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Thomas Blavet
Paris School of Economics (PSE), France, thomas.blavet@psemail.eu

Votsoma Djekna
Univ. Lille, CNRS, IESEG School of Management, UMR 9221-LEM-Lille Economie Management, F-59000 Lille, France | votsoma.djekna@univ-lille.fr, corresponding author

Parametric estimation of the determinants of inefficiency of microfinance institutions in the WAEMU and CEMAC countries

Thomas Blavet* Votsoma Djekna†

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Abstract

This study aims to analyse the determinants of inefficiency of microfinance institutions (MFIs) in the West African Economic and Monetary Union (WAEMU) and Economic and Monetary Community of Central Africa (CEMAC) countries. We use the stochastic frontier approach to estimate a translog cost function for a sample of 102 MFIs that operate in eight countries over the period 2003-18 by applying the method of Wang and Ho (2010), which distinguishes heterogeneity from inefficiency. We decompose operational expenses into administrative, financial, and depreciation expenses to estimate the loan production technology. The results highlight that MFIs that specialise less in lending to women and younger MFIs are more efficient and that competition deteriorates the efficiency of MFIs in these countries.

Keywords: Microfinance, Stochastic frontier, Inefficiency, Heterogeneity, Determinants

JEL Codes: C23, D24, G21

*Paris School of Economics (PSE), France, thomas.blavet@psemail.eu.
†Univ. Lille, CNRS, IESEG School of Management, UMR 9221-LEM-Lille Economie Management, F-59000 Lille, France; votsoma.djekna@univ-lille.fr, corresponding author.

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1. Introduction

Microfinance has become a major player in the fight against poverty. In developing countries, microfinance mobilises funds in the informal sector for people excluded from the traditional banking sector and/or those who are financially limited. Bangoura et al. (2016); Clark and Spraggon (2022); Diaz-Serrano and Sackey (2022); Lahkar and Pingali (2016); Sahoo and Dash (2013) show that microfinance improves the income and the savings of the poor and reduces inequality by increasing the number of borrowers while simultaneously being financially sustainable.

Microfinance institutions (MFIs) are developing strategies to improve their financial and social performance (Hermes and Hudon, 2018) to produce and offer more financial services to low-income households. Viability and sustainability require management style, optimal cost management, respect for constraints, and specific objectives. The principal main of this study is to analyse the determinants of the inefficiency of MFIs in West and Central Africa. This concerns the CEMAC, which includes six countries: Cameroon, Congo, Gabon, Equatorial Guinea, Central African Republic, and Chad, and the WAEMU, which includes eight countries: Benin, Burkina Faso, Ivory Coast, Guinea Bissau, Mali, Niger, Senegal, and Togo.

Traditional banks and microfinance institutions can be considered as two types of financial intermediaries of different essences (Uddin et al., 2022) but they often have the same objective: to collect savings from surplus agents for the financing of projects deemed profitable (Fall, 2009, 2011). Moreover, stylised facts for the period 1980-2019 in the WAEMU and CEMAC countries clearly show an increase in complementary banking microfinance. Moreover, as Kouakou (2020) shows, this combination of banking and microfinance activities would only be beneficial for growth. While formal banks learn about proximity intermediation, MFIs learn about banking knowledge. This conception of the financial institution guides the choice of products (outputs) and production factors (inputs) in this study.

Nevertheless, banks and microfinance differ in their intermediation logic, scale of their operations, temporality of their contracts, and mechanisms used to select and monitor projects (Fall, 2011). In the WAEMU and CEMAC countries, the legal status of banks and MFIs is another distinction. Banking institutions are supervised by the central bank and regulated by banking law, while microfinance structures depend on the Ministry of Economy and Finance and are regulated by a specific law. Banks are monetary financial institutions because they have the power to create money, whereas MFIs do not have this licence. MFIs are non-monetary institutions that operate solely based on the resources they collect.

Economic and financial literature models banking and microfinance inputs and outputs through two main approaches: production and intermediation. The production approach considers that banks produce various categories of deposits, loans, and other services using physical factors, such as physical capital, labour, materials, and area (Benston, 1965; Bell and Murphy, 1968; Berger and Humphrey, 1991). The intermediation model[1] considers financial

[1] The intermediation approach is divided into three components.
The first component considers financial intermediation as the main activity of the bank. Deposits, other liability accounts, and real resources are considered as inputs and loans, while balance sheet assets (which use the funds

institutions as agents (or intermediaries) that move funds between agents with financing needs and those with financing capacities. In this view, the factors of production are labour, physical capital, and sometimes equity to convert financial capital such as deposits and other funds into loans, securities, investments, and other income-generating assets. The institution then produces intermediation services to the extent that its outputs emanate from the firm's assets in different types of loans and investments, and the financial costs of accounts are recorded in the liabilities (Sealey Jr and Lindley, 1977).

There are several reasons for choosing the intermediation approach to analyse the efficiency of MFIs in this study. First, Berger and Mester (1997) note that the intermediation approach is more appropriate, as financial institution managers focus on reducing total costs, and not only non-interest rate costs. Ohene-Asare (2011) confirms that this approach encompasses bank's total costs and does not exclude interest expenses, because these expenses constitute a significant part of the bank's total cost, and their elimination could bias the empirical results. The second reason, as given by Sealey Jr and Lindley (1977), is the nature of financial institutions' businesses. As financial institutions specialise in the transformation of deposits and credits, the deposits collected constitute part of the funds used to grant credits and make investments. Deposits are, therefore, considered as inputs and not outputs, as in the production approach which may be more appropriate, as Ohene-Asare (2011) points out, for studies of efficiency at the bank branch level.

For Ferrier and Lovell (1990), the intermediation approach is the best when the objective is the economic viability of the financial institution, as it incorporates all general banking costs, unlike the production approach which focuses mainly on operating costs. There is no consensus on the use of some outputs and inputs in the analysis of financial institutions' efficiency, although the intermediation approach is dominant.

As mentioned above, the objective of this study is to analyse the determinants of the inefficiency of MFIs in the WAEMU and CEMAC countries. Given that MFIs vary from one area to another, depending on the specificities of each financial system, poverty levels, extent of subsidies, and involvement of public authorities (Fall and Servet, 2010), we use the methodology developed by Wang and Ho (2010). One of the first contributions of this study is the use of the model of Wang and Ho (2010), which has not yet been used in the microfinance sector, to our knowledge. This estimation method makes it possible to distinguish, for each institution, time-invariant heterogeneity from time-varying inefficiency. The heterogeneity of

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that generate most of the returns received by the bank) are considered as outputs (Ohene-Asare, 2011; Sealey Jr and Lindley, 1977).

The second component (user cost) was proposed by Barnett (1978), Donovan (1978), and Hancock (1985) to determine whether deposits were a product or an input. Under this component, banks transform non-financial inputs such as labour, capital, and purchased materials into financial products. User costs categorise the inputs and outputs of a bank product according to their net contribution to the bank's turnover or the signs of their derivatives in a bank profit function. The financial returns on an asset must be greater than the opportunity cost of funds for a financial product to be considered an output (or conversely the financial cost on the claim must be less than the opportunity cost).

The last component of value-added concerns the modelling of the bank's behaviour. It has been developed by Berger et al. (1987) and Berger and Humphrey (1992). Here, the outputs are represented by the supply of loans and the inputs by the labour and physical capital that are used.

each institution is necessary for at least two reasons. The first is to estimate the production technology by considering heterogeneity in the form of fixed effects. This heterogeneity is reflected in the estimation of the production technology by a different constant for each institution, and thus, results in a different part of the production cost (in the case of the estimation of a cost function). The second reason is to estimate the inefficiency correctly. If heterogeneity is not considered, a part of it is reflected in the inefficiency estimation. This leads to overestimation or underestimation.

Although necessary, considering heterogeneity by integrating fixed effects into the estimation of technology may cause estimation problems. Indeed, the latter is potentially subject to an incidental parameter problem, because there are as many effects to be estimated as there are institutions in the sample. The estimation of these fixed effects is problematic in cases in which each institution is observed for a limited number of years.

To avoid this potential problem of incidental parameters while distinguishing heterogeneity from inefficiency, Wang and Ho (2010) propose a first difference or within-transformation. These methods estimate production technology without being subject to this incidental parameter problem, as fixed effects will be removed from the estimation, but the production technology will still be correctly estimated.

We use Wang and Ho's (2010) method to estimate a translog cost function to characterise MFIs' production technology and analyse the determinants of inefficiency. To the best of our knowledge, another contribution of this study is that it is the first to decompose operational expenses into administrative, financial, and depreciation expenses to estimate the loan production technology. The estimates are carried out on a sample of 102 MFIs from eight countries of West and Central African economies for a period of 16 years from 2003 to 2018.

This study highlights that in the WAEMU and CEMAC economies, three determinants are important: percentage of women borrowers, market share concentration, and age of the firm. MFIs that specialise in lending to women are less efficient, and the youngest MFIs are the most efficient. We also find that the less competition there is in the microfinance sector at the local level, the more efficient it is.

The remainder of this paper is organised as follows. Section 2 presents related literature. Section 3 presents the methods used to consider the determinants of inefficiency and, in particular, the methods used to decompose inefficiency from heterogeneity. In particular, this section presents the approach of Wang and Ho (2010) which is applied in the remainder of the study. This section also presents the estimation strategy that decomposes operational expenses into administrative, financial, and depreciation expenses to estimate the loan production technology, ensuring that homogeneity is imposed, and presents the specification of the inefficiency determinants. Section 4 presents the sample of microfinance institutions in the WAEMU and CEMAC countries and the data used. Finally, Section 5 presents the empirical results and interpretations of the results.

2. Related literature

Existing literature dealing with the measurement of MFI inefficiency or efficiency applies two main approaches: the parametric and non-parametric approach.

Since Benston (1965), Berger and Humphrey (1991), and Sealey Jr and Lindley (1977), inefficiency or efficiency measurement models applied in other fields have been imported into the financial sector.

2.1. Analysis of the determinants of inefficiency using data envelopment models

Many authors have focused on data envelopment analysis (DEA) to analyse the efficiency of MFIs. Without claiming to be exhaustive, we present a few key studies related to our study.

