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Employee turnover and the credit risk of microfinance institutions (MFIs): International evidence

Md Imran Hossain [a,b], Md Aslam Mia [a,*], Chee-Wooi Hooy [a]

[a] *School of Management, Universiti Sains Malaysia, 11800, Penang, Malaysia*
[b] *Department of Finance, Jagannath University, Dhaka, 1100, Bangladesh*

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Abstract

In today's competitive world, credit risk poses a significant challenge to lending institutions such as microfinance institutions (MFIs) due to its impact on their long-term institutional and financial viability. In recent years, high employee turnover has also emerged as a threat to the sustainability of MFIs. Therefore, this study investigates the impact of employee turnover on the credit risk of MFIs using nine years of unbalanced panel data (from 2010 to 2018) of 1266 unique MFIs from 101 countries, obtained from the World Bank databases. In general, we observe that employee turnover raises the credit risk of MFIs. The result is robust to endogeneity-correction techniques (e.g., Hausman-Taylor) and other alternative specification/robustness tests. The findings offer valuable insight for MFI managers, enabling them to make informed decisions about employee turnover management to mitigate credit risks.

JEL classification: G21; G23; J63

Keywords: Credit risk; Employee turnover; Institutional sustainability; Microfinance institutions; Portfolio risks; Write-off ratio

1. Introduction

Microfinance institutions (MFIs) have been in operation for decades, with the goal of empowering financially excluded rural and low-income people by offering them a variety of financial services (Littlefield, Morduch, & Hashemi, 2003; Mia, 2022a). In particular, the primary objective of MFIs is to serve the poor, also known as social outreach. However, in the long run, servicing only the poor by relying on donations or aid is unsustainable for MFIs; therefore, policy makers emphasize financial sustainability as the secondary goal of MFIs (Nourani, Malim, & Mia, 2021). However, to achieve both social and financial sustainability, institutional sustainability in terms of risk reduction is required.

In general, MFIs face a variety of risks, including credit risk, portfolio risk, liquidity risk, strategic risk, and operational risk (Zamore, Beisland, & Mersland, 2019). However, they are most vulnerable to credit risk because of their dependence on credit products and services (Armendariz & Labie, 2011). In other words, because MFIs largely depend on credit to clients, the failure of borrowers to repay their loans tends to shrink the profit of MFIs. Therefore, credit risk is considered to have a significant negative impact on the profitability of banking and financial institutions (Fang & van Lelyveld, 2014), including MFIs. Furthermore, MFIs are more vulnerable to credit risk than banks because of the shorter maturity (one year or less) of their credit. This means that if MFI borrowers skip one or two repayments, the MFI's overall credit risk increases. It has also been said that default breeds default, meaning that if a few borrowers fail to repay on time, the payment patterns of other MFI borrowers might change (Bond & Rai, 2009), particularly in a group lending setting. Moreover, the high credit or default

* Corresponding author.
E-mail addresses: jnuimran@gmail.com (M.I. Hossain), aslammia@usm.my (M.A. Mia), cwhooy@usm.my (C.-W. Hooy).
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risk of MFIs may be due to the provision of collateral-free loans (Ibtissem & Bouri, 2013). Therefore, to guarantee the long-term sustainability of MFIs, it is crucial to concentrate on credit risk reduction strategies and policies.

We observe that the average write-off ratio and the average portfolio risk over 30 days, two common tools used for measuring credit risk (Blanco-Oliver, Reguera-Alvarado, & Veronesi, 2021; Zamore et al., 2019), for global MFIs is rising and becoming unstable over time (see Fig. 1). For example, in 2018 the average portfolio risks per 30 days in Africa, Eastern Europe, Central Asia, Latin America, and the Caribbean region were as high as 8.2 percent, 7.8 percent, and 6.9 percent, respectively. From 2010 to 2018, the credit risk for MFIs in these regions fluctuated, which suggests that MFIs must control and minimize credit risk to ensure long-term institutional sustainability.

In a bid to minimize credit risk among MFIs, scholars are now focused on understanding the various drivers of risks in the microfinance context. The factors investigated so far include the role of financial technology (Banna, Mia, Nourani, & Yarovaya, 2022), loan officers' overconfidence (Fersi & Boujelbène, 2022), managerial competency (Nkundabanyanga, Opiso, Balunywa, & Nkote, 2015), CEO power (Galema, Lensink, & Mersland, 2012), board gender diversity (Adusei, 2020), credit technologies (Schulte & Winkler, 2019b), group lending techniques, women borrowers, diversification (Lassoued, 2017), geographic diversification (Zamore et al., 2019), and the lender-borrower relationship (Shahriar & Garg, 2017) in the credit risk of MFIs. However, to our knowledge, few studies have been conducted in recent years that explicitly investigate the nexus between employee turnover and the credit risk of MFIs, perhaps because of the unavailability of institutional-level data on employee turnover before 2019.[1] Thus, the recent global availability of such data motivated us to further enrich the risk literature in the microfinance context.

This investigation is crucial for the efficient management of microfinance businesses, which rely heavily on human capital for their operations. Unlike commercial bank customers, clients of MFIs rarely visit a branch location to apply for a loan. Rather, MFI loan officers frequently go to potential customers' homes and engage them. This one-on-one contact fosters trust and cordial relations between clients and loan officers. As a result, these loan officers gain exclusive access to all the clients' soft data (Uzzi & Lancaster, 2003), which later aid the process of loan recovery. This highlights the crucial role of loan officers in ensuring the timely recovery of loans (Sangwan, Nayak, Harshita, & Sangwan, 2021). The loan repayment structure of MFIs is significantly influenced by the employee-borrower relationship because of their use of relationship-lending approach. Moreover, for the most part, MFI loans to customers are not backed by physical collateral, which guarantees that employees maintain a close and trustworthy relationship with borrowers to foster loan recovery. According to the social capital theory, the departure of employees from an organization not only disrupts the relationship between the organization and its credit customers but also leads to the loss of clients' soft information (Berger & Udell, 2002). Therefore, employee turnover, even at very low to moderate levels, might promote borrowers' patronage of new MFIs for further loan services while neglecting the repayment of previous loans (Drexler & Schoar, 2014). This ultimately increases repayment problems and the credit risks of MFIs.

This research contributes to the existing literature in several ways. First, our findings will help scholars better understand the impact of staff turnover on the credit risk of organizations, particularly MFIs. As this topic is relatively understudied in the context of the microfinance industry, our results will support future research on strategies for managing credit risks that arise from employee turnover at MFIs. Second, most of the earlier literature on employee turnover and organizational performance uses a cost-based or human capital approach. However, the microfinance model is based on a relationship-lending approach, which is driven by an employee-client relationship. Therefore, we use the lens of social capital theory to empirically enrich the existing literature on the effect of employee turnover on the credit risk of MFIs. Third, by using global data rather than focusing on a single country or region, this study enables policy makers and managers to develop effective policies aimed at reducing the credit risk of MFIs. Moreover, several robustness tests are conducted to attain robust and reliable results so that credible policy implications can be offered.

The rest of the paper is organized as follows: Section 2 reviews the existing literature and presents our conceptual framework; Section 3 discusses the methodology, including data sources and model development; Section 4 advances our empirical analysis and discussion; and Section 5 consists of the conclusion, implications, and future research directions.

2. Literature review

2.1. Employee turnover and why it matters?

Employee turnover means the loss of employees over a period of time (March & Simon, 1958). However, according to Lee (2018), job transfer within an organization can also be regarded as employee turnover. Several authors divide employee turnover into voluntary and involuntary, and each of these types of employee turnover has a different impact on organizations. For example, a low to moderate level of employee turnover allows firms to attract competent staff to the office that needs them. However, when the turnover rate reaches a moderate to high level, the organization's performance tends to fall, indicating that a weakly negative link exists between staff transfers and organizational performance. Likewise, when employees voluntarily leave an organization, the organization may suffer lower performance and productivity for several reasons. In general, employee turnover results in three types of losses for organizations: (1) monetary loss from hiring and replacing the employee, (2) loss of the skill and experience

[1] Data on organizational level variables were mostly subscription based prior to 2019 by the MIX Market.

