Micro Loans, Macro Changes: Investigating the Ambiguous Impact of Microfinance on Female Empowerment in Sub-Saharan Africa

by

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Abstract

The present thesis examines the impact of outreach and financial performance measures of microfinance institutions (MFI) on female empowerment in 18 countries of Sub-Saharan Africa, during the ten-year period of 2008-2018. In this context, Gender Inequality Index (GII) and Gender Development Index (GDI) are employed as proxies of female empowerment and plotted against various measures of outreach and financial performance of MFI. The research uses cross-sectional data collected from the MiX Market and the World Data Bank, and explores the data using a Pooled OLS model, a fixed effects model, and a random effects model, together with statistical tests which provide indication about the most appropriate model to study each of the two outcome variables. Ultimately, this study concludes that when GII is used as an empowerment proxy, a random effects model is more appropriate. Alternatively, when GDI is used as an empowerment proxy, the fixed effects model is deemed more appropriate. For both the GII and GDI, only outreach measures of MFI show significant effects on female empowerment – yet, this effect is ambiguous, with average loan size being positively associated with female empowerment, and an increased average number of borrowers leading to a bigger gap between male and female measures of empowerment. Although the remaining results are mainly inconclusive, this paper underscores the need for context-sensitive interventions and provides valuable insights for both future researchers and policymakers, in order to maximize the transformative potential of microfinance in developing countries.

Keywords: microfinance institutions, gender inequality, financial performance, outreach, Sub-Saharan Africa, welfare

JEL Classification: J16, G21, I38, O55

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I. Introduction

According to the Global Financial Inclusion Index, designed by The World Bank (2021(a)), 11.8% of individuals aged 15 or older in the Euro Area had borrowed money from a formal financial institution or used a credit card, in 2011. In North America and East Asia and Pacific, respectively, 20.2% and 8.8% of respondents reported the same. Ten years later, in 2021, these regions of the globe have seen exponential increases in the benefits brought by formal financial institutions and reported new values of 48.2%, 36.4%, and 67.8% of borrowers among the respective populations. However, when we re-scope our analysis and look into Sub-Saharan Africa, the same variable was measured at 4.7% and 9.8%, in 2011 and 2021. This represents an extremely smaller increase in the accessibility to formal financial institutions, and means that, even in 2021, only 9.8% of the Sub-Saharan African population benefitted from the services of formal financial institutions. In order to tackle this underdevelopment of formal banking accessibility and financial inclusion, as well as to improve the low purchasing power of this region, the concept of microfinance has been increasingly explored in recent decades. Microfinance is a branch of finance, defined as the provision of financial services in the form of small capital loans, microcredits, insurance schemes, and establishment of savings accounts to individuals and microenterprises who typically have constrained access to traditional banking services. Essentially, microfinance institutions (MFIs) aim to promote financial inclusion, economic growth, and equality of opportunity amongst low-income households. According to the Microfinance Information Exchange (MIX) Market (The World Bank, 2021(b))– a database that gathers data on financial statements, operations, financial products, end clients, and social performance reported by MFIs – recent figures report that the fast-growing microfinance industry in Sub-Saharan Africa has a gross loan portfolio of US$8.5 billion, reaching a consumer base of more than 8 million people - of which 65% are women. These figures have shown an exponential growth of more than 1,300 percent between 2002 and 2018, which leaves big room for empirical analysis and debate on how these institutions are actually impacting the socio-economic status of the developing countries in question. On a different light, female empowerment and reduced gender inequality gap have been highlighted by the United Nations as the fifth of the Sustainable Development Goals (SGDs) in 2015. Specifically in Sub-Saharan African (SSA) countries, women face several economic and social disadvantages relatively to men, and this gap is increasingly noticeable amongst lower-income families. For this reason, microfinance schemes have been adopted as an added means to promote the empowerment of women by providing them with tools for small businesses creation and financial support to their families.

However, given limited empirical data, and the novelty of this concept in Sub-Saharan African countries, the real impact of microfinance on female empowerment is still a topic of wide debate and little literature. Authors like Aruna and Jyothirmayi (2011), and Swain and Wallentin (2009) have concluded that microfinance and self-help groups play a significantly positive role in upgrading women empowerment in India. Similarly, a more recent study conducted by Niaz and Iqbal (2019) argues that exposure to microfinance programs has a positive impact on female empowerment, poverty alleviation and social equality of women, contributing to the fulfillment of the SGDs in Pakistan. On the other hand, Leach and Sitaram (2002) have

explored a NGO microfinance project in India, and concluded that although this was targeted to empower women, it ended up reinforcing the male dominant role in the labor market. On a similar light, Duvendack et al. (2011, 2014) and Stewart et al. (2010) argue that the conclusions on the effects of microcredit report to a limited extent on female empowerment effects worldwide and have questioned the poor methodology of previous studies.