Nghiem et al. (2006) focus on 46 MFIs in Vietnam, using labour and non-labour costs as inputs and the number of savers, borrowers, and groups as outputs. They conclude that the average technical efficiency of MFIs in Vietnam is 80 percent and that the age and location of the MFI significantly influence the efficiency of these MFIs. Gutiérrez-Nieto et al. (2007) examine the efficiency of MFIs in Latin America. Using as inputs the number of loan officers and operating expenses and as outputs the interest income and fees, the gross loan portfolio, and the number of outstanding loans, they show the presence of a country effect as the location and nature of the MFI influence technical efficiency. They are joined by Haq et al. (2010), who examine 39 MFIs in Asia, Africa, and Latin America and find that the nature of the MFI, especially NGOs, is more efficient. Gutiérrez-Nieto et al. (2009) further focus on financial and social efficiency in 89 MFIs worldwide. They use total assets, costs, and number of employees as inputs and outputs; first, loans and revenues to measure financial efficiency; and second, the number of female borrowers and the poverty index to measure social efficiency. They find a weakly positive relationship between outreach and financial efficiency. Bassem (2008), on the other hand, analyses the efficiency of a panel of 35 MFIs in the Mediterranean area from 2004 to 2005 and finds a negative relationship between MFI size and efficiency.

Segun and Anjugam (2013) examine another aspect of MFIs: client service delivery. In a sample of 27 MFIs in 25 countries in Saharan Africa, they conclude that MFIs are inefficient in performing their financial intermediation function. Using outreach and financial viability as an angle of observation for 52 rural banks in Cameroon, Piot-Lepetit and Nzongang (2014) use a multi-DEA methodology to measure the efficiency of rural banks in Cameroon and make a trade-off between outreach and financial viability. Lebovics et al. (2016) find no relationship between financial and social efficiency. In a sample of 28 MFIs in Vietnam, they use variable inputs such as total liabilities, operating costs, and number of employees, and use gross loan portfolios and financial income as financial outputs and poverty outreach and number of depositors as social outputs.

In an extension of the studies using the data envelopment methods mentioned, Fall (2018) uses Simar and Wilsons (2007) truncated double-bootstrap method to analyse the technical efficiency of MFIs in the UEMOA zone. Fall (2018) finds that economic profitability is a key determinant of financial and social efficiency. Similarly, MFIs with a non-commercial profile are the most efficient from a social point of view. In the following section, we present the main studies using the stochastic frontier (SF) method to analyse the determinants of MFI inefficiency.

2.2. Analysis of the determinants of inefficiency using stochastic frontiers

The application of stochastic frontiers (SFA) to analyse the efficiency of MFIs has been quite recent. However, we can cite the works of Desrochers and Lamberte (2005), Hermes et al. (2011), Oteng-Abayie (2011), Paxton (2007), Servin et al. (2012), and Mimouni et al. (2022), who focused on SFA methods for MFIs.

Desrochers and Lamberte (2005) investigate whether rural cooperative banks in the Philippines minimise agency costs in their management. In a sample of 50 rural cooperative banks from 1995 to 1999, they use, on the one hand, the intermediation approach which considers the firm as a producer of two goods (loans and deposits) and, on the other hand, an SFA and free distribution approach to estimate a cost function. Outputs are estimated as the number of accounts, amount of loans and investments, and inputs as the value of deposits, capital, wages, and interest. They conclude that agency costs significantly reduce the cost efficiency of rural cooperative banks. Thus, an increase in management remuneration would result in improved bank performance and higher productivity. Finally, they find that more profitable cooperative banks are better able to cope with external shock.

Gregoire and Tuya (2006) examine efficiency by MFI type in Peru. In a sample of 28 MFIs with 1,864 observations over the period 1999 to 2003, they use Battese and Coelli's (1995) methodology to estimate a cost function through the SFA approach. Following the intermediation approach, the loan portfolio is the only output they retain. Labour and physical capital represent necessary inputs and deposits as fixed inputs. They conclude that only the concentration index, size, and credit to the agricultural sector are negatively correlated with the inefficiency of MFIs in Peru. In contrast, for this sample, the coefficient of the average loan portfolio and MFI type are positive and statistically significant with the inefficiency of these MFIs.

Paxton (2007) uses an SF method to analyse the technical efficiency of 190 semi-formal MFIs in Mexico by estimating a translog production function. The dependent variable is the logarithm of the volume of outstanding loan portfolios, investments, and demand deposits, and the inputs are the logarithms of capital, labour, and loaned funds. Using Wang's (2002) model and cross-sectional data from 2001, Paxton (2007) concludes that technological tools (number of computers per employee), average loan portfolio size, outreach (average loan portfolio per borrower), and MFI age are positively correlated with the technical efficiency of MFIs in Mexico. In a similar lode, Masood and Ahmad (2012), use the methodology developed by Battese and Coelli (1995) to measure the level of efficiency and the determinants of inefficiency on an unbalanced panel of 40 MFIs in India over the period 2005 to 2008. They conclude that MFI age is a positive determinant of efficiency, although size does not explain it. They also find that the larger the outreach of the MFI, the more effective the MFI is and that geographical location affects the effectiveness of MFIs, as those operating in southern states appear to be more effective than their counterparts in northern states.

Similarly, Oteng-Abayie (2011), using an intermediation approach, uses Cobb-Douglas on 135 MFIs located in Ghana from 2007 to 2010. These results confirm those obtained by Masood and Ahmad (2012) and Paxton (2007). There is a positive relationship between efficiency and age of the MFI and a positive relationship between MFI efficiency and outreach, but a negative relationship with the number of deposits per saver. They also find a positive relationship between efficiency and operational expenses, loans per loan officer, and deposits per loan officer.

Quayes et al. (2013) confirm the results obtained by their predecessors. Using cross-sectional data on 45 MFIs in Bangladesh in 2013, Quayes et al. (2013) estimate a cost function based on the methodology developed by Battese and Coelli (1995), following the intermediation approach. The output is the average loan portfolio, while the prices are the price of labour, cost of capital, cost of borrowed funds, and cost of deposits and fixed inputs to highlight the determinants of inefficiency, such as the age of the MFI, size, average loan portfolio, and total loans. They conclude that the age of the MFI (not significant), total membership, average loan portfolio, and local loans are negatively correlated with MFI inefficiency. Riaz (2015) estimates a Cobb-Douglas function by applying the one-step methodology developed by Battese and Coelli (1995) on an unbalanced panel ranging from 2007 to 2013 of MFIs in Pakistan. He uses the intermediation approach to identify three inputs (cost per borrower, financial expenditure, and total assets) and two outputs (financial margin and average loan portfolio). He concludes that, on the one hand, age and the number of branches are significantly and negatively correlated with the inefficiency of MFIs in Pakistan and, on the other hand, the number of staff, number of women borrowers, and average loan portfolio per borrower are significantly and positively correlated with the inefficiency of these MFIs.

In addition, Hermes et al. (2011) measure the outreach and efficiency of 435 MFIs worldwide from 1997 to 2007. They estimate a cost function using the intermediation approach that describes as output the average loan portfolio and as inputs the price of a unit of labour per year, interest per unit of deposit, and use as determinants of inefficiency, the age of the MFI, percentage of female borrowers, average loan portfolio per borrower, and type of loans provided primarily by the MFI. They find a positive and significant coefficient between the age of the MFI and inefficiency; that is, younger MFIs are more efficient than older MFIs. According to Hermes et al. (2011, 2018), younger MFIs have enough time to learn from the failures of older MFIs and are therefore more cautious, and hence more efficient. They also find a positive and significant relationship between the percentage of female borrowers and inefficiency: the more an MFI specialises in lending to women, the more inefficient it becomes. They also found a positive relationship between individual loans, village loans, and inefficiency. On the contrary, they find a negative relationship between the average loan portfolio per borrower, group lending, and mixed lending. The same results are confirmed by Hermes et al. (2018) in an analysis of the relationship between financial development and MFI efficiency using a sample of 372 MFIs worldwide. They again estimate a cost function following the intermediation approach. In addition to the determinants used by Hermes et al. (2011), use a financial development indicator, the number of borrowers, and region fixed effects. They reach the same conclusions about the efficiency of young MFIs and the inefficiency of MFIs specialising in lending to women. Conversely, in a recent study, Fall et al. (2021) find that gender diversification increases the efficiency of MFIs. They use a non-parametric method (Free Disposal Hull) as well as its robust version of order α, on a sample of 680 MFIs in six countries for the year 2011.

Kumar and Sensarma (2017) analyse the efficiency of MFIs in India using a stochastic distance function approach. They find an inverse relationship between inefficiency and the percentage of female borrowers, microfinance size, profitability, and leverage in Indian microfinance in a panel of 75 MFIs from 2004 to 2011. Hermes et al. (2011, 2018) find a positive relationship between inefficiency and the age of MFIs.

Servin et al. (2012) in a sample of 315 MFIs, for 1681 observations, in 18 Latin American countries over the period from 2003 to 2009, analyse the technical efficiency of MFIs and find that the ownership structure and the nature of the MFI[2] are associated with technical efficiency. In addition, they show that non-governmental MFIs and cooperatives have less efficient technologies than banks and non-financial institutions with respect to their objectives.

There is still controversy regarding the link between competition and the efficiency of financial institutions. Two conflicting approaches underlie the relationship between competition and firm efficiency: structure-conduct-performance (SCP) paradigm and efficient structure hypothesis. While the SCP paradigm concludes that there is a negative correlation between market power and the profitability and efficiency of firms, the efficient structure hypothesis states a positive correlation, even if most authors find that competition improves the efficiency of institutions.

Empirical studies on the effects of competition on the efficiency of MFIs date back to the 2000s, and have mainly focused on Latin America.

This is the case of Christen (2000) who focuses on commercialization and mission drift of MFIs in Latin America. After defining the commonality between commercialisation and competition, the author shows that competition leads to increased market penetration and, in some countries, to market saturation, as well as to the deterioration of portfolio quality. Extreme market saturation can be observed, resulting from the effects of increased competition in the Bolivian MFI sector (Dannon et al., 2019).

Navajas et al. (2003) highlight the ambiguous effects of competition in a study of two MFIs in Bolivia. According to them, competition leads to innovation on the one hand and to the reduction of lenders' possibilities to subsidise unprofitable activities on the other. Moreover, McIntosh and Wydick (2005) confirm these results by indicating that competition between MFIs amplifies information asymmetry and, in particular, related adverse selection. MFIs do not have sufficient information about clients before they grant loans. They then show that increased competition between lenders can reduce the ability of MFIs to cross-subsidise poor and less-poor borrowers.