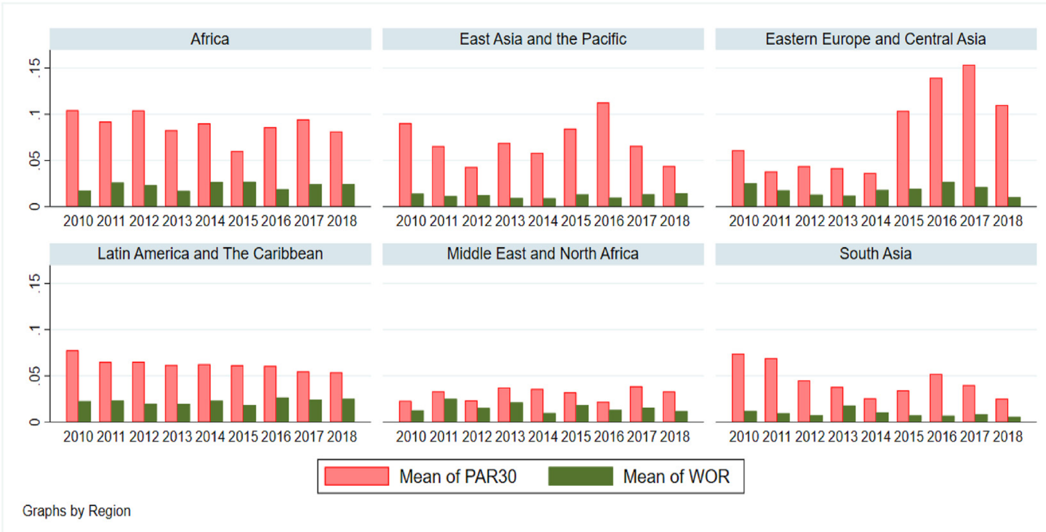

Fig. 1. Regional average Portfolio Risk Over 30 days (PAR30) and Average Write-Off Ratio (WOR). Sources: Authors computation.

of the former employee, and (3) loss of the clients' relationship network along with their soft information.

Three theories have developed in the literature concerning the three types of losses due to employee turnover. First, the cost-based theory (Dalton & Todor, 1979) states that employee turnover causes a firm to incur additional costs for the recruitment and training of new employees. Second, human capital theory (Becker, 2009) argues that every employee has unique qualities or traits, skills, knowledge, and experience, which have a direct impact on the performance of their organization. Hence, the departure of an employee from an organization amounts to a loss of certain qualities, skills, knowledge, and experience, which may take the organization ages to recover. Third, social capital theory (Leana & Van Buren, 1999) suggests that every employee has a methodology or strategy to develop a long-term relationship with customers. Some employees can develop a good rapport with clients, which promotes customer retention. However, when these employees leave the organization, their clients may also lose interest in the organization, which is often the case at financial institutions, such as banks and MFIs (Drexler & Schoar, 2014).

In Fig. 2, we demonstrate the overall employee turnover rates in the global microfinance industry. The employee turnover rate in this industry is, on average, more than 20 percent and in some years as much as 23 percent.

2.2. Brief review of existing employee turnover literature

Over the past few decades, employee turnover has piqued the interest of researchers in various fields, including those in finance (Allen, Bryant, & Vardaman, 2010; Kurniawaty, Ramly, & Ramlawati, 2019; Mia, Banna, Noman, Alam, & Rana, 2022). Earlier studies have found a linear negative relationship between employee turnover and organizational performance in sectors such as financial services, technology, and professional services (Hancock, Allen, Bosco, McDaniel, & Pierce, 2013; Shaw, 2011). They argue that the turnover of skilled employees has two consequences for an organization. First, it results in the loss of human capital (Hausknecht & Trevor, 2011), and, second, it has financial implications, as the organization will have to spend more money to recruit and train new employees (Allen et al., 2010). However, the resignation of employees who are inefficient, less skilled in technology and communication, and unproductive gives the organization financial relief (Alexander, Bloom, & Nuchols, 1994). Employee turnover can sometimes be advantageous for organizations, as it enables them to attract new employees with valuable skills and innovations (Abelson & Baysinger, 1984).

In addition to the linear link, a curvilinear relationship, specifically, an inverted-U-shaped relationship, has also been documented between employee turnover and financial performance (Glebbeek & Bax, 2004; Meier & Hicklin, 2008). This suggests that employee turnover is beneficial for firms to a certain (optimal) level, after which the benefits turn into disadvantages, such as high cost and poor financial performance. Furthermore, De Winne, Marescaux, Sels, Van Beveren, and Vanormelingen (2019) argue that, rather than an inverted-U-shaped relationship, an attenuated negative relationship exists between employee turnover and firm performance. However, limited research has been conducted on the impact of employee turnover on the credit risk of the MFIs.

Because MFIs rely on relationship lending, their loan repayment structure is significantly driven by the employee-borrower relationship. The business model of MFIs permits the extension of loans to customers who do not provide collateral. Thus employees are expected to maintain a close and trusting relationship with borrowers to ensure loan recovery. According to social capital theory, the departure of employees from an organization not only disrupts the relationship between the organization and its credit customers but also leads to the loss of clients' soft information (Berger & Udell, 2002), whose collection is the result of a long-standing connection between employee and borrowers. This

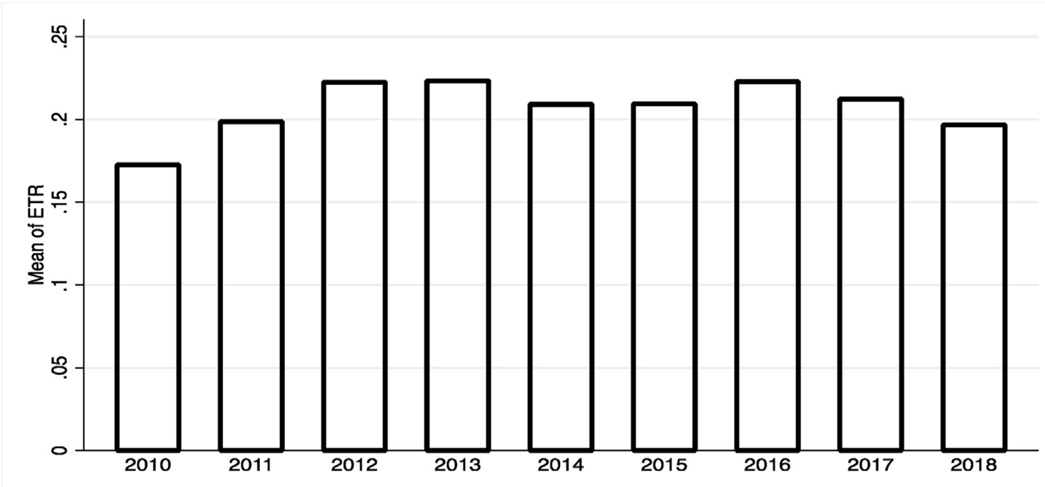

Fig. 2. Employee turnover rates in the global microfinance industry (2010–2018). Source: Authors computation.

soft information, which helps in reducing information asymmetry between MFIs and potential credit clients (Elsas & Krahnen, 1998), is often lost due to employee turnover. Even when the MFI replaces the departed employees, the recovery of all the clients' information and the restoration of social relations with clients take a long time. Moreover, borrowers may be reluctant to divulge personal information to a new loan officer, thus exposing MFIs to the risk of borrower turnover (Drexler & Schoar, 2014).

Furthermore, loan officers' close monitoring of borrowers has a large impact on their loan recovery (Blanco-Oliver et al., 2021). Therefore, employee turnover may encourage borrowers to seek new MFIs to obtain additional loan services while neglecting repayment of previous loans (Drexler & Schoar, 2014). According to Canales and Greenberg (2016), when a credit officer is transferred during the loan period, their customers are more likely to forget to make a payment. However, they discovered that the impact of employee turnover on loan repayment in that case is moderated by coherence in the relationship approach taken by the subsequent loan officer. Consistent with these studies, the relationship-lending approach, microfinance literature, and other research, we contend that a change in loan officers may affect clients' repayment willingness. Therefore, if an employee switches MFIs, which commonly occurs in the sector, the MFI suffers two consequences: first, a higher cost of administration and, second, increased credit risk (Pagura & Growth, 2004).

In view of the foregoing, we posit the following hypothesis.

Hypothesis 1. The relationship between employee turnover and MFIs' credit risk is positive and statistically significant.

3. Methodology

3.1. Data and sources of data

For institutional-level data, we use the popular dataset from the World Bank, which was previously available in the MIX Market database. The collaboration between the MIX Market and the World Bank in 2019 improved accessibility to the global MFI database for microfinance research. The MIX Market database is a voluntary database, in which MFIs from all around the world freely share their data. As a result, data for each MFI may not be accessible every year, making it an unbalanced panel dataset. Although the database covers MFI data from 2000 to 2019, we used only the data covering the period 2010–2018 because employee turnover data were unavailable before 2010. After correcting for input errors and duplication, we obtained a total of 1266 MFIs data from 101 countries. The list of countries and regions included in this study and their distribution are provided in Appendix A.