Since the existing studies are highly contradictory, rather outdated, and mainly focused in Southeast Asian countries, India, and Pakistan, exploring a geographical area that has been given less research may reach conclusions that are specifically relevant for the implementation of effective microfinance schemes in Sub-Saharan Africa. This developing region is home to nearly 600 million female inhabitants, of which 54.8% were reported by the Institute for Security Studies [ISS] (2022) to live in extreme poverty conditions. Studying the effects of microfinance and identifying ways to maximize the positive impact of this poverty alleviation tool, can potentially provide insights and inform policy decisions aimed at promoting economic development in Sub-Saharan African countries. Hence, this thesis' research question arises as follows:

> *To what extent did outreach and financial performance measures of microfinance institutions impact female empowerment across 18 countries in Sub-Saharan Africa, during the period of 2008 – 2018?*

This research question leads to four main hypotheses, one null and three alternative hypotheses. The null hypothesis (H_0) is defined as neither outreach nor financial performance measures having a significant impact on female empowerment across the selected countries. The first alternative hypothesis (H_1) is that only outreach measures have a significant impact on female empowerment across the selected countries. The second alternative hypothesis (H_2) is that only financial performance measures have a significant impact on female empowerment across the selected countries. Lastly, the third alternative hypothesis (H_3) arises as a combination of H_1 and H_2, and is supported if both outreach and performance measures of microfinance institutions have a significant impact on female empowerment across the selected Sub-Saharan African countries.

II. Theoretical Framework

1. Microfinance Institutions

The previously defined research question relies on the clear conceptualization of several terms. For the purpose of this thesis, microfinance institutions (MFI) are defined by the Hardy et al. (2002) as non-traditional financial institutions committed to assisting poor households and small enterprises in gaining access to otherwise restrained financial services. MFI typically offer credit in the form of small working capital loans, but can expand their services to provide insurance, savings accounts, and money transfers (FINCA International, 2023). Essentially, these financial services are targeted at improving monetary self-sufficiency of micro-entrepreneurs, women and low-income families - who otherwise would not have access to the necessary funds to invest in their health, education or new businesses. In SSA, microfinance has been expanding and is now one of the world's most productive developmental poverty eradicating tools, measured in terms of financial and social performance (Fadikpe et al, 2022).

Financial outreach is one of the core purposes of microfinance and refers to the ability to provide the maximum number of poor individuals with access to otherwise restrained financial services. Previous studies further classify two components of outreach, namely breadth and depth of outreach (Memon et al., 2022(a)). For the purpose of this thesis, breadth of outreach will be measured by the average number of active borrowers. According to the MIX Market metadata, this is defined as the average number of individuals who have an outstanding loan balance with the MFI or are primarily responsible for repaying any portion of the gross loan. Similarly, depth of outreach will be measured by average loan balance per borrower, which is obtained by dividing the gross loan portfolio by the number of active borrowers. Outreach measures are an appropriate way of capturing the impact of microfinance because, as highlighted by Beck et al. (2008), these are correlated to both aggregate country-level figures and micro-level indicators of barriers to financial access.

Following, the financial performance of MFI will be measured according to Operational Self-Sufficiency (OSS), and profitability figures – namely Return on Assets (ROA), Return on Equity (ROE). OSS indicates whether MFI are earning enough revenue through interest, fees, and commissions to support their total financial, operational and loan loss costs (Esampally & Joshi, 2016). ROA and ROE signal efficiency of MFI in generating profits. These measures are in line with the work of Rosenberg (2009) and Barguellil & Bettayeb, (2020), and are generally accurate indicators of financial sustainability. Research shows that MFI that are top performers on ROA and ROE are significantly more likely to stand on their own and create real positive impact (Tucker & Miles, 2004). Additionally, measures of portfolio at risk for 30 (PaR30) and 90 (PaR90) days will be included in the model, as it is anticipated that these have a negative impact on MFI financial performance (Ayayi & Sene, 2010). Supporting this, Rai & Rai (2012) used empirical financial data of MFI from India and Bangladesh to show that PaR30 is one of the main factors affecting financial sustainability of microfinance institutions. All these financial variables will be later described in mathematical terms.