[2] These include non-governmental organizations, cooperatives, credit unions, rural banks, non-financial institutions

Several indicators are commonly used to measure the competition. Baquero et al. (2012) use the HHI[3] to measure competition in the microfinance industry in a sample of 279 MFIs in 69 countries from 2002 to 2008. The results show a significant difference in competitive conditions for commercially oriented and non-profit-oriented MFIs.

Mersland et al. (2011) use Panzar and Rose's (1987) H-statistic on a sample of 405 MFIs in 73 countries from 1998 to 2010. The results show that on average, MFIs do not exercise monopoly or collusive oligopoly power.

Assefa et al. (2013) use the Lerner statistic to assess the impact of the microfinance market structure on the efficiency of MFIs. They use a sample of 362 MFIs in 73 countries from 1995 to 2009. They show that increased competition is generally negatively associated with MFI performance.

Kar (2016) uses the Bonne (2008) indicator to quantify the impact of marginal cost on MFI performance in ten Asian and Latin American countries. The results obtained by the author show a significant decrease in competition between MFIs in Bangladesh and Bolivia due to the partial reconstitution of the market power of large MFIs in these countries.

Finally, Fecher and Pestieau (1993) analyse the correlation between efficiency and concentration in the financial sector and find a negative correlation. In another framework, Kouakou (2020) shows that the microfinance market could be shared with banks, and that in case of competition, banks win and the efficiency of MFIs decreases.

Recently, Mimouni et al. (2022) evaluate how subsidies and deposit mobilisation affect the cost inefficiency of MFIs. The authors use data from the Mix Market database on 1,582 MFIs in 92 countries from 2003 to 2018 and employ a baseline cost SF approach, a two-step system GMM. The findings of their study suggest that deposits alleviate cost inefficiency, while subsidies worsen it, and that cost inefficiencies are highly correlated with key microfinance indicators. Negative relationship with operational self-sufficiency and positive relationship with microcredit interest rates. Lower microcredit interest rates are among the other indicators of the social impact of microfinance, such as the depth of reaching the poorest borrowers, represented by the percentage of female borrowers.

Table 1 summarises the studies developed in the SF analysis framework in MFIs.

To reconcile the results of different studies, a meta-analysis was performed by Fall et al. (2018). They show that the average technical efficiency scores of MFIs have increased over time, although there is heterogeneity depending on the methodological approach used. On the one hand, they find higher scores for studies using more inputs and outputs, as well as for those using an output approach. On the other hand, they find lower scores for studies with a large number of MFIs and those estimating social efficiency. Finally, they find that African MFIs have low performance.

Some studies analyse the determinants of MFI inefficiency using alternative estimation methods rather than the DEA and SF approach.

[3] The Herfindahl-Hirschman Index (HHI) measures market concentration or the number of firms producing a good.

Hermes and Hudon (2018) conduct a systematic review of approximately 170 papers discussing the determinants of the financial and social performance of MFIs. Their study shows that the most important determinants addressed in the literature are MFIs' characteristics, such as size, age, type of organisation, quality of organizational governance, and macroeconomic conditions. According to this study, a consensus is far from being reached for each determinant.

Bartni and Chitnis (2016), Caudill et al. (2009), Cull et al. (2007, 2009), D'Espallier et al. (2013b, 2017a), Gohar and Batool (2015), Narwal and Yadav (2014), Rashid and Twaha (2013), Rai (2015), Wijesiri et al. (2015), Wu et al. (2016), and Zhou et al. (2020) analyse the impact of age, size, number of offices, number of personnel on MFI performance, percentage of female borrowers, GDP, inflation, market power, and competitiveness. Table 2 shows the characteristics of the literature on some determinants of microfinance inefficiency, using the SF approach and alternative estimation methods.

3. Consideration of the determinants of inefficiency and distinction from heterogeneity

3.1. Methodological issues

To estimate the efficiency of production, we have on the one hand parametric methods such as SFs and Aigner and Chu's (1968) method, and non-parametric methods such as DEA and Free Disposal Hull methods.

The SFs were developed by two papers published simultaneously: Meeusen and Van Den Broeck (1977) and Aigner et al. (1977). We can examine the determinants of the level of inefficiency.

In the literature, two-step estimation methods are used to determine the level of inefficiency and explain this level by considering exogenous variables. As we have seen in the previous section, many studies dealing with MFIs have estimated inefficiency using the DEA method and then regressed the level of technical inefficiency on exogenous variables used as proxies for the determinants of inefficiency. In the context of SF methods, an equivalent strategy has been proposed by Pitt and Lee (1981), but the estimation of the determinants of inefficiency in two steps may cause a problem because we must assume in the first step, when choosing the distribution hypothesis, that the inefficiency and the random term are homoscedastic by assuming that the variance of the inefficiency and the random term are constant. However, if we have variables that explain the difference in inefficiency between firms, we cannot assume that inefficiency is homoscedastic, because ignoring this information in the first step will lead to biased and non-convergent parameter estimates. Wang and Schmidt (2002) show that the two-step estimation of inefficiency and inefficiency determinants causes an omitted variable bias if the production technology is correlated with the variables capturing the determinants of inefficiency. This omitted variable bias problem affects the estimation of the level of inefficiency and the link between the determinants and inefficiency, even in the absence of a correlation between the technology variables and inefficiency determinants.

Therefore, one-step estimation methods were developed to avoid omitted variable bias and inconsistent parameter estimates. There are three strategies for considering the determinants of inefficiency in a one-step estimation. The first strategy is to account for the determinants of inefficiency using the inefficiency distribution assumption. Instead of assuming that the mean of inefficiency is constant and identical for all firms, Kumbhakar et al. (1991), Huang and Liu (1994), and Battese and Coelli (1995) propose to relax this assumption of constant mean of inefficiency by proposing different algebraic forms for the parameterization of the mean of inefficiency assumption. This strategy is called 'KGMHLBC' in the literature on SF estimation because of the authors' initials. The authors' strategy is to consider exogenous variables that capture the determinants of inefficiency and assume a firm-specific mean.

The second strategy considers the determinants of inefficiency based on the variance of the inefficiency distribution assumption. This method was developed by Caudill and Ford (1993), Caudill et al. (1995), and Hadri (1999) and is called 'CFCFGH'. This method relaxes the assumption of homoscedasticity by having a different variance for each firm depending on the determinants of inefficiency.

The third strategy developed by Wang and Schmidt (2002) combines the 'KGMHLBC' approach with the 'CFCFGH' approach to take the determinants of inefficiency, both in the mean and in the variance of the distributional assumption about inefficiency. The rationale for Wang and Schmidt's (2002) approach is that there is no reason to assume that the determinants will impact the mean but not the variance, or that the determinants will impact the variance but not the mean of inefficiency. To parameterise the mean and variance, Wang and Schmidt (2002) suggest using the same determinant. One of the advantages of this approach is that it relaxes the assumption of monotonicity between the determinants and the level of inefficiency whereas the 'KGMHLBC' and 'CFCFGH' approaches did not allow for a non-monotonic relationship between inefficiency and the determinants unless the variables were squared or an interaction between the variables was taken.

In the next section, we describe the data used, which are panel data observations. Working with panel data will have consequences for distinguishing between inefficiency and heterogeneity. Greene (2005a, b) is the first to address the distinction between inefficiency and heterogeneity in his studies, estimating the efficiency of healthcare systems in 194 countries over a five-year period. As these countries differ widely in terms of their economic and cultural characteristics, Greene (2004) focus on country heterogeneity, particularly the distinction between the economic and cultural characteristics of different countries and the efficiency of their healthcare systems. Greene (2004, 2005a, b) develop a true random effects model by decomposing the error term into three random terms: a random term for firm-specific and time-varying technical inefficiency, a random term for firm-specific and time-varying shock, and finally a random term for firm-specific but time-invariant heterogeneity. To estimate this true random effects model, Greene proposes the use of a distribution assumption for each random effect and use the maximum likelihood method. Colombi et al. (2014) use the model developed by Greene by adding a specific random effect for time-invariant technical inefficiency to distinguish between permanent and transient technical inefficiency. They propose using the maximum likelihood, where the sum of the four random effects has a closedskewed normal (CSN) distribution. This result was demonstrated by Arellano-Valle and Azzalini (2006), and Gonzalez-Farias et al. (2004).

Greene also develop the true fixed-effects model by decomposing the error term into two random terms: a random term for firm-specific and time-varying technical inefficiency and a random term for firm-specific random shocks. Unlike the true random-effects model, this model considers time-invariant heterogeneity in the form of a firm-specific fixed effect. This method is relatively simple because it is enough to add as many dichotomous variables as there are firms in the panel. This model could be subject to an incidental parameter problem if we have a few years of observations and many firms. Greene (2005b) shows that the incidental parameter problem does not cause a significant bias in the estimated parameters when the number of years of observation is high.

To estimate the inefficiency of MFIs, we use the model of Wang and Ho (2010) which allows to consider the determinants of inefficiency in panel data and to distinguish the heterogeneity of inefficiency, an important element as demonstrated by Greene and which was not considered by the models 'KGMHLBC' and 'CFCFGH'. The estimated model is as follows:

$$y_{it} = \alpha_i + x_{it}\beta + \varepsilon_{it}, \tag{1}$$

$$\varepsilon_{it} = v_{it} - u_{it}, \tag{2}$$

$$v_{it} \sim N(0, \sigma_v^2), \tag{3}$$

$$u_{it} = h_{it} * u_i^*, \tag{4}$$

$$h_{it} = f(z_{it}\delta), \tag{5}$$

$$u_i^* \sim N(\mu, \sigma_u^2), \text{ where } i = 1,2,\dots,N \text{ and } t = 1,2,\dots,T. \tag{6}$$

For the sake of clarity, Wang and Ho's (2010) method is presented for the case of balanced panels, but it is valid for unbalanced panels[4]. This model is based on Wang and Schmidt's (2002) model which assumes that the shape of the inefficiency distribution is the same for all firms in the panel by not including the determinants of inefficiency in the mean and variance of the distribution assumption but uses an inefficiency-multiplying function using the variables used as proxies for the determinants.