Country-specific macroeconomic variables were also collected from the World Bank. The governance data used in this study were collected from the index developed by Kauffmann, Kraay, and Mastruzzi (2010). Furthermore, we assessed the presence of outliers in the dataset, as their existence in the variables can lead to erroneous results. Therefore, to minimize the effect of extreme outliers, we winsorized the data at the 1 percent level (both the highest and lowest), consistent with the prior literature, such as Chikalipah (2018) and Mia (2022b).

3.2. Definition of variables

3.2.1. Credit risk variables

To measure the credit risk of MFIs, in the past several parameters have been used, such as the write-off ratio (Banna et al., 2022; Blanco-Oliver et al., 2021), portfolio risk over 30 days (Blanco-Oliver et al., 2021; Zamore et al., 2019), loan-loss provision (Zamore et al., 2019) and Z-score (Schulte & Winkler, 2019a; Zamore et al., 2019). To measure the credit risk of MFIs, this study uses all three parameters, namely PAR30, WOR, and the Z-score. In the microfinance industry, portfolio at risk over 30 days (PAR30) indicates the amount unpaid by the borrower for more than 30 days, and the higher the PAR30 rate is, the higher the credit risk of MFIs. Written-off loans (WOR) means the amount of a loan that will not generate income in the future or the portion of a loan considered a loss (Jayaraman & Bhuyan, 2020). Lastly, we use the Z-score to measure the overall credit risk of individual MFIs, consistent with earlier studies by Banna et al. (2022), Meslier, Morgan, Samolyk, and Tarazi (2016), and Zamore et al. (2019). However, to calculate the Z-score, we use the following equation, following Schulte and Winkler (2019a) and Tadele (2020).

$$Z-Score = (\text{ROA} + \text{Equity} / \text{Total Assets}) / (\text{SD of ROA})$$

3.2.2. Employee turnover rates

Employee turnover is the number of employees who leave an MFI in a given year, whereas the employee turnover rate refers to the ratio of the number of employees who leave in a given year to the total number of employees that year. Because of data limitations, we use the aggregate employee turnover rate (ETR) of MFIs from the World Bank database without distinguishing between the voluntary/involuntary turnover rates individually and the turnover rates at different organizational levels (Nourani, Mia, Saifullah, & Ahmad, 2022).

3.2.3. Organization-related variables

According to Nourani, Mia, Saifullah, and Ahmad (2022), employee turnover can be influenced by company size. In general, a large corporation can avoid staff turnover by offering employees more fringe benefits, paying bonuses, providing financial incentives for meeting a target, and so on, which may not be possible for a small firm. Huang and Lee (2013) argue that the size of a firm has a significant impact on its credit risk. It is assumed that a larger firm can better manage its credit risk (Duho, Duho, & Forson, 2021). In our study, we use the natural logarithm of total assets (LNTA) to assess the size of the MFIs, in line with past studies (Deng & Elyasiani, 2008; Zamore et al., 2019).

There are different types of MFIs globally, including nongovernment organizations (NGOs), co-ops, banks, and nonbank financial institutions. Their legal standing differs, which can have varying impacts on their credit risk. For instance, NGOs are thought to be less vulnerable to credit risk because of their careful oversight of borrowers (D'Espallier, Goedecke, Hudon, & Mersland, 2017). Therefore, we use the last known legal status (e.g., NGOs) in our model to investigate its impact on credit risk.

Furthermore, the profit orientation of MFIs may have an impact on their credit risk because profit-driven MFIs are likely to be aware of their lending practices. In other words, a profit-oriented company will not lend to those who may default in the future. Nonprofit MFIs, however, aim to lend to as many impoverished people as possible in order to meet their outreach goals (Nourani, Malim, & Mia, 2021). Therefore, profit-oriented MFIs are expected to be more efficient in reducing credit risk than non–profit-oriented MFIs.

According to agency theory, the size of the board of directors can have a considerable impact on a firm's credit risk. A larger board may have a more complex protocol for credit approval, reducing the chances of credit risk. Lu and Boateng (2018) find that banks with a large board tend to have lower credit risk. Tadele (2020) observes that firms with larger and more diverse board members are less likely to be affected by default risk. Therefore, to account for the impact of board size, we use the number of board members (NOBM) as a control variable.

Moreover, the social performance of MFIs in terms of serving female borrowers might have a negative effect on credit risk (Tadele, Roberts, & Whiting, 2022). For instance, women are generally more risk averse (Croson & Gneezy, 2009) and often have less access to finance than men. Therefore, female borrowers might repay their existing loans in a timely manner to ensure that they will receive further services from the MFIs (Phillips & Bhatia-Panthaki, 2007). Abdullah and Quayes (2016) suggest that having more female borrowers can have a positive effect on the financial performance of MFIs and ensure better loan repayment. Thus, it is estimated that having more female borrowers might reduce credit risk for MFIs. Therefore, we use the proportion of female borrowers (PFB) as a control variable.

According to Lassoued (2017), the average loan size may also affect credit risk for MFIs. Lassoued argues that small loan size indicates that the loans are given to the poorest people, which may increase the credit risk of MFIs because poor people often lack the education and experience necessary to make good financial decisions. Al-Azzam and Mimouni (2017) state that small loans extended without collateral are inherently more risky. However, Chikalipah (2018) suggests that larger loan size has higher credit risk for MFIs because of the difficulty that borrowers may face in repaying a high loan balance (Van Gool, Verbeke, Sercu, & Baesens, 2012). Similarly, Abdullah and Quayes (2016) stated that MFIs with broader outreach—indicated by smaller average loan balances—have better financial performance because of the lower credit risk associated with better repayment rates by small borrowers. Therefore, to understand the impact of loan size on the credit risk of MFIs, we use the natural logarithm of the average loan balance (LNALB).

Leverage can also affect the credit risk of MFIs. According to Lu and Boateng (2018), a higher leverage ratio can lead to lower credit risk for banks. A capital structure with a high ratio of equity capital to loan capital can increase the financial strength of a firm. Furthermore, unlike debt holders, equity holders have greater authority to monitor and control a firm's credit risk (Zamore et al., 2019). Therefore, we use the debt-to-equity (DTE) ratio as an indicator of the leverage of MFIs in our analysis.

The liquidity position of MFIs is indicated by their deposit-to-loan ratio, which also affects their credit risk. A lower deposit-to-loan ratio indicates a higher probability of credit risk because MFIs with higher liquidity tend to make riskier lending decisions (Ghosh, 2015). Furthermore, if an MFI disburses most of its deposits as loans to borrowers, this may indicate that its loan officers are incentivized to make decisions on excessive lending without considering risk factors or recovery rates. Thus, a lower deposit-to-loan ratio can influence the credit risk of MFIs. According to Schulte and Winkler (2019a), the upward trend in the liquidity of MFIs is associated with a decline in the risk-adjusted return on assets. Therefore, we use the deposit-to-loan (DTL) ratio as an indicator of MFIs' liquidity position in the analysis.

3.2.4. Industry-specific variables

Market concentration (the opposite of market competition) has a significant impact on credit risk (Huang & Lee, 2013). In competitive markets, firms may offer loans more frequently to maintain their profit margin. Therefore, lower market concentration (higher competition) will lead to higher credit risk due to moral hazard (Leroy & Lucotte, 2017; Soedarmono, Machrouh, & Tarazi, 2013). However, Martín-Oliver, Ruano, and Salas-Fumás (2020) and Brei, Jacolin, and Noah (2020) argue that lower concentration fosters lower credit risk up to a certain threshold. The Herfindahl-Hirschman Index (HHI) is one of the most popular measures of market concentration among researchers (Ali, Khattak, & Alam, 2023; Martín-Oliver et al., 2020). HHI is calculated by summing the square of the market shares (gross loan portfolio) of each individual MFI using the following equation:

$$HHI = \sum_{i=1}^{n} Xi^2$$

where X represents the gross loan portfolio as a proxy for the market share of an individual MFI. A higher HHI value indicates higher market concentration, whereas an HHI value close to zero indicates a lower concentration or highly competitive market.

3.2.5. Country-specific variables

Each country has unique macroeconomic characteristics that influence the credit risk of firms, regardless of their type. One such factor is the growth rate in the gross domestic product (GDPGR). According to Lassoued (2017), during periods of economic expansion, the income level and loan repayment capacity of borrowers tends to increase. In contrast, during an economic contraction, the income level and repayment capacity of borrowers tends to shrink. To control for the effects of GDP growth, we use GDPGR, obtained from the World Bank database.

Inflation has a significant impact on the credit risk of MFIs. When inflation rates are unstable, even in times of high economic growth, people's purchasing power and loan repayment ability tend to decline (Lassoued, 2017; Nkusu, 2011). Therefore, when investigating the relationship between employee turnover and the credit risk of MFIs, it is crucial to control for the country-level inflation rate (INFR).