2. Female empowerment

On the other hand, it is relevant to define female empowerment, as this is a subjective term and takes different forms in literature. For the purpose of this study, female empowerment or women empowerment will be referred to as granting women their rights and enhancing opportunities to education, health, labor market, decision-making power, as well as eliminating oppressive legal systems (Addae, 2015). Similarly, Alsop & Heinsohn (2005) define female empowerment as women's ability to transform choices into desired actions and outcomes, depending on the capacity to make a purposive choice and the institutional context in which this choice is made. Kabeer (2001) restructures this thought and describes empowerment as the process of expansion in a woman's ability to make life choices in a context where this ability was previously oppressed by external factors. Moreover, in the 1995 UN Fourth World Conference on Women in Beijing, it was established that "Women's empowerment and their full participation on the basis of equality in all spheres of society, including participation in the decisionmaking process and access to power, are fundamental for the achievement of equality, development and peace" (UN 1995). As a result, several country-based indices were developed over the years to track the progress of gender equality and empowerment as defined by the United Nations. One relevant index is the Gender Empowerment Measure (GEM), created to measure the extent to which women and men are able to actively participate and take part in decision-making within economic and political life. However, as highlighted by Jager and Rohwer (2009), the GEM can produce biased figures as it only measures inequality amongst the higher-income and economically advantaged members of the population. For the purpose of the present study, this represents a big limitation, as the core population under analysis classifies as low-income. Moreover, when calculating the GEM, the same weight is given to all different dimensions of female empowerment, which can fail to capture the relative importance of some indicators as compared to others.

For this reason, the present thesis uses the Gender Inequality Index (GII) and the Gender-related Development Index (GDI) as proxy measures for female empowerment instead. The GII, developed by the UNDP (2023(a)), aggregates harmonic means of measures of health, empowerment and labor market across genders. According to the program, this relatively more recent index aims at displaying the loss in potential human development due to inequality between female and male achievements. As explained by UNDP, GII is an updated version of the gender inequality index which excludes income-related inputs due to associated biases and measurement errors (2010). This index has been used as a female empowerment proxy in similar literature, such as in Zhang & Posso (2017) and Abdal (2022). Given this, the initial stage of this thesis' analysis will be using GII as a dependent variable to measure women empowerment figures across SSA countries and over the selected time period. However, as highlighted by Abdal (2022), using GII as a proxy can have limitations and underestimate the real impact of microfinance performance measures. This can happen because microfinance is likely creating more noticeable impact on a community and household level, rather than at the national level. Since the GII includes measures of political empowerment, for instance, the

real microfinance community-related effect is likely to be underestimated when regressed against these variables.

Therefore, on a second stage of the analysis, the GDI will be employed as the dependent variable representing a second proxy for women's empowerment. The GDI, also developed by UNDP (2023(b)), adjusts each country's average human development achievement in life expectancy, educational attainment, and income according to the degree of disparity in achievement between male and female genders. As with the GII, the GDI has also been employed in the literature of Zhang & Posso (2017) as a proxy for women's empowerment. Similarly, Swain's (2007) research on microfinance self-help groups in India indicates that access to microfinance services could be leading to improved female empowerment, measured by GDI figures. Consequently, although there exist limitations to the calculation of this index, there is reason to believe this is an appropriate proxy to use in the present research.

All things considered, the GII and GDI are two equally appropriate proxies for female empowerment, but are negatively correlated, because of how each index is built. The GDI uses components of the Human Development Index (HDI) to reveal whether the human development achievements of longevity, education, and income are evenly distributed amongst the genders. For this reason, it focuses more on variables presented as ratios of women to men. On the other hand, GII employs in its calculation additional components of reproductive health, labor market participation, and empowerment, in absolute values, that mainly measured the female side. Ultimately, GII varies between 0 – when women and men are equal – and 1 – when one of the genders is fare poorly in comparison to the other. Contrarily, for GDI, higher index values indicate worst achievements, with 0 meaning no gender parity in the country, and 1 meaning perfect equality. Hence, opposite results are expected in the two analyses.