This function, called the scaling function, allows the horizontal axis to be stretched or shrunk, but the shape of the inefficiency distribution is the same for all firms; that is, a half-normal distribution or a truncated normal distribution with the same parameter values for the mean and variance. This argument is one of the main advantages of Wang and Schmidt's (2002) model. The second argument is that the parameters of the determinants of inefficiency are semi-elastic, and the interpretation in terms of semi-elasticity is retained regardless of the distributional assumption of inefficiency. To eliminate the potential problem of incidental parameters due to the estimation of firm fixed effects α_i Wang and Ho (2010) propose using a first difference or a within-transformation to eliminate the fixed effects.

[4] Wang and Ho (2010), Estimating fixed-effect panel stochastic frontier models by model transformation, page 290, section 2.3.1.

Here, we present a model that eliminates fixed effects via within-transformation. These equations are obtained from Wang and Ho (2010). Through a within-transformation, the sample mean of each panel is subtracted from every observation in the panel. Thus, the transformation removes the time-invariant individual effect (α_i) from the model. The following notation is useful for understanding the model: $\omega_{i.} = (1/T)\sum_{i=1}^{T}\omega_{it}$, $\omega_{it.} = \omega_{it} - \omega_{i.}$, and stacked vector of $\omega_{it.}$ for a given i is $\widetilde{\omega}_{i.} = (\omega_{i1.}, \omega_{i2.}, \dots, \omega_{iT.})'$. The model after transformation is:

$$\tilde{y}_{i.} = \tilde{\chi}_{i.}\beta + \tilde{\varepsilon}_{i.}, \tag{7}$$

$$\tilde{\varepsilon}_{i.} = \tilde{v}_{i.} - \tilde{u}_{i.}, \tag{8}$$

$$\tilde{v}_{i.} \sim MN(0, \Pi), \tag{9}$$

$$\tilde{u}_{i.} = \tilde{h}_{i.}u_i^*, \tag{10}$$

$$u_i^* \sim N^+(\mu, \sigma_u^2),\ i = 1,2, \dots, N. \tag{11}$$

The variance-covariance matrix of $\tilde{v}_{i.}$ is

$$\Pi = \begin{bmatrix} \sigma_v^2(1-1/T) & \sigma_v^2(-1/T) & \dots & \sigma_v^2(-1/T) \\ \sigma_v^2(-1/T) & \sigma_v^2(1-1/T) & \dots & \sigma_v^2(-1/T) \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_v^2(-1/T) & \sigma_v^2(-1/T) & \dots & \sigma_v^2(1-1/T) \end{bmatrix}, \tag{12}$$

$$= \sigma_v^2\left[I_T - \frac{\iota'\iota}{T}\right], \tag{13}$$

$$= \sigma_v^2 M, \tag{14}$$

where ι is a $T \times 1$ vector of 1's and $u_{it.} = u_{it} - u_{i.} = h_{it}u_i^*\left(\frac{1}{T}\sum_{i=1}^{T}h_{it}\right) = (h_{it} - h_{i.})u_i^* = h_{it.}u_i^*$.

The authors show that the first and within transformations are mathematically equivalent. This transformation was used for the estimates in this study.

3.2. Estimation method

To our knowledge, Wang and Ho's (2010) methodology, which distinguishes heterogeneity from inefficiency, has not yet been used in the analysis of the inefficiency. We characterise production technology using a translog cost function. The translog functional form allows for great flexibility and is the best for estimating a cost function (Assefa et al., 2013; Gagne and Ouellette, 1998; Hermes et al., 2011, 2018; Karimu et al., 2021). We decompose operating expenses into three variable inputs: administrative, financial, and depreciation expenses, taking care to impose homogeneity of degree one by dividing the total cost and input prices by the price of depreciation and amortisation. Our analysis focuses on MFIs in West and Central African countries.

The total translog cost function that we estimate is the following:

$$
\begin{aligned}
\ln\left(\frac{TC_{it}}{DEP_{it}}\right) = {} & \beta_1 \ln\left(\frac{PERSO_{it}}{DEP_{it}}\right) + \beta_2 \ln\left(\frac{ADM_{it}}{DEP_{it}}\right) + \beta_3 \ln\left(\frac{FIN_{it}}{DEP_{it}}\right) + \beta_4 \ln(GLP_{it}) \\
& + 0.5\beta_5 \ln\left(\frac{PERSO_{it}}{DEP_{it}}\right)^2 + 0.5\beta_6 \ln\left(\frac{ADM_{it}}{DEP_{it}}\right)^2 + 0.5\beta_7 \left(\frac{FIN_{it}}{DEP_{it}}\right)^2 + 0.5\beta_8 \ln(GLP_{it})^2 \\
& + \beta_9 \ln\left(\frac{PERSO_{it}}{DEP_{it}}\right) \ln\left(\frac{ADM_{it}}{DEP_{it}}\right) + \beta_{10} \ln\left(\frac{PERSO_{it}}{DEP_{it}}\right) \ln\left(\frac{FIN_{it}}{DEP_{it}}\right) \\
& + \beta_{11} \ln\left(\frac{PERSO_{it}}{DEP_{it}}\right) \ln(GLP_{it}) + \beta_{12} \ln\left(\frac{PERSO_{it}}{DEP_{it}}\right) Trend \\
& + \beta_{13} \ln\left(\frac{ADM_{it}}{DEP_{it}}\right) \ln\left(\frac{FIN_{it}}{DEP_{it}}\right) + \beta_{14} \ln\left(\frac{ADM_{it}}{DEP_{it}}\right) \ln(GLP_{it}) + \beta_{15} \ln\left(\frac{ADM_{it}}{DEP_{it}}\right) Trend \\
& + \beta_{16} \ln\left(\frac{FIN_{it}}{DEP_{it}}\right) \ln(GLP_{it}) + \beta_{17} \ln\left(\frac{FIN_{it}}{DEP_{it}}\right) Trend + \beta_{18} \ln(GLP_{it})\, Trend \\
& + \beta_{19} Trend + 0.5\beta_{20} Trend^2 + v_{it} + u_{it} \qquad (15)
\end{aligned}
$$

where TC_{it} represents the total cost of an MFI i in year t, $PERSO_{it}$ represents the price of labour calculated as total expense on personnel per number of employees of the MFI; ADM_{it} represents the price of administration calculated as total expense on administration per number of employees of the MFI; FIN_{it} represents the price of interest expense calculated as total interest expense per dollar of deposit; DEP_{it} represents the price of capital depreciation and amortisation calculated as total depreciation and amortisation expense over the MFI's total fixed assets. Finally, GLP_{it}represents the MFI's gross loan portfolio.

Several control variables were added to the estimations to control for the overall macroeconomic conditions and differences in development across countries. The interaction between country-level macroeconomic variables and microfinance indicators has been documented by Al-Azzam and Parmeter (2021), Bangoura (2016), Gregoire and Tuya (2006), Hermes et al. (2009, 2011, 2018), D'Espallier (2013a), Masood and Ahmad (2012), and Mimouni et al. (2022).

We include gross domestic product (GDP), consumer price index (Inflation) and Human Development Index (HDI). Real GDP growth, which controls for overall developmental and technological progress, is used as an indicator of economic growth. High economic growth may increase micro-enterprise returns and demand for microcredit, allowing MFIs to increase interest rates. High growth may also raise household incomes and reduce demand for microcredit and interest rates. Inflation is used as an indicator of overall living standards. Higher inflation rates lead to a higher dispersion of prices, resulting from the cost of time and activities needed to search for the lowest prices (Benabou, 1992). In addition, higher inflation rates can lead to an increase in bad debt and its associated management which increases MFIs' costs. We also use the HDI to assess the level of development of countries based strictly on economic data, but on the quality of life of their citizens. We estimate GDP and HDI individually because of collinearity.

In addition to Table 1, which summarises a number of studies on the determinants of MFIs and clearly shows that there is no consensus on the relationship between different determinants and MFI inefficiency, Hermes and Hudon (2018) survey the determinants of MFI performance. They cross-reference 170 studies and find that the most relevant determinants are size, age, and macroeconomic conditions. We then specify our model as follows:

$$z_{it} = \delta_1 Women_{it} + \delta_2 HHI_{it} + \delta_3 Age_{it} + \delta_4 Equity_{it} + \delta_5 ALB_{it} + \delta_6 ASB_{it} + \delta_7 LLR_{it}. \qquad (16)$$

where z_{it} represents the vector of inefficiency determinants of firm i in period t.

$Women_{it}$ represents the percentage of female borrowers out of all borrowers in the total portfolio of each MFI for each year. A high value for this variable could indicate the extent and specification of the MFI in lending to women (usually associated with poor borrowers). A positive sign of this coefficient indicates that MFIs that specialise in lending to women are less efficient. This variable has been used, for example, by Alinsunurin (2014), Hermes et al. (2011, 2018), and Mimouni et al. (2022), among others, to incorporate the social outreach of the MFI.

HHI_{it} represents the HHI, which measures the concentration of the local market at a given time. The HHI is calculated by squaring the market share of the gross loan portfolio of each MFI competing in a country each year and then adding across these squared shares. A larger HHI value conveys a greater concentration. A value close to zero indicates a purely competitive microfinance industry and a value of one indicates a purely monopolistic industry. A negative sign of this variable indicates that the less competition there is, the more efficient the MFIs are. An increase in the number of banks leads to a decrease in each bank's profit and a low optimal level of efficiency to compensate for the loss of profit due to competition (Weill, 1998). This variable has also been used by Al-Azzam and Parmeter (2021), Demsetz (1973), Gregoire and Tuya (2006), and Nurboja and Košak (2017).

Age_{it} is a measure of the age of a microfinance institution. It is the natural logarithm of the number of years the institution has existed since its inception. It captures the number of years of experience of the MFI since its creation and the behaviour of the firm over time. In general, there are two different approaches to hypothesising the effects of firm age on efficiency: the ecological approach based on Hannan and Freeman (1984), and the evolutionary approach based on Jovanovic (1982). The addition of this variable makes it possible to test the hypothesis that older and more experienced MFIs are more efficient. The alternative hypothesis could be that older institutions have had to learn to cope with microfinance practices through trial and error, while more recently established institutions can benefit from the knowledge of microfinance practices accumulated over the past decades. The new MFIs can then outperform older institutions in terms of efficiency. The truth of the first hypothesis implies a negative and significant coefficient for the variable Age, whereas for the alternative hypothesis, the coefficient will be positive. This variable was used by Fall (2018), Hermes and Hudon (2018), Hermes et al. (2011, 2018), Mimouni et al. (2022), Narwal and Yadav (2014), Oteng-Abayie (2011), Quayes et al. (2013), Rai (2015), and Wijesiri and Meoli (2015).