3.2.5. Governance variable

Governance indicators impose a regulatory framework on firms to control for nonperforming loans (NPLs) and ultimately reduce their credit risk (Godlewski, 2005). This suggests that credit risk is lower at firms (MFIs) in countries with an effective governance or regulatory framework (Lassoued, 2017). Hence, we use the governance index developed by Kauffmann et al. (2010) in our analysis. In particular, we employ the variable for average governance (AGOV), calculated with six parameters of governance, consistent with Mia and Lee (2017) and Zamore et al. (2019).

3.3. Econometric model

To investigate the relationship between employee turnover and the credit risk of MFIs, we use the following regression models:

$$\begin{aligned} Y_{ijt} = {} & \beta_0 + \beta_1 ETR_{ijt} + \beta_2 LNTA_i + \beta_3 DTE_{ijt} + \beta_4 LNNOBM_{ijt} \\ & + \beta_5 DTL_{ijt} + \beta_6 PFB_{ijt} + \beta_7 LNALB_{ijt} + \beta_8 PS_i + \beta_9 LS_i \\ & + \beta_{10} HHI_{jt} + \beta_{11} GDPGR_{jt} + \beta_{12} INFR_{jt} + \beta_{13} AGOV_{jt} \\ & + \varepsilon_{ijt} \end{aligned} \tag{1}$$

where *i* is an individual MFI, *j* is a country, *t* is the year, and ε_{ijt} is the standard error. To determine the credit risk of MFIs, denoted here as Y_{ijt}, we use three alternative credit risk factors as dependent variables: portfolio at risk over 30 days (PAR30), write-off ratio (WOR), and the volatility of return on assets indicated as credit risk (Z-score). We use the natural logarithm of the Z-score (LNZ-score) to measure overall credit risk.

Considering all these factors, we test the impact of employee turnover on PAR30, the write-off ratio, and the LNZ-score simultaneously using the following three models:

$$\begin{aligned} PAR30_{ijt} = {} & \beta_0 + \beta_1 ETR_{ijt} + \beta_2 LNTA_i + \beta_3 DTE_{ijt} + \beta_4 LNNOBM_{ijt} \\ & + \beta_5 DTL_{ijt} + \beta_6 PFB_{ijt} + \beta_7 LNALB_i + \beta_8 PS_i + \beta_9 LS_i \\ & + \beta_{10} HHI_{jt} + \beta_{11} GDPGR_{jt} + \beta_{12} INFR_{jt} + \beta_{13} AGOV_{jt} \\ & + \varepsilon_{ijt} \end{aligned} \tag{2}$$

$$\begin{aligned} WOR_{ijt} = {} & \beta_0 + \beta_1 ETR_{ijt} + \beta_2 LNTA_i + \beta_3 DTE_{ijt} + \beta_4 LNNOBM_{ijt} \\ & + \beta_5 DTL_{ijt} + \beta_6 PFB_{ijt} + \beta_7 LNALB_i + \beta_8 PS_i + \beta_9 LS_i \\ & + \beta_{10} HHI_{jt} + \beta_{11} GDPGR_{jt} + \beta_{12} INFR_{jt} + \beta_{13} AGOV_{jt} \\ & + \varepsilon_{ijt} \end{aligned} \tag{3}$$

$$\begin{aligned} LNZ - Score_{ijt} = {} & \beta_0 + \beta_1 ETR_{ijt} + \beta_2 LNTA_i + \beta_3 DTE_{ijt} \\ & + \beta_4 LNNOBM_{ijt} + \beta_5 DTL_{ijt} + \beta_6 PFB_{ijt} \\ & + \beta_7 LNALB_i + \beta_8 PS_i + \beta_9 LS_i + \beta_{10} HHI_{jt} \\ & + \beta_{11} GDPGR_{jt} + \beta_{12} INFR_{jt} + \beta_{13} AGOV_{jt} \\ & + \varepsilon_{ijt} \end{aligned} \tag{4}$$

In Table 1, we define the variables used in the study.

Before running these models, we assess the relationships between the variables using pooled ordinary least squares (POLS), a random-effects model (REM), and a fixed effects model (FEM). Additionally, we use the Breusch–Pagan Lagrange multiplier (BPLM) test (Greene, 2003) to determine whether POLS or REM is the most appropriate model. The results of the BPLM test indicate that the REM is statistically preferable. We then perform the Hausman (1978) test to compare REM and FEM and find that FEM is the statistically preferable model in terms of PAR30 and WOR. However, the use of FEM has some limitations. For instance, when using FEM, we cannot incorporate the effect of time-invariant variables, such as profit status (PS) and legal status (LS), on the credit risk of MFIs. Therefore, we rely primarily on the REM results in explaining the findings from the baseline results. To address the issues of autocorrelation and heteroskedasticity, we estimate robust standard errors, which are clustered at the firm level.

4. Analysis and discussion

4.1. Descriptive statistics and pairwise correlations

Table 2 presents the descriptive statistics of the variables used in our study. The average PAR30 for MFIs is 6.4 percent, and that of WOR is 1.7 percent. The sum of PAR30 and WOR yields average credit risk of 8 percent. The mean ETR in the global microfinance industry is 20.9 percent, which is higher than that of the banking and financial sector in Malaysia, 18.3 percent (Letchumanan, Apadore, & Ramasamy, 2017). The mean debt-equity ratio for MFIs is 4.18, indicating that for most of the MFIs, debt is 4.18 times higher than equity capital. In our sample, approximately 65 percent of the borrowers are female, and the average loan balance/size is US$1486; 41 percent and 34 percent of the MFIs are NGOs and profit oriented, respectively. Not all MFIs accept deposits from clients, so the mean DTL ratio, 34.8 percent, indicates lower solvency or liquidity. On average, each MFI has seven board members.

Table 2
Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Z-Score	2847	67.091	150.566	−1.338	1183.664
LNZ-Score	2789	3.315	1.315	−3.910	7.076
PAR30	4382	0.064	0.106	0.000	0.735
WOR	4382	0.017	0.028	0.000	0.155
ETR	3723	0.209	0.189	0.000	1.012
TA	4382	92.900	235	<0.001	1610
LNTA	4382	16.614	1.934	12.334	21.201
DTE	4382	4.178	4.450	−5.850	28.170
NOBM	4382	7.460	4.520	1.000	35.000
LNNOBM	4382	1.873	0.522	0.000	3.555
DTL	4382	0.348	0.481	0.000	2.357
PFB	4220	0.650	0.261	0.100	1.000
ALB	4359	1486.382	2147.973	69.000	13103.000
LNALB	4359	6.521	1.268	4.234	9.481
PS	4382	0.411	0.492	0.000	1.000
LS	4382	0.342	0.474	0.000	1.000
HHI	4382	0.324	0.256	0.066	1.000
GDPGR	4382	4.852	2.566	−3.100	11.178
INFR	4382	5.259	3.497	−0.897	17.150
AGOV	4382	−0.492	0.372	−1.466	0.665

Source: Authors computation. Note: All continuous variables are winsorized at 1% and 99% levels. TA = total assets (in Million US$), LNTA = natural logarithm of the total assets, LNZ-Score = natural logarithm of the Z-Score, NOBM = number of board members, LNNOBM = natural logarithm of the number of board members, DTE = debt to equity ratio, DTL = deposit to loan ratio, PFB = proportion of female borrowers, LNALB = natural logarithm of the average loan balance, PS = profit status, LS = legal status, GDPGR = GDP growth rate, INFR = inflation rate, AGOV = average governance indicator.

The microfinance industry is moderately competitive, with an average HHI of approximately 0.32. Among the macroeconomic variables, the mean inflation rate and GDP growth are 5.25% and 4.85%, respectively. The governance index averages −0.49.

We also test for the existence of multicollinearity problems among the independent variables (see Table 3). Most of the

Table 1
Description of the variables.