3. Literature Review

All in all, theory suggests that the implementation of microcredit schemes in rural areas creates a significant impact on the lives of developing communities. Intuitively, if individuals who were previously restrained access to formal financial institutions are given a chance to borrow small amounts of money to invest in education, consumption or business creation, then the economy should feel a positive impact. This theory has been supported by empirical evidence in various literature. Results from the study conducted by Imai et al. (2011) suggest that countries with higher MFI's gross loan portfolio per capita have seen reduced levels of poverty indices at a macro level. Similarly, Murad and Idewele (2017) studied the impact of MFI in the economic growth of Nigeria and concluded that microloans significantly boost economic growth in the short-term - through consumption - and in the long-run - through investment and capital accumulation. Barguellil and Bettayeb (2020) further suggest, through a time-series vector autoregressive model (VAR), that microfinance performance indicators have a negative and significant impact on the ratio of poverty per capita in Tunisia, and that MFI contribute more effectively to economic development through their social performance. Certainly, as aforementioned, there are still contradictions among the literature, and authors

Wachukwu et al. (2018) found through a time series regression model that specific indicators of MFI, such as bank credit growth and investment growth, were significantly but negatively correlated to the real gross domestic product of Nigeria.

In literature, these macro-level studies have been expanded to study the impact of microfinance in women's empowerment specifically. The present thesis aims at contributing to this side of the existing microfinance literature, and for this reason, it is important to review the prevailing empirical evidence. Similar studies started being conducted in the last decades, with primary focus on South and Southeast Asian economies, where the concept of microfinance emerged. Khandker (2005) used panel data from Bangladesh in a household fixed-effects estimation to conclude that access to microfinance schemes contributes to poverty alleviation, especially for rural female participants. On a similar light, the quasi-experimental household analysis conducted by Swain and Wallentin (2009) on a microfinance Self-Help Group in India showed evidence of a significant increase in the empowerment of women that actively participated in the microfinance program. On this sequence, Brune (2009) took existing research a step further and included data collected from African countries on the empirical analysis of the impact of MFI on development. The author concluded that although African development is typically delayed compared to Asia, there is no statistical evidence for differences in the marginal impact of MFI subject to geography. This encouraged the scientific community to expand their research on microfinance impact in Africa, which accompanied the growth of this development tool. In recent years, more and more studies have emerged, including the works of Binaté Fofana et al. (2015), Haile et al. (2012), Mannah-Blankson (2018), Van Rooyen et al. (2012), and Addae (2015). The first authors focus on empirical analyses of available data through propensity score matching, chi-square comparison tests and cross-sectional regression methods, respectively, while the latter two works give systematic reviews of the evidence to the date. Overall, the studies demonstrate that there is a positive, significant correlation between participation in microfinance programs and women's empowerment. Results show that introduction to microfinance is associated with lower gender asset gaps within and across SSA households (Mannah-Blankson, 2018) and that access to microcredit loans tend to increase women's decision-making power in the household (Binaté Fofana et al., 2015). Moreover, microfinance clients appear to display better health practices and nutrition than non-clients, and their children also seem to reap the benefits through increased investment in education (International Labour Office [ILO], 2008).

All in all, existing theory suggests that there is a positive and significant relationship between MFI and women's empowerment in SSA countries. However, there is still little empirical evidence that makes use of cross-country panel data, covering a broader range of SSA countries. Additionally, there has been little versatility in trying to include more appropriate measures of gender empowerment. As highlighted by Addae (2015) in a review of the literature, most of the studies to date have considered only certain dimensions in women's empowerment. The author suggests that future research must also focus on psychological empowerment at a household/individual level, whereas panel and cross-country studies are desirable to assess national level and country-specific impacts. The present thesis aims at filling the existing knowledge gap, by

making use of panel data model estimation techniques that are employed to explain the effect of microfinance indicators on different measures of female empowerment.