$Equity_{it}$ represents the ratio of equity to total assets. It measures the strength and risk-taking differences of an MFI. This variable has been used by Berger and Mester (1997), Dietsch and Lozano-Vivas (2000), Grigorian and Manole (2006), Hermes et al. (2011, 2018), and Lozano-Vivas et al. (2001).

ALB_{it} represents the logarithm of the average loan portfolio per borrower. Like the $Woman$ variable, it measures social outreach, so a high value of this variable could indicate a lower outreach correlated with the exclusion of the poor from the MFI's target segment. This variable has been used by Fall (2018), Hermes et al. (2011, 2018), Quayes et al. (2013), and Schreiner (2002).

ASB_{it} represents the average savings balance per saver. It is the ratio of total deposits by the number of savers, and indicates the social outreach of the MFI. A high (lower) value for this variable would indicate the rich (poor) nature of the MFI's clients. This variable was used by Oteng-Abayie (2011).

LLR_{it} represents the loan loss provision divided by the gross loan portfolio. It considers differences in the risk-taking strategies among MFIs. This variable has been used by Fries and Taci (2005), Lensink et al. (2008), and Hermes et al. (2011, 2018).

4. Data

We use unbalanced panel data with a sample of 102 MFIs located in Central Africa and West Africa over a 16-year period from 2003 to 2018. The data used come from the Mix Market database, a World Bank database on microfinance worldwide, operated by the Microfinance Information Exchange (MIX) and covering thousands of financial service providers. There were 530 observations during this period.

The use of the Mix Market database is growing in the microfinance literature (Al-Azzam and Pameter, 2021; Fall, 2018; Fall et al., 2021; Hermes et al., 2018; Li et al., 2019; Karimu et al., 2021; Mimouni et al., 2021; Wijesiri, 2016). MIX is an online microfinance platform that discloses information on more than 2,500 MFIs worldwide. It also provides financial transparency for MFIs, thus addressing the main problem of MFIs related to the lack of reliable, comparable, and publicly available information. However, the MIX database has several limitations. The first is sample selection bias, which we did not control for in this study. The MIX is a self-reported database, and MFIs voluntarily disclose information. The second factor is the reliability of the data. MIX data are of uneven quality; MIX ranks MFIs according to their level of transparency and reliability. The third is the size of the base relative to reality. In reality, the MFI sector comprises hundreds of thousands of institutions worldwide, the vast majority of which do not report financial data to MIX. Sometimes, this is simply because many MFIs are very small and have unreliable information systems.

In our sample, we retained only the MFIs that collected deposits for two reasons. The first reason is that the construction of some variables is based on deposits, and the second reason is that it is difficult to distinguish between the data of MFIs that do not collect deposits, those that collect but did not fill in the value, or those that fill in the value zero either to say that they do not collect or that did not collect at that moment. We also retained the MFIs whose data were complete for all the variables and deleted all the MFIs with aberrant data.

Table 3 presents the number of observations per year, and Table 4 presents the number of MFIs in relation to the number of years for which the MFI was observed. The vast majority of 530 observations are concentrated between 2006 and 2017.

Table 5 shows the distribution of the MFIs by country. We have retained only those observations for which, in a given country in a given year, the number of MFIs is greater than two; the objective is to eliminate from the sample MFIs that are not subject to competition.

Table 6 presents the descriptive statistics of the variables in the model (the technology, control, and inefficiency determinant variables), and Table 7 presents the definitions of all the variables used in this study. The definitions are taken from the Mix Market and the International Monetary Fund website.

Table 8 provides a correlation matrix for all the variables used. There is no significant correlation between the explanatory variables. There is a strong correlation between the logarithm of the gross loan portfolio and the logarithm of the total cost, because the more loans an MFI grants, the more its total cost increases. The same level of correlation can be observed in Hermes et al. (2011, 2018).

5. Results and discussion

Table 9 shows the estimation results. The procedure used to generate these results is as follows. As mentioned before, Wang and Ho's (2010) method that we used simultaneously estimates the production technology and the determinants of inefficiency. With respect to the cost function, we perform estimations using the specification of Equation (16) without control variables. Our baseline estimate is shown in column (5), in which we include only the technology variables and the set of inefficiency determinants.

The coefficient for $Women$ is positive and significant at the 1 percent level across all specifications, which means that MFIs in West and Central African countries that specialise in lending to women are less efficient or more cost-inefficient than MFIs that serve the general population.

Although much of the literature focuses on the positive impact of female borrowers on MFI efficiency, the impact of targeting women on cost inefficiency remains empirically ambiguous. The focus on female borrowers in microfinance programs has been inspired by the belief that women are more likely to repay, and the growing influence of donor agencies (Weber, 2006). However, specialising in lending to women may be more cost-inefficient because women have less access to formal credit markets and receive smaller microloans (D'Espallier et al., 2011, 2013; Basharat et al., 2015). In this sample of West and Central African countries, women are indeed associated with a lower average loan balance per borrower, with a correlation of -0.32. In developing countries, as is the case in West and Central African countries, women tend to be less mobile, less educated, and more likely to need additional training and other services. These borrowers require additional and special follow-up. These results are consistent with those reported by D'Espallier et al. (2011, 2013) and Mimouni et al. (2022). These factors, together with the fact that women borrow smaller amounts, reinforce the inefficiency of costs.

Therefore, MFIs that specialise in lending to women should continue to lend to women but should diversify to improve their efficiency (D'Espallier et al., 2011, 2013; Hermes et al., 2011, 2018; Riaz, 2015).

The results of the estimation of equation (16) show that specialisation in lending to women increases the inefficiency of MFIs in the WAEMU and CEMAC countries. We examine these results by creating four dummy variables according to the percentage of female borrowers. The first quartile represents MFIs that are least specialised in lending to women. The dummy variable (Quartile 1. Women) takes the value of 1 when the MFI is in the 25 percent of MFIs with the lowest percentage of women borrowers. Conversely, the fourth quartile represents the MFIs that are most specialised in lending to women and takes the value of 1 when the MFI is among the 25 percent of MFIs with the highest rate of women borrowers. The fourth quartile is used as the reference. Thus, our model can be represented as follows:

$$z_{it} = \gamma Women_{it}^{Quartiles} + \delta_1 HHI_{it} + \delta_2 Age_{it} + \theta X_{it}. \quad (17)$$

where $Women_{it}^{Quartiles}$ represents the vector of the quartiles of the percentage of female borrowers of firm i in period t, γ is the parameter of different quartiles to estimate, and X_{it} the MFI-specific variables ($Equity$, ALB, ASB, LLR). This specification allows us to determine whether the percentage of female borrowers has an impact on the inefficiency of MFIs.

For example, if we find that γ is negative with the coefficients of the first quartile higher than the second quartile and the coefficients of the first and second quartiles higher than the third quartile, then as the MFI specialises in lending to women, it is less efficient. These estimates are presented in Table 11 from columns (2) to (4). The reference quartile (fourth quartile) represents MFIs with the highest percentage of female borrowers. More precisely, the results indicate significance at the 5 percent level for the first and second quartiles, with coefficients of -0.071 and -0.063, respectively. The third quartile is non-significant; nevertheless, it has a negative coefficient and is lower than the first and second quartiles (-0.028), confirming that the more female borrowers there are, the less effective MFIs are.

The coefficient of the variable HHI is significant and negative at the 1 percent level across all specifications, meaning that the less competition there is in the MFI sector at the local level, the more efficient they are. Our results agree with those found by Assefa et al. (2013), Gregoire and Tuya (2006), Rai (2015), and Wijesiri and Meoli (2015), but are contrary to Ayayi and Sene (2010), Cull et al. (2007), Dannon et al. (2019), Narwal and Yadav (2014), Wijesiri et al. (2015), and Wu et al. (2016).

This seemingly counterintuitive result can be explained by the fact that firms in a competitive situation seeking to expand their loan portfolios do not contain their costs (Nurboja and Košak, 2017). Based on a theoretical model, Weill (1998) demonstrates that an increase in the number of banks leads to a reduction in their efficiency. Indeed, when the number of banks increases, the profit of each bank reduces for a given level of efficiency. Thus, to reach the minimum profit level, banks are forced to modify their production technology (without considering the competition which reacts in the same way). Following the modification of its technology, the increase in the efficiency of a bank implicitly causes a reduction in the profit of its competitors, which leads the latter to react to compensate for this loss of profit. Therefore, the increase in the efficiency of each bank leads to a reduction in profit and vice versa. Consequently, as new banks enter the sector, each bank is forced to reduce its efficiency to compensate for the loss of profit due to this new competition. Previous studies, such as Demsetz (1973) and Fecher and

Pestieau (1993), also show a negative correlation between the efficiency of financial institutions and the level of competition.

Another finding of the estimation of equation (16) is that competition increases the inefficiency of MFIs in the WAEMU and CEMAC countries. In the same way as for the specialisation of MFIs in lending to women, we checked the result on the level of competition by creating four dummy variables according to the value of the HHI and thus the level of competition. The first quartile represents MFIs that are most subject to strong competition. This dummy variable (Quartile 1 HHI) takes the value of 1 when the MFI is part of the 25 percent of MFIs that are in the most competitive markets. Conversely, the fourth quartile represents the MFIs that are the least competitive, and therefore, are in more concentrated markets. This fourth quartile (Quartile 4 HHI) takes the value 1 when the MFI is in the top 25 percent of MFIs with the highest HHI (indicating that competition is low and the market is highly concentrated). The fourth quartile is used as the reference.

$$z_{it} = \delta_1 Women_{it} + \gamma^* HHI_{it}^{Quartiles} + \delta_2 Age_{it} + \theta X_{it}. \tag{18}$$

where $HHI_{it}^{Quartiles}$ represents the vector of the quartiles of the degree of competition of firm i in period t, γ^* the parameters of different quartiles to estimate, and X_{it} the MFI-specific variables ($Equity$, ALB, ASB, LLR). This specification allows us to determine whether the percentage of HHI has an impact on the inefficiency of MFIs.