Variable	Definitions	Type	Expected Sign
PAR30	The amount of loan that is due for at least 30 days.	Ratio	
WOR	The amount of loan written off per gross loan portfolio	Ratio	
Z-score	(Return on Assets + Equity/Total Assets)/(Standard Deviation of Return on Assets)	Ratio	
LNZ-Score	Natural logarithm of Z-Score	Ratio	
ETR	The number of employees that leave the organization/total number of employees	Ratio	+
DTE	Total debt/total equity	Ratio	+
LNTA	Natural logarithm of total assets	Number	–
PS	If the MFI is profit-oriented, it is valued 1, 0 otherwise	Dummy	+
LS	If the MFI is an NGO, the value is 1, 0 otherwise	Dummy	+
PFB	Proportion of female borrowers	Ratio	–
LNALB	Natural logarithm of average loan balance	Number	+/–
LNNOBM	Natural logarithm of the number of board members	Number	–
DTL	Deposit-to-loan ratio	Ratio	+/–
HHI	HHI value is calculated based on the gross loan portfolio	Ratio	–
GDPGR	Gross domestic product (GDP) at market price growth rate for individual country	Ratio	–
INFR	The inflation (as measured by consumer price index) rate of an individual country	Ratio	+/–
AGOV	Average of six parameters of governance from the world governance indicators*	Ratio	–

Source: Authors compilation from the World Bank and World Governance Indicators.
* The six parameters are, namely, Voice and Accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law and Control of Corruption.

Pearson correlation values, shown in Table 3, are below 0.40, which is below the threshold suggested by Hair (2009). Moreover, we calculate the Variance Inflation Factors (VIF) among the independent variables to assess the impact of multicollinearity among the explanatory variables. The results further show that the value remains within the threshold (VIF should be below 10) recommended by Hair (2009). Therefore, our models are free of serious multicollinearity issues.

4.2. Baseline regression results

The initial results of panel data regression for the credit risk of MFIs are presented in Table 4. We examine the impact of ETR on the credit risk of MFIs using three dependent variables: LNZ-score, PAR30, and WOR. We start with a pooled POLS regression model (Models 1, 4, and 7), followed by FEM (Models 3, 6, and 9), and REM (Models 2, 5, and 8). Table 4 presents models 1–9 without initially calculating robust standard errors. The BPLM test results reported in the table indicate that REM is preferred to the POLS model. Then, we conduct the Hausman test, which indicates that FEM is preferable in the two models for PAR30 and WOR. However, for the model based on LNZ-score, the results suggest that REM is better than FEM. Furthermore, FEM does not address time-invariant variables such as profit status and legal status, which have a significant impact on credit risk. Hence, although the Hausman test indicates support for FEM in two models, the results of REM are preferred. Consequently, we report a robust REM model (Models 10–12) in Table 4.

The F statistics or χ^2 of each model indicate that the models are reliable and fit at a 1 percent level of statistical significance. Moreover, the value of R^2, which indicates the explanatory power of the model, is 20 percent, 7.6 percent, and 10 percent for the LNZ-score, PAR30, and WOR, respectively (Models 10 to 12). Although the explanatory power is low, it is consistent with previous studies on MFIs, such as Blanco-Oliver et al. (2021). Moreover, we include year-fixed effects and regional dummies (RD) in all the models (unless otherwise stated) to account for technological progress over time and regional differences, respectively.

Based on the empirical results, we discover that higher ETR leads to higher risk for MFIs. This relationship is significant at the 1 percent level for all three measures of credit risk. All the variables that have a negative effect on the LNZ-score increase credit risk, whereas positive effects on PAR30 and WOR also increase credit risk for MFIs.[2] Based on the empirical results, this research indicates that MFIs are more vulnerable to credit risk when current staff quit. The results demonstrate that, in accordance with social capital theory, employee turnover may lead to the breakdown of social ties with borrowers, which, in turn, might encourage borrowers to leave and ultimately raise credit risk for MFIs. Moreover, these results suggest that employees of MFIs act as significant intermediaries for holding borrowers' soft information, and their departure can lead to the loss of this information, thereby increasing credit risk. Our

[2] Risk declines when the Z-score increases and vice versa.

Table 3
Pairwise correlations & variance inflation factors (VIF).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	VIF
(1) ETR	1													1.15
(2) LNTA	−0.017	1												1.63
(3) DTE	−0.017	0.210***	1											1.27
(4) LNNOBM	−0.111***	0.278***	0.120***	1										1.36
(5) DTL	−0.170***	0.267***	0.259***	0.244***	1									1.86
(6) PFB	0.088***	−0.162***	0.009	0.084***	−0.27***	1								2.78
(7) LNALB	−0.067***	0.344***	0.052***	−0.063***	0.250***	−0.701***	1							3.78
(8) PS	0.169***	0.259***	0.053***	−0.109***	0.062***	−0.063***	0.071***	1						1.88
(9) LS	−0.039***	−0.269***	−0.096***	0.010	−0.325***	0.318***	−0.363***	−0.562***	1					2.05
(10) HHI	−0.087***	−0.055***	−0.099***	−0.095***	0.079***	−0.158***	0.041***	0.057***	−0.044***	1				1.55
(11) GDPGR	0.041***	−0.013	0.068***	0.037***	−0.014	0.275***	−0.266***	0.107***	0.020	−0.07***	1			1.40
(12) INFR	0.064***	−0.138***	0.049***	−0.03**	−0.065***	0.24***	−0.370***	0.112***	0.063***	−0.006	0.087***	1		1.52
(13) AGOV	0.103***	−0.018	−0.063***	−0.08***	−0.163***	0.088***	0.099***	−0.030**	0.047***	0.095***	−0.004	−0.218***	1	1.23

Source: Authors computation. ***p < 0.01, **p < 0.05, *p < 0.1. Please see Table 1 for definition of all variables.

Table 4
Panel regression model results based on OLS, FEM, and REM.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	DV: LNZ-Score			DV: PAR30			DV: WOR			Z-Score	PAR30	WOR
	Without RSE									With RSE		
	OLS	FEM	REM	OLS	FEM	REM	OLS	FEM	REM	REM		
ETR	−0.892***	−0.401**	−0.551***	0.043***	0.035***	0.037***	0.017***	0.009***	0.012***	−0.551***	0.037***	0.012***
	(0.146)	(0.182)	(0.148)	(0.010)	(0.009)	(0.008)	(0.002)	(0.003)	(0.002)	(0.169)	(0.013)	(0.003)
LNTA	0.127***	0.264***	0.131***	−0.006***	−0.016***	−0.009***	0.000	−0.001	0.000	0.131***	−0.009***	0.000
	(0.017)	(0.085)	(0.026)	(0.001)	(0.004)	(0.002)	(0.000)	(0.001)	(0.000)	(0.024)	(0.003)	(0.000)
DTE	−0.130***	−0.115***	−0.116***	−0.000	0.002***	0.001***	−0.000	0.000	0.000	−0.116***	0.001**	0.000
	(0.007)	(0.013)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.001)	(0.000)
LNNOBM	0.030	−0.149	−0.000	−0.007*	−0.003	−0.006	−0.001	−0.002	−0.002*	−0.000	−0.006	−0.002
	(0.057)	(0.097)	(0.068)	(0.004)	(0.005)	(0.004)	(0.001)	(0.001)	(0.001)	(0.084)	(0.006)	(0.001)
DTL	0.099	−0.306	−0.043	0.028***	0.005	0.025***	−0.003**	0.009**	0.000	−0.043	0.025***	0.000
	(0.073)	(0.273)	(0.107)	(0.005)	(0.013)	(0.007)	(0.001)	(0.004)	(0.002)	(0.125)	(0.007)	(0.002)
PFB	0.224	−0.138	0.042	−0.108***	−0.032	−0.090***	−0.015***	−0.002	−0.009***	0.042	−0.090***	−0.009*
	(0.159)	(0.393)	(0.210)	(0.011)	(0.020)	(0.014)	(0.003)	(0.006)	(0.003)	(0.189)	(0.020)	(0.005)
LNALB	0.121***	−0.104	0.088*	−0.007***	−0.007	−0.006*	−0.003***	−0.006***	−0.004***	0.088	−0.006	−0.004***
	(0.038)	(0.116)	(0.052)	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)	(0.001)	(0.057)	(0.004)	(0.001)
PS	−0.302***	–	−0.367***	0.000	–	0.000	0.007***	–	0.007***	−0.367***	0.000	0.007***
	(0.067)		(0.107)	(0.005)		(0.009)	(0.001)		(0.002)	(0.112)	(0.008)	(0.002)
LS	−0.389***	–	−0.415***	0.000	–	−0.010	0.005***	–	0.004**	−0.415***	−0.010	0.004**
	(0.074)		(0.118)	(0.005)		(0.010)	(0.001)		(0.002)	(0.123)	(0.009)	(0.002)
HHI	−0.303**	−0.102	−0.203	−0.000	−0.001	0.004	0.007***	−0.004	0.002	−0.203	0.004	0.002
	(0.123)	(0.186)	(0.141)	(0.008)	(0.010)	(0.009)	(0.002)	(0.003)	(0.002)	(0.152)	(0.010)	(0.003)
GDPGR	0.045***	0.051***	0.049***	−0.003***	−0.004***	−0.004***	−0.002***	−0.001***	−0.001***	0.049***	−0.004***	−0.001***
	(0.011)	(0.013)	(0.011)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.012)	(0.001)	(0.000)
INFR	−0.009	0.001	0.003	0.002***	0.002***	0.002***	−0.000**	−0.000*	−0.000*	0.003	0.002*	−0.000
	(0.009)	(0.012)	(0.010)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.011)	(0.001)	(0.000)
AGOV	0.403***	−0.170	0.292***	0.026***	0.060***	0.026***	0.002	−0.003	0.001	0.292**	0.026***	0.001
	(0.077)	(0.367)	(0.113)	(0.005)	(0.019)	(0.008)	(0.001)	(0.006)	(0.002)	(0.121)	(0.008)	(0.002)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
RD	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES	YES	YES
CONS	1.695***	0.528	1.694***	0.312***	0.422***	0.343***	0.044***	0.079***	0.041***	1.694***	0.343***	0.041***
	(0.388)	(1.364)	(0.535)	(0.026)	(0.057)	(0.035)	(0.006)	(0.017)	(0.009)	(0.572)	(0.053)	(0.010)
Observations	2385	2385	2385	3608	3608	3608	3608	3608	3608	2385	3608	3608
R^2	0.211	0.084	0.204	0.090	0.089	0.0762	0.113	0.049	0.102	0.204	0.0762	0.102
F/Chi^2	25.29***	8.102***	339.7***	13.66***	12.79***	311.5***	17.52***	6.655***	227.9***	258.3***	191.8***	197.5***
# of MFIs		773	773		1110	1110		1110	1110	773	1110	1110
BPLM			273.19***			696.06***			578.27***			
Hausman Test			17.13		75.00***			73.22***				

