	0.0381	0.0057***	0.0079***
	(0.0117)	(0.0419)	(0.0017)	(0.0020)
Group	-	0.5341*	-0.1781	0.0774
	-	(0.2782)	(0.2950)	(0.2422)
MFI size	0.3191	-1.1888**	-0.0312	-0.0833
	(0.4719)	(0.4995)	(0.4703)	(0.1693)
Leverage	-1.0149	-0.1723	-1.9988	-0.6395
	(0.9069)	(1.0554)	(2.1095)	(0.5420)
MFI experience	-0.0036	0.4665***	0.2270	0.1193**
	(0.1417)	(0.1717)	(0.1400)	(0.0485)
Governance index	0.0001	-0.4049	0.2848	0.0884
	(0.2080)	(0.4920)	(0.2985)	(0.1359)
GDP per capita	-5.8405**	-3.0894	-6.3545*	-2.4677***
	(2.4193)	(3.4044)	(3.2341)	(0.8609)
Shareholder firm	1.0689	0.8743**	0.1373	0.2170
	(1.0376)	(0.4280)	(0.3523)	(0.3143)
Constant	44.8250**	36.7957	53.2684*	21.0886***
	(18.0804)	(28.2888)	(27.9075)	(6.5895)
Observations	259	294	272	825
R-squared	0.111	0.162	0.091	0.062
Number of MFIs	192	203	166	380
F-test (p-value)	0.3625	0.0565	0.0000	0.0000
Estimator	Fixed effects	Fixed effects	Fixed effects	Fixed effects

Notes: This table lists fixed-effects estimates across different periods of the sample. The dependent variable is z-score. 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.
*** p<0.01, ** p<0.05, * p<0.1.

In Table 5, 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 5 show, this is indeed the case. It is clearly seen that there is a strong positive relationship between number of branches and risk in terms of PaR30 (as well as the other 3 risk metrics, according to the untabulated results) in the non-shareholder group.

Table 5: Geographic diversification and credit risk: An organizational comparative analysis

	(21) SHF	(22) NonSHF
Branches	0.0009	0.0134***
	(0.0140)	(0.0051)
Group	-2.0069***	-2.3523***
	(0.7347)	(0.5957)
MFI size	-1.0215***	-1.1732***
	(0.3589)	(0.2353)
Leverage	-4.6016**	0.6609
	(1.9253)	(1.6821)
MFI experience	0.3074***	0.1694***
	(0.1126)	(0.0487)
Governance index	0.5441***	0.0792
	(0.1852)	(0.1588)
GDP per capita	-1.2654***	-1.3541***
	(0.4705)	(0.3828)
Crisis	-0.0868	0.2087
	(0.4886)	(0.4673)
Constant	33.1635***	33.4804***
	(7.7881)	(5.0290)
Observations	414	571
Number of MFIs	200	282
R-squared	0.1192	0.1388
Chi2 test (p-value)	0.0002	0.0000
Estimator	Random effects	Random effects

Notes: This table lists random-effects estimates across different organizational types of MFIs. The dependent variable is PaR30. SHF = shareholder firms; NonSHF = non-shareholder firms. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In other tests we check how the positive effect of diversification on risk might be mitigated. First, we repeat models (1–8) 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 rerun models (1–8). The results (see Table A3 in the Appendix) 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 Table 3, but that the interaction term between branches and group lending is negatively (all models) and significantly (in 5 out of 8 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 (Armendáriz & Morduch, 2010; Ghatak & Guinnane, 1999).

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 (see Table A4 in the Appendix) show that number of branches is no longer significantly correlated with risk and that internal audit is negatively related with risk but is significant only in the LLP model. The interaction term between the two variables has no strong statistical influence on risk. Overall, the internal audit function seems to 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 (1–8) using a standard OLS estimator, first using number of branches as the test variable and, second, replacing branches with the *rural-urban* dummy. In both robustness tests, the (untabulated) results show that the positive relationship between diversification and risk remains unchanged. Our final robustness check relates to a possible reverse causality concern, which we address by using a GMM estimator. Again, the results (see Table A5) suggest a positive relationship between number of branches and credit risk. The result is statistically significant for the loan-loss provision model.