For example, if we find that γ^* is positive with the coefficients of the first quartile higher than the second quartile and the coefficients of the first and second quartiles higher than the third quartile, then competition worsens the efficiency of MFIs. These estimates are presented in Table 12 from columns (2) to (4). The reference quartile (fourth quartile) represents the highest concentration market, where there is less competition or few MFIs. More precisely, the results indicate significance at the 1 percent level for all specifications: 0.071, 0,064 and 0.044, respectively. Once again, as we expected, the more female borrowers there are, the less effective the MFIs are.

The variable Age is significant, with a positive coefficient at the 1 percent level in all specifications, meaning that the youngest MFIs in West and Central African countries are more efficient. Our results are consistent with the findings of Fall (2018), Hermes et al. (2011, 2018), Kumar and Sensarma (2017), Nghiem et al. (2006), Narwal and Yadav (2014), Oteng-Abayie (2011), Rai (2015), Singh et al. (2013), Tewari (2016), Wijesiri and Meolli (2015), and Zamoure et al. (2021). The younger MFIs in our sample would benefit from the knowledge of microfinance practices that have been accumulated in the past. They benefit from existing information and knowledge to cope better with shocks and manage to improve the efficiency of their activities. However, as mentioned by Hermes and Hudon (2018), young organisations have the advantage of backwardness, and they may more easily adopt new management information systems and develop mobile banking platforms. They may benefit from recent technologies or innovations when starting their operations. The more mature the institution, the more it is stuck in older and less efficient processes that make it comparatively less efficient. This is why, according to Rai (2015), young MFIs grow faster and hold higher-quality assets.

On the other hand, Lundvall and Battese (2000) highlight aging liability. It was explained that older firms tend to employ capital of earlier vintage, which is less productive than the industry average and reduces their efficiency.

The variable ALB is not significant in explaining the inefficiency of MFIs in West and Central African countries.

The coefficient of the variable ASB is weakly significant, and it seems that the more savers there are in the portfolio of West and Central African country MFIs, the more efficient they are. Therefore, these MFIs must be mobilised in the collection of savings. Similar results are obtained by Oteng-Abayie (2011).

In addition to the decomposition of the HHI and female borrowers, additional tests were performed, as shown in Table 10. In Table 10, after adding control variables such as GDP, inflation, and HDI, the results remain robust to these modifications.

6. Conclusion

This study aimed to analyse the determinants of MFI inefficiency in the WAEMU and CEMAC countries using the methodology developed by Wang and Ho (2010) to consider the heterogeneity of each institution. This estimation method makes it possible to distinguish between the time-invariant and time-varying inefficiencies for each institution. Considering heterogeneity is necessary to correctly estimate production technology and the determinants of inefficiency.

Using a sample of 102 MFIs with 530 observations, we estimated production technology using a translog total cost function. Applying Wang and Ho's (2010) method, we find that the true determinants of inefficiency in West and Central African countries are the percentage of female borrowers, HHI, and age of MFI. The older the MFI, the less efficient it is, and MFIs that specialise in lending to women are also less efficient.

Another variable that explains the inefficiency of MFIs in West and Central African countries is the competition indicator which is also significant. This shows the importance of local market concentration of MFIs as a determinant of their performance. Although this result is normatively opposed to policies of deregulation of the banking sector in most countries in order to increase competition in the banking sector, our conclusion on the MFI sector in West and Central African countries refutes the argument of policymakers that high competition would increase the competitiveness of banks.

The results remained robust and significant after the addition of control variables. To improve the efficiency of MFIs in West and Central African countries, we suggest several ways forward. The first is the improvement and control of regulation; the oldest MFIs need to be better supervised, and follow-up liberalisation remains indispensable in the sector. Second, MFIs diversify their portfolios without specialising in particular client segments, particularly women.

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Appendix

Table 1 – Survey on stochastic frontier literature on microfinance

N°	Authors	Data	Sample Period	Number of Observations	Estimate Methodology	Estimate Function	Countries/ Regions
1	Desrochers and Lamberte (2005)	Panel	1995-1999	50	Coelli (1996)	Production	Philippines
2	Gregoire and Tuya (2006)	Panel	1999-2003	1,864	Battese et Coelli (1995)	Cost	Peru
3	Paxton (2007)	Cross-section	2001	190	Wang (2002)	Production	Mexico
5	Hermes et al. (2011)	Panel	1997-2007	435	Battese et Coelli (1995)	Cost	World
6	Oteng-Abayie (2011)	Panel	2007-2010	135	Battese et Coelli (1995)	Cost	Ghana
7	Masood and Ahmad (2012)	Panel	2005-2008	40	Battese et Coelli (1995)	Production	India
8	Servin et al. (2012)	Panel	2003-2009	1,681	Servin et al. (2012) *	Production	Latin America
9	Quayes et al. (2013)	Cross-section	2004	45	Battese et Coelli (1995)	Cost	Bangladesh
10	Bos and Millone (2015)	Panel	2003-2010	3,880	Battese et Coelli (1988)	Cost	World
11	Riaz (2015)	Panel	2007-2013	148	Battese et Coelli (1995)	Cost	Pakistan
12	Abdulai and Tewari (2016)	Panel	2003-2013	619	Battese et Coelli (1995)	Cost	Africa
13	Mor (2016)	Cross-section	2014	78	Coelli et Battese (1996)	Production	India
14	Bensalem and Ellouze (2017)	Panel	2007-2013	723	Battese et Coelli (1995)	Production	World
15	Kumar et Sensarma (2017)	Panel	2004-2011		Coelli (1996)	Cost	India
16	Kendo (2017)	Panel	2004-2011	1,205	Kendo (2017) *	Cost	Africa
17	Pal and Mitra (2017)	Panel	2006-2013	6,162	Battese et Coelli (1995)	Production	World
18	Hermes et al. (2018)	Panel	2008-2009	977	Battese et Coelli (1995)	Cost	World
19	Mimouni et al. (2022)	Panel	2003-2018	4,294	Battese et Coelli (1995)	Cost	World

Note: *In these articles, a methodology was developed by the authors.

Source: Authors

Table 2 – Characteristics of the literature on determinants of microfinance inefficiency and excepted sign.

N°	Authors	Data	Sample Period	Countries / Regions	Determinants of Inefficiency													
					HHI	H-Stat	CON	LER	BOO	WOM	AGE	SIZ	EQU	ALB	ASB	GDP	HDI	INF
Stochastic frontier approach (SFA)																		
1	Desrochers and Lamberte (2005)	Panel	1995-1999	Philippines	*							- +	*					
2	Gregoire and Tuya (2006)	Panel	1999-2003	Peru	+							-		+		+		
3	Paxton (2007)	Cross-section	2001	Mexico							-			-				
4	Hermes et al. (2011)	Panel	1997-2007	World						+	+			-				
5	Oteng-Abayie (2011)	Panel	2007-2010	Ghana						+	+			+	-			
6	Masood and Ahmad (2012)	Panel	2005-2008	India							-	*	*					
7	Quayes et al. (2013)	Cross-section	2004	Bangladesh							*	- (1)		-				
8	Bos and Millone (2015)	Panel	2003-2010	World						-				*				
9	Riaz (2015)	Panel	2007-2013	Pakistan						+ -	-			+ -				
10	Abdulai and Tewari (2016)	Panel	2003-2013	Africa						-	*			-				
11	Mor et al. (2016)	Cross-section	2014	India									*					
12	Bensalem and Ellouze (2017)	Panel	2007-2013	World							- *	+ - *						
13	Kumar and Sensarma (2017)	Panel	2004-2011	India						- *	+	-		- +				
14	Kendo (2017)	Panel	2004-2011	Africa									- *					
15	Pal and Mitra (2017)	Panel	2006-2013	World												- +		
16	Hermes et al. (2018)	Panel	2008-2009	World						+	+			-	*			
17	Mimouni et al. (2022)	Panel	2003-2018	World				-		+	- *					- +		+
Alternative methods																		
1	Cull et al. (2007)	Panel	1999-2002	World							-	-						
2	Caudill et al., 2009	Panel	2003-2004	E. Europe & C. Asia							-	-						
3	Ayayi and Sene (2010)	Panel	1998-2006	World	-					+	-							
4	Narwal and Yadav (2014)	Panel	2005-2011	India	-						+	-						
5	Gohar and Batool (2015)	Panel	2005-2009	Pakistan							+ - *	+ - *						
6	Wijesiri et al. (2015)	Cross-section	2010	Sri Lanka							+ -		+ *					
7	Wijesiri and Meoli (2016)	Panel	2009-2012	Kenya							+							
8	D'Espallier et al. (2017a)	Panel	1993-2011	World						-	+	- *					- *	
9	Fall (2018)	Cross-section	2009	Uemoa						- *	+ *	+ *						
10	Dannon et al. (2019)	Panel	2010-2014	Uemoa	-	+		+				-	+ *					

Note: HHI=Herfindahl-Hirschman Index, H-Stat=Panzar and Rosse (1977) Statistic, CON=Concentration of k-biggest banks, LER=Lerner index, BOO=Boone indicator, WOM=Percentage of female borrowers, AGE=Age of MFI, SIZ=Size of MFI, EQU=Equity or capital ratio, ALB=Average loan balance, ASB=Average savers balance. (**–**) means negative relation between the determinant and inefficiency of MFI, that is, a decrease in inefficiency as the value of the variable increases. (**+**) means positive relationship between the determinant and inefficiency of MFI, that is, an increase in inefficiency as the value of the variable increases. (*****) means that variable is used but not significant at least at 10 percent level.
Source: Authors

Table 3 – Number of observations per year

Years	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
Number of observations	4*	8	13	25	35	42	47	48	59	50	45	43	38	33	25	15	530

Note: *Read, for example, in 2003, just 4 MFIs in our sample are observed, 8 MFIs in 2004 and 15 MFIs in 2018. The sample covers 2003 to 2018.
Source: Authors' computation based on Mix Market.

Table 4 – Number of observations by MFIs

Number of observations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Total
Number of IMFs	24	8	10	7	14	5	5	5	8	8	2	0	3*	1	2	0	530

Note: *Read, for example, three MFIs are observed for 13 years. Then, no MFI are observed successively for 12 years or 16 years. The sample covers 2003 to 2018.
Source: Authors' computation based on Mix Market.

Table 5 – Number of IMFs by country

Countries	Benin	Burkina Faso	Cameroon	Ivory Coast	Mali	Niger	Senegal	Togo	Total
Number of IMFs	15	15	13	17	12	10	11	9	102
Number of observations	120	70	70	44	52	40	82	52	530

Note: The sample covers 2003 to 2018. We have the most observations in Benin and Senegal for the 15 MFIs observed. The observations are broadly similar for the other countries in our sample. Unfortunately, we kept only Cameroon as country in the CEMAC area due of missing data and outliers.
Source: Authors' computation based on Mix Market.