Source: Authors computation. Note: (Robust) Standard errors in parentheses ***p < 0.01, **p < 0.05, *p < 0.1. Note: RSE = Robust Standard Errors, and RD = Region dummies. Please see Table 1 for definition of all variables.

Table 5
Sub-sample analysis by regions (REM).

	13	14	15	16	17	18	19	20	21	22	23	24
	DV: LNZ-Score						DV: PAR30					
	Africa	EAP	EECA	LAC	MENA	SA	Africa	EAP	EECA	LAC	MENA	SA
ETR	0.857	−0.731	−1.022***	−0.331	2.627*	−0.511**	0.075**	−0.041*	0.040*	0.007	−0.01	0.029
	(0.868)	(0.773)	(0.323)	(0.258)	(1.503)	(0.250)	(0.034)	(0.023)	(0.023)	(0.025)	(0.026)	(0.021)
LNTA	0.293**	0.161**	0.152***	0.168***	0.435***	0.082*	−0.011	−0.011**	−0.001	−0.011**	0.002	0.009
	(0.127)	(0.082)	(0.056)	(0.043)	(0.142)	(0.049)	(0.007)	(0.006)	(0.004)	(0.004)	(0.003)	(0.006)
DTE	−0.208***	−0.108***	−0.240***	−0.215***	−0.271**	−0.067***	0.002	0.000	0.007***	0.000	0.003***	0.000
	(0.044)	(0.024)	(0.032)	(0.020)	(0.110)	(0.012)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
LNNOBM	0.147	0.154	−0.222	−0.102	0.967**	0.169	0.003	−0.022**	−0.024**	0.009	0.002	−0.007
	(0.243)	(0.237)	(0.174)	(0.095)	(0.483)	(0.166)	(0.013)	(0.010)	(0.012)	(0.011)	(0.010)	(0.010)
DTL	0.511	−0.386	0.046	0.565***	−2.823*	0.261	0.033*	0.039**	0.005	−0.002	−0.027*	0.01
	(0.330)	(0.241)	(0.294)	(0.190)	(1.578)	(0.265)	(0.019)	(0.018)	(0.022)	(0.008)	(0.016)	(0.015)
PFB	0.43	0.724	−0.372	−0.175	−0.788	0.065	−0.042	−0.253***	−0.111***	−0.054	−0.041*	−0.077**
	(0.647)	(0.656)	(0.508)	(0.402)	(1.338)	(0.420)	(0.033)	(0.061)	(0.034)	(0.045)	(0.024)	(0.039)
LNALB	0.082	0.135	0.179	0.178**	0.02	−0.051	−0.001	−0.016	−0.002	0.013	−0.012	−0.037***
	(0.18)	(0.14)	(0.12)	(0.09)	(0.39)	(0.17)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
PS	0.035	−0.287	−0.485**	−0.134	−0.121	−0.143	−0.022	−0.012	−0.01	0.035***	−0.004	−0.035
	(0.378)	(0.316)	(0.210)	(0.169)	(1.145)	(0.259)	(0.024)	(0.023)	(0.017)	(0.012)	(0.018)	(0.028)
LS	0.707	−0.582	−0.565	−0.167	−0.634	−0.395	−0.052***	−0.02	0.049*	0.035**	−0.005	−0.038
	(0.45)	(0.37)	(0.45)	(0.19)	(0.53)	(0.25)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.03)
HHI	−0.431	0.266	0.169	−0.391*	0.512	0.221	0.003	−0.082***	−0.070**	−0.015	−0.013	0.005
	(0.401)	(0.424)	(0.417)	(0.222)	(0.664)	(0.517)	(0.015)	(0.029)	(0.029)	(0.015)	(0.017)	(0.025)
GDPGR	0.063	0.093**	0.086***	0.023	0.115**	0.038	0.001	−0.003	−0.010***	−0.005***	−0.006*	−0.001
	(0.039)	(0.044)	(0.025)	(0.019)	(0.053)	(0.039)	(0.002)	(0.004)	(0.002)	(0.001)	(0.004)	(0.001)
INFR	−0.02	0.095*	−0.003	−0.009	−0.039	0.047	−0.001	0.006**	0.006**	0.001	−0.002***	−0.003
	(0.025)	(0.054)	(0.020)	(0.021)	(0.043)	(0.040)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)
AGOV	−0.917**	0.939*	0.418*	−0.02	−0.658	0.996***	−0.026	0.094***	0.023**	0.012	−0.026	0.044*
	(0.429)	(0.569)	(0.243)	(0.186)	(0.590)	(0.296)	(0.027)	(0.027)	(0.011)	(0.014)	(0.021)	(0.023)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
RD	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
CONS	−2.686	−0.125	1.077	1.015	−5.897	2.176*	0.271**	0.661***	0.192**	0.186**	0.109	0.278**
	(2.093)	(1.568)	(1.261)	(1.004)	(3.704)	(1.216)	(0.110)	(0.131)	(0.093)	(0.080)	(0.074)	(0.120)
Observations	216	260	336	967	80	526	418	409	526	1308	133	814
Chi^2	46.354***	61.866***	120.819***	204.081***	64.474***	75.754***	69.039***	84.951***	59.402***	87.661***	78.686***	59.891***
R^2	0.246	0.23	0.342	0.25	0.65	0.199	0.174	0.406	0.286	0.081	0.289	0.05
# of MFIs	93	90	115	255	24	196	184	138	165	319	45	259

	25	26	27	28	29	30
VARIABLES	DV: WOR					
	Africa	EAP	EECA	LAC	MENA	SA
ETR	0.018	0.013**	0.025***	0.018***	0.009	0.002
	(0.014)	(0.006)	(0.007)	(0.006)	(0.014)	(0.004)
LNTA	−0.003*	−0.001	0.001	0.000	−0.002	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
DTE	0.000	0.000	0.002***	0.001	0.001	−0.000***
	0.000	0.000	(0.001)	0.000	(0.001)	0.000

(continued on next page)

Table 5 (*continued*)

	25	26	27	28	29	30
LNNOBM	0.002	0.006**	−0.011***	−0.002	0.006	−0.002
	(0.005)	(0.003)	(0.004)	(0.002)	(0.005)	(0.002)
DTL	−0.001	0.002	−0.007	0.000	0.007	−0.004
	(0.004)	(0.003)	(0.005)	(0.003)	(0.006)	(0.005)
PFB	0.007	−0.022***	0.016	−0.018*	−0.027	−0.018**
	(0.013)	(0.008)	(0.012)	(0.010)	(0.020)	(0.008)
LNALB	0.003	−0.001	−0.002	−0.007***	−0.014***	−0.004*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PS	0.009**	0.003	0.001	0.014***	−0.004	0.000
	(0.005)	(0.003)	(0.004)	(0.003)	(0.010)	(0.004)
LS	−0.001	0.002	0.007	0.013***	0.008	−0.004
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
HHI	−0.001	0.001	0.007	−0.004	−0.004	−0.005
	(0.006)	(0.005)	(0.011)	(0.007)	(0.008)	(0.010)
GDPGR	0.000	−0.001**	−0.002***	−0.002***	0.001	0.001
	(0.001)	0.000	(0.001)	0.000	(0.001)	(0.001)
INFR	0.000	0.000	−0.001**	0.000	−0.003***	−0.002**
	0.000	0.000	(0.001)	(0.001)	(0.001)	(0.001)
AGOV	−0.001	0.013**	0.002	0.001	0.022***	−0.011**
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Year FE	YES	YES	YES	YES	YES	YES
RD	YES	YES	YES	YES	YES	YES
CONS	0.038	0.051***	0.034	0.075***	0.148***	0.054**
	(0.030)	(0.014)	(0.021)	(0.024)	(0.039)	(0.021)
Observations	418	409	526	1308	133	814
Chi^2	30.652*	49.333***	67.225***	148.845***	524.224***	70.913***
R^2	0.078	0.117	0.172	0.184	0.542	0.132
# of MFIs	184	138	165	319	45	259

Source: Authors computation. Note: Robust Standard errors in parentheses. Please see Table 1 for definition of all variables. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

observation partly corroborates the findings by Sangwan et al. (2021), who state that the departure of loan officers from MFIs stalls the recovery of loans processed by them, thereby raising the credit risk of their organizations.