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 and higher loan-loss provisions as well as higher volatility of earnings. 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 and the internal audit function. Thus, diversification can be beneficial to MFIs if internal control and monitoring are improved.

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 (Bandelj, 2016; Goetz et al., 2012). 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 et al., 2006). In microfinance, monitoring by owners may be weaker than it is 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.

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 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, 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 nonperforming loans, which in turn leads to 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 as well as better internal controls.

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 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 would be willing to increase their risk if the outcome were 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.

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Appendix

Table A1: Distribution of number of microfinance institutions by country

#	Country	No. of MFIs	#	Country	No. of MFIs	#	Country	No. of MFIs
1	Albania	3	30	Mexico	31	59	Tajikistan	11
2	Argentina	2	31	Moldova	2	60	Croatia	1
3	Armenia	6	32	Morocco	8	61	Chad	3
4	Benin	8	33	Nicaragua	14	62	Rwanda	12
5	Bolivia	17	34	Pakistan	2	63	Zambia	3
6	Bosnia and Herzegovina	12	35	Paraguay	2	64	China	5
7	Brazil	14	36	Peru	40	65	Serbia	2
8	Bulgaria	3	37	Philippines	22	66	Ghana	5
9	Burkina Faso	9	38	Romania	7	67	Malawi	2
10	Cambodia	14	39	Russia	17	68	Gambia	1
11	Chile	2	40	Senegal	12	69	Kosovo	5
12	Colombia	14	41	South Africa	4	70	Congo	1
13	Dominican Republic	7	42	Sri Lanka	2	71	Burundi	6
14	Ecuador	20	43	Tanzania	8	72	Niger	8
15	Egypt	6	44	Togo	5	73	Dem. Rep. Congo	1
16	El Salvador	7	45	Trinidad and Tobago	1	74	Afghanistan	2
17	Ethiopia	10	46	Tunisia	1	75	Costa Rica	3
18	Georgia	8	47	Uganda	25	76	Lebanon	2
19	Guatemala	8	48	Montenegro	2	77	Turkey	1
20	Haiti	3	49	Cameroon	5	78	Palestine	3
21	Honduras	13	50	Guinea	3	79	Comoros	1
22	India	32	51	Timor	1	80	Italy	3
23	Indonesia	4	52	Bangladesh	2	81	Samoa	1
24	Jordan	3	53	Nepal	5	82	Sierra Leone	1
25	Kazakhstan	8	54	Vietnam	4	83	South Sudan	1
26	Kenya	18	55	Azerbaijan	9	84	United Kingdom	1
27	Kyrgyz Republic	9	56	Mongolia	4	85	Yemen	1
28	Madagascar	3	57	Nigeria	6	86	Angola	1
29	Mali	11	58	Mozambique	1	87	Macedonia	1
							Total	**607**

Table A2: Definitions of variables

Variable	Definition
Portfolio at Risk	Fraction of loan portfolio in arrears for more than 30 days.
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 experience	Number of years in operation as a microfinance institution.
MFI size	Total assets (log values used in estimations).
Leverage	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.
NGO	1 = nongovernmental organization, 0 = otherwise.
Cooperative	1 = if MFI is registered as a cooperative, 0 = otherwise.
Bank	1 = if MFI is registered as a bank, 0 = otherwise.
Nonbank	1 = nonbank financial institution, 0 = otherwise.
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).
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.