Table 6 – Summary statistics

Variables	Units	Mean	Sd. Dev.	Min.	Max.
Total cost	Dollar	4774521	7789559	18923	8.09e+07
Personnel expense	Dollar	1609949	2228398	5098	1.16e+07
Administration expense	Dollar	1721466	2806477	6227	2.37e+07
Depreciation and amortization expense	Dollar	480637.1	939266.3	454	7053714
Financial expense	Dollar	962469.3	2741985	4	4.74e+07
Gross loan portfolio	Dollar	2.39e+07	3.83e+07	2171	2.35e+08
Number of personnel	Number	239.9671	320.2496	3	2009
Fixed assets	Dollar	2827139	5690187	5219	6.54e+07
Total deposits	Dollar	2.36e+07	4.80e+07	30262	2.82e+08
Trend	1 à 16	9.267925	3.521995	1	16
Human Development Index (HDI)	Index	.4602358	.0557562	.314	.557
Gross domestic product per capita (GDP)	Index	978.6969	315.3348	465.0038	1600.765
Consumer price index, Inflation	Index	2.194425	2.491432	-2.248021	11.30511
Personnel price	Index	5888.935	3205.85	1049.713	18147
Administration price	Index	6293.9	3744.365	1043.968	31891.59
Financial price	Index	.0668801	.0946967	7.90e-06	1.406891
Depreciation and amortization price	Index	.3128816	.4928535	.0096581	5.923357
Age	Index	2.417401	.6922115	0	3.912023
Herfindahl-Hirschman index (HHI)	Index	.4539107	.1958038	.2198687	.9768976
Percentage of female borrowers (Women)	Percentage	53.40635	25.67197	.11	100
Financial independence ratio (Equity)	Index	.2243348	.3086748	-4.077847	.9734545
Average loan balance (ALB)	Index	6.379672	1.024557	3.375591	8.957542
Average savers balance (ASB)	Index	4.904111	1.094078	.9746972	7.730952
Loan Loss Rate (LLR)	Index	1.105158	3.78544	-22.31	43.12

Note: Averages are shown over the period 2003-18. Dollar, index or percentages are used where appropriate.
Sources: Mix Market; WDI. Authors' calculations.

Table 7 – Definition of variables

Variables	Definition
Total cost	The sum of the costs of labour input, the costs of fixed capital, and the remuneration of deposits calculated. Total cost of the MFI.
Personnel expense	Includes wages and salaries, other short-term employee benefits as bonuses and compensated absences, post-employment benefit expense, termination benefit expense, share-based payment transactions, other long-term benefits, and other employee benefits.
Administrative expense	Non-financial expenses excluding personnel directly related to the provision of financial services or other services that form an integral part of a financial institution's financial services relationship with clients.
Depreciation and amortization expense	Systemic allocation of an asset (tangible or intangible) according to its useful life.
Financial expense	Includes all financial income and other operating revenue generated from non-financial services. Operating income also includes net gains (losses) from holding financial assets (changes on their values during the period and foreign exchange differences). Donations or any revenue not related with a financial institution's core business of making loans and providing financial services are not considered under this category.
Gross loan portfolio	All outstanding principals due for all outstanding client loans. This includes current, delinquent, and renegotiated loans, but not loans that have been written off.
Number of personnel	The number of individuals actively employed by an entity. This number includes contract employees or advisors who dedicate a substantial portion of their time to the entity, even if they are not on the entity's employees' roster.
Fixed assets	Tangible assets held by an enterprise for use in the production or supply of goods or services or for administrative purposes, and are expected to be used during more than one period, net of accumulated depreciation.
Total deposits	The total value of funds placed in an account with a financial institution that are payable to a depositor. This includes accounts such as current / transactional accounts, term accounts, interest bearing accounts, and e-money accounts.
Trend	A dummy variable which runs from 1 to 16 to account for technology changes over time.
Human Development Index (HDI)	A statistic composite index of life expectancy, education, and per capita income indicators, which is used to rank countries into four tiers of human development.
Gross domestic product (GDP)	All outstanding principals due for all outstanding client loans. This includes current, delinquent, and renegotiated loans, but not loans that have been written off.
Inflation, consumer price index	The index number that measures changes in the prices of goods and services purchased or otherwise acquired by households, which households use directly, or indirectly, to satisfy their own needs and wants.
Personnel price	Relative price of personnel expense.
Administrative price	Relative price of administrative expense.
Financial price	Relative price of financial expense.
Depreciation and amortization price	Relative price of depreciation and amortization expense.
Age	The age of the MFI, that is, the number of years since its establishment.
Herfindahl-Hirschman Index (HHI)	An index measuring market concentration, measuring the number of firms producing a good. It is calculated as the sum of the MFI's market shares squared.
Percentage of female borrowers (Women)	The number of individuals who currently have an outstanding loan balance with the financial institution or are primarily responsible for repaying any portion of the gross loan portfolio. Individuals who have multiple loans with a financial institution should be counted as a single female borrower. Number of active female borrowers / Number of active borrowers.
Financial independence ratio (Equity)	An indicator used to determine the level of dependence of a company on external financing.
Average loan balance (ALB)	Gross loan portfolio / Number of active borrowers.
Average savers balance (ASB)	Deposits / Number of depositors.
Loan Loss Rate (LLR)	(Write-offs - Value of loans recovered) / Average gross loan portfolio.

Note: The definitions are taken from Mix Market and International Monetary Fund website.

Table 8 – Correlation matrix

	TC	PERSO	ADM	FIN	GLP	HDI	GDP	LLR	AGE	HHI	WOM	EQU	ALB	ASB	INF
TC	1.00														
PERSO	0.60	1.00													
ADM	0.53	0.66	1.00												
FIN	0.22	0.26	0.19	1.00											
GLP	0.95	0.59	0.46	0.19	1.00										
HDI	0.34	0.12	0.00	0.12	0.33	1.00									
GDP	0.39	0.31	0.28	0.09	0.35	0.75	1.00								
LLR	0.09	0.08	0.04	0.07	0.08	0.02	0.09	1.00							
AGE	0.40	0.08	0.07	-0.01	0.42	0.15	-0.03	-0.03	1.00						
HHI	-0.20	-0.20	-0.10	-0.28	-0.22	-0.36	-0.38	-0.02	0.03	1.00					
WOMEN	-0.26	-0.05	-0.29	-0.02	-0.25	-0.05	-0.06	-0.01	-0.33	-0.01	1.00				
EQUITY	-0.14	0.06	-0.06	-0.07	-0.07	-0.18	-0.16	-0.03	-0.02	0.00	0.24	1.00			
ALB	0.37	0.30	0.28	0.13	0.40	0.27	0.31	0.11	0.15	-0.00	-0.32	-0.18	1.00		
ASB	0.32	0.18	0.31	0.00	0.33	0.26	0.34	0.07	0.16	-0.06	-0.33	-0.16	0.44	1.00	
INFLATION	-0.06	-0.11	-0.06	-0.05	-0.05	-0.08	-0.06	0.11	-0.03	-0.09	-0.03	-0.06	0.00	0.06	1.00

Note: Where TC=Total cost, PERSO=Personal price (natural logarithm), ADM=Administrative price (natural logarithm), FIN=Financial price (natural logarithm), GLP=Gross loan portfolio, HDI=Human Development Index, GDP=Gross domestic product, LLR=Loan loss rate, Age=Age of the microfinance (natural logarithm), HHI= Herfindahl-Hirschman index, WOM=Women, EQU=Equity, ALB=Average loan balance (natural logarithm), ASB=Average savers balance (natural logarithm). There is a strong correlation between gross loan portfolio and total cost because naturally the more loans an MFI grants, the more its total cost increases. This same level of correlation can be observed in Hermes et al. (2011, 2018).

Source: Mix Market; WDI. Authors' calculations.

Table 9 – Estimation results

	(1)	(2)	(3)	(4)	(5)
The cost frontier					
ln(Personnel price/ Depreciation and amortization price)	0.403	0.403	0.403	0.403	0.425
	(0.422)	(0.422)	(0.422)	(0.422)	(0.425)
ln(Administrative price/ Depreciation and amortization price)	0.555	0.555	0.555	0.555	0.530
	(0.390)	(0.390)	(0.390)	(0.390)	(0.394)
ln(Financial price/ Depreciation and amortization price)	0.172	0.172	0.172	0.172	0.175
	(0.172)	(0.172)	(0.172)	(0.172)	(0.173)
ln(Gross loan portfolio)	0.242	0.242	0.242	0.242	0.252
	(0.222)	(0.222)	(0.222)	(0.222)	(0.222)
ln(Personal price/ Depreciation and amortization price)^2	0.237***	0.237***	0.237***	0.237***	0.234***
	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)
ln(Administrative price/ Depreciation and amortization price)^2	0.061	0.061	0.061	0.061	0.064
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
ln(Financial price/ Depreciation and amortization price)^2	0.014	0.014	0.014	0.014	0.014
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
ln(Gross loan portfolio)^2	0.039**	0.039**	0.039**	0.039**	0.039**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
ln(Personnel price/ Depreciation and amortization price) × ln(Administrative price/ Depreciation and amortization price)	-0.122**	-0.122**	-0.122**	-0.122**	-0.122**
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)
ln(Personal price/ Depreciation and amortization price) × ln(Financial price/ Depreciation and amortization price)	-0.012	-0.012	-0.012	-0.012	-0.011
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
ln(Personal price/ Depreciation and amortization price) × ln(Gross loan portfolio)	-0.083***	-0.083***	-0.083***	-0.083***	-0.082***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
ln(Personnel price/ Depreciation and amortization price) × Trend	0.009	0.009	0.009	0.009	0.009
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
ln(Administrative price/ Depreciation and amortization price) × ln(Financial price/ Depreciation and amortization price)	-0.013	-0.013	-0.013	-0.013	-0.014
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
ln(Administration price/ Depreciation and amortization price) × ln(Gross loan portfolio)	0.033*	0.033*	0.033*	0.033*	0.032*
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
ln(Administration price/ Depreciation and amortization price) × Trend	-0.006	-0.006	-0.006	-0.006	-0.005
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
ln(Financial price/ Depreciation and amortization price) × ln(Gross loan portfolio)	0.020***	0.020***	0.020***	0.020***	0.020***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
ln(Financial price/ Depreciation and amortization price) × Trend	-0.007**	-0.007**	-0.007**	-0.007**	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ln(Gross loan portfolio) × Trend	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Trend	0.026	0.026	0.026	0.026	0.025
	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)
Trend^2	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
The inefficiency equation					
Women	**0.001*****	**0.001*****	**0.001*****	**0.002*****	**0.002*****
	(0.000)	**(0.000)**	**(0.000)**	**(0.001)**	**(0.001)**
Herfindahl-Hirschman Index	**-0.146*****	**-0.146*****	**-0.130*****	**-0.160*****	**-0.161*****
	(0.041)	**(0.041)**	**(0.042)**	**(0.049)**	**(0.048)**