The relationship between the size (LNTA) of MFIs and credit risk (LNZ-score and PAR30) is negative at the 1 percent level of significance. However, the relationship with WOR is statistically insignificant. This indicates that larger firms are less vulnerable to credit risk, as they can process credit client data more systemically because of their vast resources (Chikalipah, 2018).

Furthermore, we find that the leverage ratio has a significantly positive relationship with the portfolio credit risk of MFIs at the 1 percent level of significance for LNZ-score and 5 percent level of significance for PAR30. This can be attributed to higher debt levels, which push MFIs to extend more loans in the hope of earning enough profit to repay the interest on the debt. However, the impact of leverage on WOR is insignificant. Furthermore, MFIs with a large number of board members should be able to minimize credit risk by ensuring proper monitoring and oversight of loans (Lu & Boateng, 2018). Although we find a negative relationship, the result is not statistically significant.

According to Ghosh (2015), banks with more liquidity tend to provide more loans, which might increase credit risk. The results in Table 4 support this statement and show that, for MFIs, a higher DTL ratio indicates higher solvency, which drives higher portfolio risk. However, credit risk in terms of LNZ-score and WOR is not statistically significant in our study. According to Tadele et al. (2022), female borrower have a negative effect on the credit risk of MFIs. The results in Table 4 corroborate this conclusion and illustrate that a higher proportion of female borrowers reduces credit risk for MFIs in terms of PAR30 and WOR at the 1 percent and 10 percent level of statistical significance, respectively. Furthermore, the analysis shows that the average loan balance is negatively associated with credit risk in terms of WOR at the 1 percent level of significance. However, our results do not provide evidence of a significant relationship between female borrowers and credit risk in terms of LNZ-score and PAR30.

The analysis also shows that profit-oriented MFIs are more susceptible to credit risk than their nonprofit counterparts, particularly in terms of LNZ-score and WOR, according to the REM results. However, the relationship is statistically insignificant when credit risk is measured by PAR30. This finding suggests that profit-oriented MFIs may prioritize clients with higher loan volume in pursuit of higher returns, which lead to increased credit risk. This result is similar to that of Blanco-Oliver et al. (2021) but unlike the findings by Lassoued (2017), who states that profitable MFIs are more discerning in selecting credit customers, resulting in lower credit risk.

In Table 4, the REM analysis reveals that the legal status of MFI as an NGO has a positive effect on WOR. Moreover, our findings suggest that the legal status of the MFIs increases the credit risk measured by LNZ-score at the 1 percent level of significance. This contradicts the study by D'Espallier et al. (2017), who argue that NGOs are less vulnerable to credit risk than their counterparts. The results suggest that NGOs, which typically extend loans to poorer people, may be more vulnerable to credit risk because of the difficulty of recovering loans without active monitoring of fund utilization by borrowers. However, for credit risk in terms of PAR30, the coefficient is found to be statistically insignificant.

Our analysis shows that GDPGR has a significantly negative association with credit risk at the 1 percent level. This is because economic growth promotes cash flow, which, in turn, enhances the loan repayment capacity of borrowers (Lassoued, 2017). In contrast, we find a positive association between the inflation rate (INFR) and credit risk (in terms of PAR30). The finding is interesting because previous studies by Lassoued (2017) and Blanco-Oliver et al. (2021) find the opposite relationship. Inflation can indicate two things: higher commodity prices and people's increased liquidity or cash availability relative to available products. The positive effect of INFR on the credit risk of MFIs can be attributed to clients' increased spending on commodities, which can lead to a shortage of funds to repay their debt.

Banking institutions in countries with good governance practices tend to have reduced credit risk. Accordingly, we found a positive association, at a 5 percent level of significance, between the indicator of good governance (AGOV) and LNZ-Score, which indicates that good governance practice can reduce the credit risk of MFIs. This result is in agreement with the study of Hasan and Ashfaq (2021), who concluded that governance practice can minimize credit risk. Similarly, we observed a positive relationship between governance and portfolio risk (PAR30), which contradicted our initial expectation. One possible explanation for this result is that when the economy has good governance practices, borrowers may prioritize investing in financial well-being over timely loan repayment. As a result, their ability to repay loan within 30 days may be affected.

4.3. Robustness/additional test

To ensure the reliability and consistency of our findings, we conduct several robustness tests. As geographic diversity has been shown to increase the credit risk of MFIs (Zamore et al., 2019), we developed a subsample comprising six regions: Africa, East Asia and the Pacific (EAP), Eastern Europe and Central Asia (EECA), Latin America and the Caribbean (LAC), the Middle East and North Africa (MENA), and South Asia (SA).

Based on the LNZ-score, we consistently find that employee turnover increases credit risk for MFIs in the EECA and SA regions (Table 5). Moreover, in terms of PAR30, we consistently observe similar results in Africa and the EECA region. We also find a similar outcome in terms of WOR in the EAP, EECA, and LAC regions (Table 5). However, we observe the opposite relationship in the MENA region. Our findings are consistent with those of Mia, Ahmad, and Halim (2022), who find that employee turnover has a positive effect on the financial performance of MFIs in the MENA region. According to Alexander et al. (1994) and Abelson and Baysinger (1984),

Table 6
Hausman-taylor approach and G2SLS.

	31	32	33	34	35	36
	Hausman-Taylor			G2SLS (REM)		
	Z-Score	WOR	PAR30	Z-Score	WOR	PAR30
ETR	−0.467**	0.009***	0.037**	−0.668***	0.010***	0.036***
	(0.195)	(0.003)	(0.015)	(0.196)	(0.003)	(0.012)
LNTA	0.094***	0.000	−0.008***	0.144***	0.000	−0.007**
	(0.030)	0.000	(0.003)	(0.027)	(0.001)	(0.003)
DTE	−0.115***	0.000	0.002**	−0.122***	0.000	0.002*
	(0.013)	0.000	(0.001)	(0.012)	0.000	(0.001)
LNNOBM	−0.044	−0.003**	−0.006	−0.03	−0.002	−0.006
	(0.088)	(0.001)	(0.006)	(0.083)	(0.002)	(0.006)
DTL	0.035	0.002	0.027***	−0.096	0.000	0.029***
	(0.128)	(0.002)	(0.007)	(0.131)	(0.002)	(0.010)
PFB	−0.214	−0.012**	−0.087***	−0.029	−0.013**	−0.080***
	(0.243)	(0.005)	(0.021)	(0.196)	(0.005)	(0.020)
LNALB	0.004	−0.004***	−0.006	0.089	−0.004***	−0.004
	(0.074)	(0.001)	(0.005)	(0.060)	(0.001)	(0.005)
PS	−0.389***	0.008***	0.001	−0.278**	0.008***	−0.009
	(0.106)	(0.002)	(0.008)	(0.115)	(0.002)	(0.010)
LS	−0.523***	0.004**	−0.006	−0.331**	0.005**	−0.003
	(0.124)	(0.002)	(0.009)	(0.129)	(0.002)	(0.012)
HHI	−0.327**	0.001	0.005	−0.203	0.003	−0.003
	(0.156)	(0.003)	(0.011)	(0.158)	(0.003)	(0.011)
GDPGR	0.053***	−0.001***	−0.005***	0.048***	−0.001***	−0.002**
	(0.011)	0.000	(0.001)	(0.013)	0.000	(0.001)
INFR	0.008	−0.000**	0.001	0.001	0.000	0.003*
	(0.011)	0.000	(0.001)	(0.011)	0.000	(0.002)
AGOV	0.380***	0.003	0.039***	0.323**	0.000	0.031***
	(0.119)	(0.002)	(0.010)	(0.133)	(0.002)	(0.009)
Year FE	NO	NO	NO	YES	YES	YES
RD	YES	YES	YES	YES	YES	YES
CONS	3.373***	0.064***	0.305***	1.652***	0.045***	0.260***
	(1.152)	(0.015)	(0.064)	(0.610)	(0.011)	(0.056)
Observations	2385	3608	3608	1943	2001	2001
Chi^2	9164.002***	732.011***	723.325***	248.462***	197.069***	106.745***
R^2				0.221	0.142	0.089
# of MFIs	773	1110	1110	671	689	689

Source: Authors. Note: Robust Standard errors in parentheses. Please see Table 1 for definition of all variables. ***p < 0.01, **p < 0.05, *p < 0.1.

organizations may benefit from employee turnover because they can recruit new employees, who bring new skills and innovations with them to the organization. Our results suggest that this might be the case for MFIs in the MENA region.