Table A3: Geographic diversification and credit risk: Interaction between branches and lending method

	PAR30	LLP	Z-score	StdROA	PAR30	LLP	Z-score	StdROA
Branches	0.0171*	0.0255***	0.0104***	0.0397***	0.0128**	0.0245***	0.0087***	0.0512***
	(0.0088)	(0.0070)	(0.0031)	(0.0102)	(0.0054)	(0.0042)	(0.0018)	(0.0103)
Group loan	0.0716	0.5509	0.4425	2.4926***	-2.2379***	0.6414	0.2158	2.6537***
	(1.0062)	(0.6409)	(0.3440)	(0.5793)	(0.5277)	(0.5635)	(0.2405)	(0.4723)
Branches*group	-0.0244	-0.0141	-0.0149**	-0.0316***	-0.0056	-0.0190*	-0.0151***	-0.0521***
	(0.0276)	(0.0175)	(0.0066)	(0.0107)	(0.0076)	(0.0099)	(0.0046)	(0.0102)
MFI size	0.1913	0.1887	-0.1909	-0.9508***	-1.0222***	-0.0416	-0.1513	-0.8952***
	(0.7601)	(0.6813)	(0.1857)	(0.2058)	(0.1894)	(0.5922)	(0.1806)	(0.1897)
Leverage	-0.5988	-2.0554	-0.1045	1.3401	-1.6609	-4.4138***	-0.6386	0.2304
	(1.9080)	(1.6555)	(0.6091)	(0.9798)	(1.1757)	(1.6654)	(0.5305)	(0.9763)
MFI experience	0.0624	0.2356***	0.2081***	-0.0498	0.2061***	0.1323	0.1515***	-0.0553
	(0.2741)	(0.0607)	(0.0220)	(0.0444)	(0.0493)	(0.1537)	(0.0510)	(0.0347)
SHF	1.3762	0.0480	0.1889	1.2447**	1.0300**	0.5223	0.2708	1.0453***
	(0.8967)	(1.0282)	(0.4493)	(0.5299)	(0.4361)	(0.7137)	(0.2890)	(0.3952)
Country*year	Yes	Yes	Yes	Yes	No	No	No	No
Gov. index					0.3044**	0.2372	0.1253	0.1814
					(0.1203)	(0.2843)	(0.1344)	(0.1190)
GDP per capita					-1.2512***	-6.3088**	-2.9216***	0.2280
					(0.3045)	(2.5356)	(0.8485)	(0.3035)
Crisis					0.0933	0.5634*	0.2439**	-0.0322
					(0.3310)	(0.3199)	(0.1097)	(0.4318)
Constant	229.6775	777.7174**	249.6275**	-436.9553***	31.3373***	57.0903***	25.7280***	17.1272***
	(554.9044)	(319.5047)	(97.1855)	(158.2151)	(4.3197)	(19.3143)	(6.5398)	(4.0540)
Observations	1,013	915	847	1,046	982	888	824	1,018
Number of MFIs	477	443	390	-	460	428	379	-
R-squared	0.230	0.236	0.225	0.297	0.108	0.069	0.086	0.074
Estimator	FE	FE	FE	OLS	RE	FE	FE	OLS

Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table A4: Geographic diversification and credit risk: Interaction between branches and internal audit