Age	**0.750*** (0.118)**	**0.748*** (0.118)**	**0.711*** (0.121)**	**0.730*** (0.124)**	**0.732*** (0.123)**
Equity		-0.041 (0.083)	-0.040 (0.081)	-0.013 (0.082)	-0.017 (0.082)
Average loan balance			0.015 (0.012)	0.021 (0.014)	0.020 (0.014)
Average savers balance				**-0.026* (0.015)**	**-0.027* (0.015)**
Loan loss rate					0.001 (0.002)
Vsigmas	-4.192***	-4.191***	-4.193***	-4.187***	-4.190***
_cons	(-54.81)	(-54.83)	(-54.89)	(-55.00)	(0.076)
Usigmas	-2.342**	-2.323**	-2.294**	-2.420**	-2.404**
_cons	(-2.48)	(-2.47)	(-2.33)	(-2.48)	(0.967)
Number of microfinance institutions	102	102	102	102	102
Observations	530	530	530	530	530

Note: The sample covers 2003 to 2018. All the estimations are based on the Wang and Ho (2010) methodology. Estimations are made step by step in this table and are based on specification (15) for the technology and (16) for the determinants of inefficiency. The vector of inefficiency determinants is: $z_{it} = \delta_1 Women_{it} + \delta_2 HHI_{it} + \delta_3 Age_{it} + \delta_4 Equity_{it} + \delta_5 ALB_{it} + \delta_6 ASB_{it} + \delta_7 LLR_{it}$. Standard errors are shown in brackets. (***, **, *) indicate significance at the 1%, 5%, and 10% level, respectively.

Table 10 – Robustness tests: estimations with control variables

z_{it} = vector of inefficiency	(1)	(2)	(3)	(4)	(5)	(6)
The cost frontier						
Control variables	No	Yes	Yes	Yes	Yes	Yes
GDP growth		0.000			0.000	
		(0.000)			(0.000)	
Human development indicator			-1.367			-1.449
			(1.919)			(1.915)
Inflation, Consummation Price Index				0.004	0.004	0.004
				(0.003)	(0.003)	(0.003)
The inefficiency equation						
Women	**0.002*** **	**0.002*** **	**0.002*** **	**0.002*** **	**0.002*** **	**0.002*** **
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.000)**
Herfindahl-Hirschman index	**-0.166*** **	**-0.157*** **	**-0.162*** **	**-0.166*** **	**-0.167*** **	**-0.158*** **
	(0.050)	**(0.048)**	**(0.048)**	**(0.050)**	**(0.050)**	**(0.048)**
Age	**0.740*** **	**0.727*** **	**0.737*** **	**0.740*** **	**0.745*** **	**0.731*** **
	(0.124)	**(0.123)**	**(0.122)**	**(0.124)**	**(0.123)**	**(0.121)**
Equity	-0.019	-0.013	-0.024	-0.019	-0.027	-0.021
	(0.084)	(0.080)	(0.083)	(0.084)	(0.085)	(0.081)
Average loan balance	0.019	0.020	0.019	0.019	0.018	0.019
	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)
Average savers balance	**-0.028***	**-0.027***	**-0.026***	**-0.028***	**-0.027***	**-0.026***
	(0.015)	**(0.015)**	**(0.015)**	**(0.015)**	**(0.015)**	**(0.015)**
Loan loss rate	0.001	0.001	0.000	0.001	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Vsigmas	-4.190***	-4.190***	-4.192***	-4.198***	-4.199***	-4.201***
_cons	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)
Usigmas	-2.404**	-2.449**	-2.360**	-2.412**	-2.455***	-2.368**
_cons	(0.967)	(0.965)	(0.965)	(0.954)	(0.951)	(0.951)
Number of microfinance institutions	102	102	102	102	102	102
Observations	530	530	530	530	530	530

Note: The sample covers 2003 to 2018. Column (1) represents our main estimation. All the estimations are based on the Wang and Ho (2010) methodology. We added step by step control variables, here there are: GDP growth, Human Development Indicator, and inflation. The results in columns (2) to (6) are still the same. Standard errors are shown in brackets. (***, **, *) indicate significance at the 1%, 5%, and 10% level, respectively, and the vector of inefficiency determinants is: $z_{it} = \delta_1 Women_{it} + \delta_2 HHI_{it} + \delta_3 Age_{it} + \delta_4 Equity_{it} + \delta_5 ALB_{it} + \delta_6 ASB_{it} + \delta_7 LLR_{it}$.

Table 11 – Robustness tests: quartile Women

z_{it} = vector of inefficiency	(1)	(2)	(3)	(4)
The cost frontier				
Control variables	No	No	Yes	Yes
GDP growth				0.000
				(0.000)
Human development indicator			-1.112	
			(1.919)	
Inflation, Consummation Price Index			0.004	0.004
			(0.003)	(0.003)
The inefficiency equation				
Women	**0.002*** **			
	(0.001)			
Herfindahl-Hirschman index	**-0.166*** **	**-0.172*** **	**-0.171*** **	**-0.179*** **
	(0.050)	**(0.048)**	**(0.048)**	**(0.049)**
Age	**0.740*** **	**0.717*** **	**0.718*** **	**0.732*** **
	(0.124)	**(0.120)**	**(0.119)**	**(0.120)**
Equity	-0.019	-0.019	-0.022	-0.028
	(0.084)	(0.077)	(0.077)	(0.080)
Average loan balance	0.019	**0.023* **	**0.022* **	**0.022* **
	(0.014)	**(0.013)**	**(0.013)**	**(0.013)**
Average savers balance	**-0.028* **	-0.019	-0.019	-0.020
	(0.015)	(0.014)	(0.014)	(0.014)
Loan loss rate	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Quartile 1. Women		**-0.071** **	**-0.071** **	**-0.073** **
		(0.029)	**(0.028)**	**(0.029)**
Quartile 2. Women		**-0.063** **	**-0.062** **	**-0.063** **
		(0.025)	**(0.025)**	**(0.026)**
Quartile 3. Women		-0.028	-0.027	-0.028
		(0.020)	(0.020)	(0.020)
vsigmas	-4.190***	-4.191***	-4.199***	-4.199***
_cons	(0.076)	(0.076)	(0.076)	(0.077)
usigmas	-2.404**	-2.075**	-2.060**	-2.146**
_cons	(0.967)	(0.922)	(0.912)	(0.908)
Number of microfinance institutions	102	102	102	102
Observations	530	530	530	530

Note: The sample covers 2003 to 2018. Column (1) represents our main estimation. All the estimations are based on the Wang and Ho (2010) methodology. The results in column (2) are based on estimation without control variables and in columns (3) and (4), we added control variables. Standard errors are shown in brackets. (***, **, *) indicate significance at the 1%, 5%, and 10% level, respectively, and the vector of inefficiency determinants is: $z_{it} = \gamma Women_{it}^{Quartiles} + \delta_1 HHI_{it} + \delta_2 Age_{it} + \theta X_{it}$.

Table 12 – Robustness tests: quartile HHI

z_{it} = vector of inefficiency	(1)	(2)	(3)	(4)
The cost frontier				
Control variables	No	No	Yes	Yes
GDP growth				0.000
				(0.000)
Human development indicator			-1.852	
			(1.902)	
Inflation, Consummation Price Index			0.004	0.004
			(0.003)	(0.003)
The inefficiency equation				
Women	**0.002*** **	**0.002*** **	**0.002*** **	**0.002*** **
	(0.001)	**(0.000)**	**(0.000)**	**(0.000)**
Herfindahl-Hirschman index	**-0.166*** **			
	(0.050)			
Age	**0.740*** **	**0.749*** **	**0.748*** **	**0.759*** **
	(0.124)	**(0.124)**	**(0.121)**	**(0.123)**
Equity	-0.019	-0.028	-0.034	-0.041
	(0.084)	(0.082)	(0.081)	(0.084)
Average loan balance	0.019	0.010	0.009	0.008
	(0.014)	(0.014)	(0.014)	(0.014)
Average savers balance	**-0.028***	**-0.025***	**-0.024***	**-0.025***
	(0.015)	**(0.014)**	**(0.014)**	**(0.014)**
Loan loss rate	0.001	0.001	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Quartile 1. Herfindahl-Hirschman index		**0.070*** **	**0.070*** **	**0.071*** **
		(0.021)	**(0.021)**	**(0.021)**
Quartile 2. Herfindahl-Hirschman index		**0.064*** **	**0.062*** **	**0.064*** **
		(0.017)	**(0.016)**	**(0.017)**
Quartile 3. Herfindahl-Hirschman index		**0.044*** **	**0.042*** **	**0.044*** **
		(0.013)	**(0.012)**	**(0.013)**
Vsigmas	-4.190***	-4.211***	-4.227***	-4.222***
_cons	(0.076)	(0.076)	(0.076)	(0.076)
Usigmas	-2.404**	-2.649***	-2.571***	-2.663***
_cons	(0.967)	(0.976)	(0.953)	(0.961)
Number of microfinance institutions	102	102	102	102
Observations	530	530	530	530

Note: The sample covers 2003 to 2018. Column (1) represents our main estimation. All the estimations are based on the Wang and Ho (2010) methodology. The results in column (2) are based on estimation without control variables and in columns (3) and (4), we added control variables. Standard errors are shown in brackets. (***, **, *) indicate significance at the 1%, 5%, and 10% level, respectively, and the vector of inefficiency determinants is: $z_{it} = \gamma^{*} HHI_{it}^{Quartiles} + \delta_1 Women_{it} + \delta_2 Age_{it} + \theta X_{it}$.