Additionally, employees working for companies with a high credit risk may experience significant pressure. The company may urge loan officers to recover every debt, even when it is not realistically possible. As a result, employees may feel compelled to leave and seek employment elsewhere. Given this scenario, we suspect that our model may be subject to endogeneity issues concerning staff turnover and the credit risk of MFIs. Thus, to address the reverse-causality issue, we use the Hausman and Taylor (1981) approach, following studies by Mia (2022b), Quayes (2015), and Mia, Banna, Noman, Alam, and Rana (2022). The results are reported in Table 6 (Models 31 to 33). In addition to addressing endogeneity issues, this test combines the advantages of REM and FEM. It can handle time-invariant variables, such as REM, and can control for individual heterogeneity, such as FEM. This result confirms our previous finding that ETR increases the credit risk of MFIs.

Furthermore, although we use year-fixed effects and regional impacts through dummies for the year dummy and region in all the estimates, several other unobservable variables might influence our models. Therefore, we add instrumental variables (IV) to our models and test the random-effects using a generalized two-stage least squares (G2SLS) technique. Consistent with Ain, Yuan, Javaid, Usman, and Haris (2020), we implement lagged values of employee turnover, in conjunction with organizational characteristics, as IVs in estimating the random-effects G2SLS model. The results, presented in Table 6 (Models 34 to 36), confirm that employee turnover increases the credit risk of MFIs at the 1 percent level of statistical significance for all three proxies.

5. Conclusion, implications, and future research directions

Almost every industry experiences some level of employee turnover, but the extent of its effects may vary. In the microfinance industry, even minimal levels of employee turnover can have serious consequences due to the loss of soft knowledge about credit clients (Berger & Udell, 2002). When an employee, particularly a loan officer, leaves one MFI for another, essential information about borrowers is lost, which disrupts loan recovery and, ultimately, increases the credit risk of the MFI (Blanco-Oliver et al., 2021). Given the limited attention to this important topic, we examine the impact of employee turnover on the credit risk of MFIs using data on 1266 MFIs in 101 countries from 2010 to 2018 gathered from the World Bank databases.

We discover a significantly positive link between employee turnover and credit risk, using static models, such as POLS, FEM, and REM. Furthermore, we conduct robustness tests using a subsample based on geographic location, with the Hausman-Taylor and G2SLS techniques. Overall, our results suggest that employee turnover has a positive effect on the credit risk of MFIs, except in a few cases.

The results of our research lead to a recommendation that policy makers, the government, and MFI management reassess their human resource management policies. Our findings suggest that employee turnover not only leads to a loss of human capital and to costs for MFIs but also to a loss of social capital, ultimately increasing the credit risk of MFIs. Therefore, this research emphasizes the need for MFIs to develop strategies that reduce voluntary staff turnover through offering better employment benefits, both monetary and nonmonetary, in order to minimize credit risk. However, as per Frederick Herzberg's two-factor theory (1959), employees tend to leave an organization when they are dissatisfied with their job (Deri, Zaazie, & Bazaanah, 2021). In other words, if employees are discontent with the work environment, they may seek better opportunities and eventually resign from their incumbent position (Alarcon, Eschleman, & Bowling, 2009). However, MFIs can avoid this situation by implementing strategic policies (Bauer, Derwall, & Hann, 2009), such as promoting a positive relationship between the organization and employees to enhance their job satisfaction.

Although we contribute empirically to the risk literature in the microfinance context, this research has some limitations that could be addressed by future researchers. In this study, we only consider the linear relationship between employee turnover and credit risk, despite reports of a nonlinear association between employee turnover and MFI performance. For instance, Glebbeek and Bax (2004) and Meier and Hicklin (2008) suggest that the relationship is more inverted-U-shaped, whereas De Winne et al. (2019) argue for a negative relationship. Therefore, we strongly recommend that future research consider the nonlinear impact of employee turnover on the credit risk of MFIs. Moreover, examining the specific dynamics between loan officer turnover and the credit risk of MFIs could lead to valuable insights for MFI management and policy makers. Our study is limited by the unavailability of data on specific employee turnover rates at different organizational levels. If such data becomes available in the future, it could yield interesting findings on the employee turnover-credit risk relationship.

Data availability statement

The empirical data used in this study is available in the world-bank database. Data can be availed from the following link.

https://datacatalog.worldbank.org/search/dataset/0038647.

Declaration of competing interest

The authors declare that they have no known conflict of interest associated with the study.

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Appendix A

List of Countries used in the Study.

Region	Country	Freq.
Africa	Angola	2
Frequency: 562	Benin	44
Percentage: 12.83	Burkina Faso	34
No of MFIs: 230	Burundi	6
	Cameroon	29
	Central African Republic	2
	Chad	3
	Comoros	1
	Congo, Republic of the	1
	Cote d'Ivoire (Ivory Coast)	22
	Ethiopia	12
	Gabon	1
	Ghana	36
	Guinea	1
	Kenya	37
	Liberia	10
	Madagascar	45
	Malawi	17
	Mali	17
	Mozambique	17
	Niger	21
	Nigeria	47
	Rwanda	26
	Senegal	22
	Sierra Leone	10
	South Africa	6
	Sudan	4
	Tanzania	23
	Togo	27
	Uganda	28
	Zambia	9
	Zimbabwe	2

(*continued on next page*)

(*continued*)

Region	Country	Freq.
Total	**32**	**562**
East Asia and the Pacific (EAP)	Cambodia	97
Frequency: 528	China, People's Republic of	48
Percentage: 12.05	Fiji	7
No of MFIs: 167	Indonesia	58
	Laos	29
	Malaysia	1
	Myanmar (Burma)	24
	Papua New Guinea	42
	Philippines	157
	Samoa	6
	Solomon Islands	2
	Thailand	2
	Tonga	5
	Vietnam	50
Total	**14**	**528**
Eastern Europe and Central Asia (EECA)	Albania	8
	Armenia	42
Frequency: 620	Azerbaijan	96
Percentage: 14.15	Belarus	5
No of MFIs: 189	Bosnia Herzegovina	50
	Bulgaria	41
	Georgia	46
	Kazakhstan	36
	Kyrgyzstan	56
	Macedonia	18
	Moldova	13
	Mongolia	33
	Montenegro	6
	Poland	7
	Russia	60
	Serbia	11
	Tajikistan	81
	Turkiye	5
	Ukraine	6
Total	**19**	**620**
Latin America and the Caribbean (LAC)	Bolivia	137
	Brazil	91
Frequency: 1528	Chile	17
Percentage: 34.87	Colombia	134
No of MFIs: 344	Costa Rica	59
	Dominican Republic	65
	Ecuador	366
	El Salvador	58
	Guatemala	87
	Guyana	3
	Haiti	26
	Honduras	114
	Jamaica	7
	Mexico	33
	Nicaragua	113
	Panama	27
	Paraguay	33
	Peru	154
	Suriname	1
	Uruguay	1
	Venezuela	2
Total	**21**	**1528**
Middle East and North Africa (MENA)	Egypt	34
	Iraq	24
Frequency: 147	Jordan	29
Percentage: 3.35	Lebanon	12
No of MFIs: 48	Morocco	34
	Syria	2

(*continued*)

Region	Country	Freq.
	Tunisia	8
	Yemen	4
Total	**8**	**147**
South Asia (SA)	Afghanistan	35
Frequency: 997	Bangladesh	176
Percentage: 22.75	Bhutan	3
No of MFIs: 288	India	509
	Nepal	93
	Pakistan	140
	Sri Lanka	41
Total	**7**	**997**

Source: Authors computation.

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