For the present thesis, a number of panel data estimation methods will be used, which are in line with previous literature. The first panel data estimation method used is a pooled ordinary least squares (OLS) regression. Previously, Brune (2009) used linear and logarithmic OLS regression models to study the impact of MFI operating in selected African and Asian countries on clients' average savings and loan balances, as proxies for development. Similarly, Memon et al. (2022(a)) also employed OLS linear regressions to generate functional forms of operational self-sufficiency and outreach of MFI, dependent on firm-specific and country-specific factors. An advantage of a pooled OLS regression model over other methods, such as vector autoregressive analysis, is that it can deal with cross-country panel data that is available in the MIX Market database. However, this estimation method comes with a number of methodological limitations and underlying assumptions. In a paper about women and repayment in microfinance, D'Espallier et al. (2011) stressed that if variables that are simultaneously correlated with the dependent variable and the explanatory variables are omitted, then pooled OLS could produce biased estimates. Consequently, the following thesis takes into account a set of control variables covered below, aimed at reducing omitted variable bias. Yet, in addition to a pooled OLS method, this thesis analyzes the panel data by means of a pooled fixed-effects (FE) model, as well as a pooled random-effects (RE) model. These estimation methods are preferred, as they also take into account unobserved MFI-specific factors that could further bias the final results. Generally, RE models are preferred, as these account for all unobserved heterogeneity in the panel data, reducing the concerns for omitted variable bias (Hartarska, 2005). Moreover, although RE models hold under stricter assumptions to be explored later, they can account for time-invariant covariates, unlike FE models. Given this, and following the structure of previous literature (D'Espallier et al., 2011; Berhane & Gardebroek, 2011; Imai et al., 2011; Becchetti & Conzo, 2014; Miled & Rejeb, 2015; Bibi et al., 2018; El-Nasharty, 2022; Miled et al., 2022), the present work will start by analyzing the data by means of a pooled OLS regression, followed by FE and RE estimation models conducted both on GII and GDI, as proxies for female empowerment. Subsequently, to choose the most appropriate estimation method between FE and RE, a Hausman test will be performed for both GII and GDI models. Lastly, the Lagrange multiplier test will be used to double-check whether RE method meets the underlying assumptions and should be preferred over the pooled OLS regression.

In order to further support the use of this methodology, a closer look is taken at the works of Berhane and Gardebroek (2011), Imai et al. (2011), and Miled et al. (2022), which employ these statistical methods to analyze different effects within the microfinance realm. In the first paper, the authors study the effects of microfinance in the reduction of rural poverty in Northern Ethiopia. Here, the empirical method consists of a pooled OLS analysis, as well as a standard fixed-effects model to calculate an estimator for household per-capita consumption and housing improvements. In a second stage, a random trend model is employed to calculate the same estimators. According to Berhane and Gardebroek (2011), the standard FE models mitigate selection bias coming from time-invariant unobservable variables, whereas the random trend model also accounts for individual effects in time-varying unobservable variables. For this reason, they decide to employ

both methods in their analysis. Ultimately, the authors conclude that although the results of the models differ, due to distinct assumptions and methodological specifications, all of methods suggest that length and frequency of borrowing through MFI are associated with reduced poverty level in Northern Ethiopia.

Comparably, Imai et al. (2011) test the hypothesis that MFI's gross loan portfolio per capita reduces poverty level at the macro level. The authors also use data collected from MiX Market and the World Data Bank, and employ, among others, OLS, FE, and RE estimation methods. According to the paper, this methodological construction allows for a more robust estimation of the coefficients, while taking into account time-variant changes in variables, as well as unobservable country-level effects. The analysis by Imai et al. (2011) further introduces the Hausman test as a statistical tool to help in the selection of the most appropriate model to consider. Given this, the paper consistently defends, based on its econometric results, that higher microfinance loans per capita tend to be significantly associated with reduced poverty levels, after controlling for the effects of other influential macro and micro factors.

Lastly, a paper by Miled at al. (2022), which uses a cross-country panel dataset to test the effect of microfinance on income inequality reduction, employs a similar methodology. The authors work with a measure of microfinance intensity (GLF) as main variable of interest to study its effect on income inequality (INEQ). Here, GLF results are estimated using pooled OLS, FE, and RE. Again, the Hausman test is added to the model in order to test and select the most appropriate estimation method. In the end, the authors defend that countries with greater MFI's gross loan portfolio per capita tend to present lower income inequality. These results are in line with the previous literature discussed. All in all, the existing literature is consistent with the methodological approach described in this paper, given the comparability of the datasets and underlying assumptions of the explanatory and control variables. Methodological assumptions and concerns will be explored in detail in the following section.