	PAR30	LLP	Z-score	StdROA	PAR30	LLP	Z-score	StdROA
Branches	0.0160	0.0293	-0.0081	0.0144	0.0056	0.0274	-0.0107	0.0038
	(0.0613)	(0.0251)	(0.0202)	(0.0114)	(0.0093)	(0.0196)	(0.0165)	(0.0092)
Internal audit	-0.9384	0.2180	-0.2943	0.5393	-0.6228	-0.5064	-0.5185**	0.5105
	(0.9047)	(0.6592)	(0.3237)	(0.7116)	(0.5223)	(0.6050)	(0.2557)	(0.7144)
Branches*audit	-0.0035	0.0001	0.0110	-0.0095	0.0000	0.0077	0.0121	-0.0092
	(0.0263)	(0.0162)	(0.0131)	(0.0104)	(0.0094)	(0.0114)	(0.0085)	(0.0098)
Group	-0.2803	0.2521	0.3501	2.0226***	-2.3053***	0.0992	0.1835	2.1302***
	(1.5119)	(0.6858)	(0.4603)	(0.7025)	(0.5435)	(0.4984)	(0.2747)	(0.4924)
MFI size	1.1193	0.4142	0.0990	-0.7457***	-1.0921***	-0.5212	0.0014	-0.6597***
	(1.0758)	(0.4671)	(0.2588)	(0.2374)	(0.2425)	(0.7106)	(0.2479)	(0.2217)
Leverage	-0.7727	-1.5198	-0.6909	1.9459*	-2.1827*	-4.6724**	-0.8187	1.7058
	(1.9516)	(1.0800)	(0.6391)	(1.1128)	(1.2826)	(1.8630)	(0.5776)	(1.1209)
MFI experience	-0.0926	0.2900**	0.2880**	-0.0666	0.2000***	0.1560	0.1208*	-0.0289
	(0.2744)	(0.1391)	(0.1142)	(0.0483)	(0.0463)	(0.1491)	(0.0673)	(0.0417)
SHF	2.0763*	0.4179	0.6196	0.7525	1.0141**	0.5385	0.3578	1.2233**
	(1.2556)	(1.1400)	(0.4144)	(0.6791)	(0.4859)	(0.8920)	(0.2447)	(0.5570)
Country*year	Yes	Yes	Yes	Yes	No	No	No	No
Gov. index					0.2386**	0.6132*	0.1396	0.1877
					(0.1177)	(0.3276)	(0.1400)	(0.1290)
GDP per capita					-1.2723***	-4.0684	-2.4355*	0.1301
					(0.3153)	(3.9643)	(1.2622)	(0.3584)
Crisis					0.3486	0.3421	0.1039	-0.1385
					(0.4207)	(0.4133)	(0.1635)	(0.5473)
Constant	348.2834	830.8341***	475.8776**	-481.4850**	33.0286***	46.9099	20.0690**	13.6077***
	(529.3721)	(303.0831)	(218.9712)	(222.3313)	(4.6860)	(29.0330)	(9.7407)	(4.8784)
Observations	673	607	553	695	651	587	537	676
Number of MFIs	439	407	362	-	425	394	353	-
R-squared	0.144	0.525	0.310	0.286	0.115	0.106	0.085	0.063
Estimator	FE	FE	FE	OLS	RE	FE	FE	OLS

Table A5: Geographic diversification and credit risk: System GMM

	PaR30	LLP	Z-score
Branches	0.0854	0.0949**	0.0284
	(0.0925)	(0.0382)	(0.0195)
Group	-1.8180	-1.9351***	-0.9583***
	(1.6253)	(0.3514)	(0.3526)
MFI size	-2.5673	-0.4533	-0.5058
	(1.7714)	(1.3316)	(0.5795)
Leverage	2.3479	-3.5073	-3.9181
	(19.2700)	(5.5125)	(2.8334)
MFI experience	2.4072*	1.9291***	1.1921**
	(1.2466)	(0.4545)	(0.5111)
Governance index	0.3869	0.2547***	0.2812***
	(0.4903)	(0.0920)	(0.0925)
GDP per capita	0.2904	0.1661	0.0348
	(0.2203)	(0.1586)	(0.0802)
Crisis	-0.3644	-0.1759	-0.2059
	(1.7756)	(0.4983)	(0.2299)
Shareholder MFI	0.4664	0.7751*	0.1706
	(0.7418)	(0.3984)	(0.1665)
Constant	30.5537	31.3452***	14.2601**
	(39.4881)	(9.3125)	(6.7764)
Observations	985	889	825
Number of MFIs	463	429	380
Number of instruments	34	35	35
AR(1) test (p-value)	0.354	0.006	0.009
AR(2) test (p-value)	0.728	0.394	0.102
Hansen test (p-value)	0.265	0.294	0.234
Chi2-test (p-value)	0.062	0.000	0.115

Notes: This table reports results of 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, which is the case for PaR30 model. For the LLP and Z-score models, there is serial correlation in the first order but not in the second order. The Hansen test of over-identification is under the null hypothesis that the instrument set is valid, as is the case here. In specifying the GMM model, we use one-year lags of PaR30, LLP, and z-score as GMM instruments, and the "collapse" option of limiting instrument proliferation. 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.