4. Choice of control variables

As previously mentioned, when examining the relationship between MFI performance and women empowerment, it is important to control variables that may be simultaneously correlated with the dependent variable and the explanatory variables of interest. Including control variables in OLS analysis is fundamental to minimize omitted variable bias, improve model specification, and enhance internal validity. For the present study, four control variables will be added to the regression models, which are in line with the works of authors such as D'Espallier et al. (2011), and Miled et al. (2022). Three of the controls will be country-specific, and aim at controlling macroeconomic factors, whereas the remaining variable will be MFI-specific, and aims at controlling institution-level factors. The first control regards the country-specific GDP per capita, calculated as a natural logarithm as done by Imai et al. (2011). This is an important variable to include in the analysis, because GDP per capita is expected to be positively related to MFI financial performance, through better measures of profitability, operating expense ratio, portfolio quality, and outreach indicators (Imai et al., 2011). Simultaneously, a higher GDP per capita has been shown by Saqfalhait et al. (2023) to be significantly

associated to reduced gender disparity and women empowerment. Comparably, Muhammad et al. (2012) concluded in a related microfinance study that GDP growth causes, on average, a significant increase in women empowerment in Pakistan.

Moreover, inflation rate will be added as a control variable, measured as the yearly percentage change in the consumer price index. This variable has been used in similar works as a proxy for country-specific macroeconomic instability (Levine et al., 2000; Donou-Adonsou & Sylwester, 2015). Although this has been shown to be a relevant factor affecting microfinance performance indicators, the direction of its effect is ambiguous. As highlighted by Crabb and Keller (2006), on the one hand, when inflation rates rise, particularly to hyperinflation levels, portfolio risk rises, since microenterprises are unable to repay their loans. However, the authors also pointed out that higher inflation rates can decrease loans repayment values if these were originally obtained under a fixed rate, dominated in the local currency. As for the impacts of inflation on women's empowerment, contractionary inflation reduction is expected to be accompanied by a loss of formal employment and a decrease in the ratio of women's to men's employment, particularly in developing countries (Braunstein & Heintz, 2008). Moreover, higher inflation rates are logically associated to higher consumer prices of food, education, health, and general household expenses. Following this, Lee et al. (2016) have studied the effects of food price inflation to conclude that higher food prices have a significant detrimental effect on children nourishment, often leading to higher figures of infant and child mortality in developing countries. Hence, inflation can undermine the effects of MFI programs on women's empowerment through decreased employment, and increased expenses.

On a similar line of thought, the following model will control the country-specific Human Development Index (HDI). This is a measure developed by the UNDP (2023(c)) that captures yearly country-specific average achievement in three core dimensions of human development – health and longevity, education, and standard of living. The index is often used as a standardized measure to assess national policy choices and development. Memon et al. (2022(b)) found through an empirical study of microfinance in South Asia that HDI has a positive significant relationship with ROA and a negative significant relationship with OSS. As noted by the authors, this implies that human development, in any of the three dimensions, is likely to positively impact the profitability of MFI. At the same time, HDI is tightly related to women's empowerment measures of education, employment, and opportunity, as empowerment is often dependent on the country-specific development measures. Consequently, HDI must be controlled for when regressing female empowerment on MFI outreach and financial performance measures.

Regarding MFI-specific indicators, it is relevant to control the underlying income level target of each institution. Each of the MFI listed on the MIX Market database specializes in servicing one specific income group. For the selected institutions, this control variable can take one of two income groups – low income or lower middle income. This indicator is logically prone to impact the MFI's profitability, as well as outreach measures. MFI serving individuals in a lower middle-income group are likely to record higher figures of average loan balance as well as better returns on assets and equity, compared to those serving low-income individuals. Moreover, individuals who are inserted in lower middle-income groups are also more likely to

achieve better values of female empowerment indices due to an advantageous access to education and health services, when compared to lower income households.

III. Methodology

1. Data and Descriptive Statistics

As previously mentioned, MFI-related data was collected from the MIX Market database, made available by the World Data Bank. The data collected covers 10 years, ranging from 2008 to 2018 – the latest available data. Data was collected for 18 SSA countries, namely Benin, Burkina Faso, Cameroon, Cote d'Ivore, Ghana, Kenya, Madagascar, Malawi, Mozambique, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Tanzania, Togo, Uganda, and Zambia. The countries were selected based on data availability and, for each country, data from 2 to 8 MFI institutions is collected, totaling 77 MFI. Although limited data can be a weakness, the decision to only assess MFI with as complete datasets as possible for the designated time period was made to avoid violations of the assumptions of the estimation methods. Moreover, for the female empowerment indices, the UNDP database was used to gather yearly figures for each of the countries. In an analogous manner, data points on country-specific control variables were collected from the World Development Indicators dataset published by The World Data Bank. The MFI-specific control variable concerning the income target of each institution was retrieved from the MIX Market metadata catalog directly. For this analytical context, the data collected was structured as panel data.

As for variable description, equations (1) through (5) summarize the financial explanatory variables in mathematical terms. All variables are measured in percentages.

$$OSS = \frac{Financial\ Revenue}{Financial\ expense + Net\ Imparment\ Loss + Operating\ Expense} \tag{1}$$

$$ROA = \frac{Net\ Operating\ Income - Taxes}{Average\ Total\ Assets} \tag{2}$$

$$ROE = \frac{Net\ Operating\ Income - Taxes}{Average\ Total\ Equity} \tag{3}$$

$$PaR30 = \frac{Loan\ Portfolio\ with\ 30\ days\ overdue\ or\ more}{Total\ Loan\ Portfolio} \tag{4}$$

$$PaR90 = \frac{Loan\ Portfolio\ with\ 90\ days\ overdue\ or\ more}{Total\ Loan\ Portfolio} \tag{5}$$

Below, Table 1 reports the number of observations, mean, standard deviation, maximum, and minimum values recorded in the sample for all dependent, explanatory and control variables employed in the current analysis. We observe that, even after a careful selection of the MFI, most explanatory values still record missing values for some of the years. This can be argued as a limitation of this data sample, for which there are no feasible solutions. Yet, it is still possible to observe that, amongst all 18 SSA countries, the mean for GII is around 0.58, on a scale from 0 to 1, where a value closer to 1 indicates greater inequality between men and women. The minimum value was recorded by Rwanda in 2018 and the most inequal country was Nigeria in the years 2012 and 2013, which registered a value close to 0.70. The GDI, on the other hand, is adjusted to development and a value closer to 1 indicates a smaller gap between male and female measures of empowerment. The observed sample registered a mean GDI of 0.89 and shows a smaller deviation between minimum and maximum figures. Regarding MFI outreach, these variables are measured in US$ and vary greatly between institutions. The average loan size among 572 observations is of US$813, but some MFI registered average loan sizes per borrower as low as US$17, in Malawi, and as high as US$7092, in Nigeria. Similarly, the sample average number of active borrowers is above 60 thousand per institution, yet some MFI work with as little as 55 borrowers, in Cote d'Ivore, and some others provide for over 834 thousand clients, in Nigeria.

Concerning financial performance measures, we observe that all display large values of standard deviation, which may indicate some degree of financial instability. PaR30 and PaR90 equal 7.30% and 5.12%, on average, which indicates that 7.30% and 5.12% of the total loan portfolio is 30 and 90 days or more overdue, respectively. However, there is a big discrepancy between minimum and maximum values, which range from 0% to 97% of portfolio at risk. OSS reflects an average of 108.73%, meaning that in general the selected MFI are operating at self-sufficiency. Yet, again, there is a considerable deviation and some prominent outliers that recorded as little as 2.16% and as high as 841.58% of operation self-sufficiency. ROA is, on average, negative, at -2.08% and ROE is on average low, but positive at 3.27%. Both variables present great values of standard deviation and significant outliers emphasized by the minimum and maximum values. This observation can be a limitation of the analysis, given that these variables are not at all stable amongst MFI.

Lastly, as far as the control variables are concerned, these largely summarize the development level of the set of countries. GDP per capita is on average, US$1303, with Malawi recording the lowest value of US$324 in 2008, and South Africa recording the highest value of US$6263 in 2013. This somewhat aligns with the extreme values for average loan size, suggesting a positive relationship between the variables. Inflation was registered, on average, at just below 7%, and the mean HDI of 0.52 reveals that the selected countries are on average below the 0.55 threshold of low human development. The exceptional countries which consecutively lie within the medium human development bracket (0.55-0.70) are Ghana, South Africa, and Zambia. This is likely to be reflected in the gender empowerment indices recorded in these countries.

Table 1. Descriptive Statistics

Variable	*Obs*	*Mean*	*St. Dev*	*Min*	*Max*
GII	847	0.580353	0.0573266	0.389	0.677
GDI	847	0.8933388	0.0439459	0.779	0.993
loan size	572	813.0524	969.2473	17	7092
borrowers	464	61827.55	127357.1	55	834567
par30days	580	7.299603	7.747104	0	97
par90days	577	5.117036	6.625984	0	94.75
OSS	626	108.7258	49.44293	2.16	841.58
ROA	554	-2.083014	12.28389	-123.11	23.31
ROE	597	3.271976	209.0935	-608.04	4947.42
GDP p/capita	847	1303.129	1142.329	324.55	6263.1
inflation	847	6.992952	5.781174	-2.25	27.28
HDI	847	0.5155218	0.0572765	0.349	0.726

Notes: This table presents descriptive statistics for all continuous variables in our sample. "Obs" refers to the total number of observations. "St. Dev" refers to standard deviation. "Min" and "Max" refer to the minimum and maximum values recorded for each variable, respectively. GII, GDI, and HDI are index measures, which range from 0-1. Loan size, number of borrowers and GDP per capita are measured in US$. The remaining variables are measured in percentages.

2. Estimation methods

2.1 Pooled OLS

For the initial analysis, the panel data was employed onto a pooled OLS, which is often used as a reference model for panel datasets. This first method ignores the panel structure of data and assumes homoskedasticity, as well as no correlation between unit observations in different periods. In this method, data points are pooled together with no assumption on individual differences. This econometric model is built upon four main assumptions, as summarized by Schmidheiny (2022). Here, the assumptions underlying pooled OLS are labeled *PLO1* through *PLO3*.

PLO1: Linearity

$$y_{it} = \alpha + \beta x'_{it} + \delta w'_{it} + \lambda z'_{i} + c_i + u_{it} \text{ , where } E[u_{it}] = 0 \text{ and } E[c_i] = 0$$

The first assumption states that the model is described by linear parameters α, β, λ, an individual-specific effect c_i that captures leftover variation unexplained by the regressors, and an idiosyncratic error term u_{it}. In equation (6), y_{it} refers to the dependent variable of individual MFI i at time t, x'_{it} denotes a row vector of time-varying explanatory variables, w'_{it} denotes a row vector of time-varying country-specific control variables, and z'_{i} denotes a row vector of time-invariant explanatory variables (excluding the constant α). In

the context of the current analysis, y_{it} alternatively refers to GII or GDI, x'_{it} refers to the set of MFI-specific social and financial performance explanatory variables, w'_{it} refers to the country-specific control variables, and z'_i refers to the MFI-specific control variable.

PLO2: Independence

This second assumption implies that the observations are independent and identically distributed across individuals, but not necessarily across time. This assumption holds if the sample is drawn randomly.

PLO3: Strict Exogeneity

$$E[u_{it}|X_i, w_i, z_i, c_i\ ] = 0$$

Under the third assumption of pooled OLS, the error term u_{it} is assumed to be uncorrelated with any explanatory or control variables of all past, current, and future time periods t for the same individual institution. Under the current analysis, this assumption is unlikely to hold as it rules out lagged dependent variables, and empowerment measures are likely to follow-up from previous periods. This assumption also assumes that the idiosyncratic error term u_{it} is uncorrelated with the individual specific effect c_i.

Since the current paper deals with non-experimental data, proper randomization of the sample selection cannot be ensured. Given this, it is unlikely that assumptions *PLO2* and *PLO3* hold. It is likely the case that the chosen variables are endogenous, and hence the panel dataset is further explored under fixed effects and random effects estimation methods. The primary advantage of such models relative to a simple pooled OLS estimation method is that FE and RE allow to control for unobserved time-invariant omitted variables (Bollen & Brand, 2011). As noted by Collischon and Eberl (2020), with these models the sources of bias are limited to time-varying variables which correlate with the explanatory and outcome variables over time, making the strict exogeneity assumption (*PLO3*) more achievable than with a pooled OLS model.

2.2 Fixed Effects Model

As aforementioned, the fixed effects model allows to relax the strict exogeneity assumption *PLO3*, by limiting the source of bias to time-varying variables. Here, the individual-specific (or MFI-specific) effect captures time-constant factors, and the updated exogeneity assumption becomes $E[u_{it}|X_i, w_i, c_i] = 0$. This means that only time-varying covariates must be uncorrelated with the time-varying error term u_{it}. Additionally, assumption *FE1* must hold as follows:

FE1: Identifiability

The fixed effects model's assumption establishes that time-varying regressors do not display of perfect collinearity. Additionally, these must have non-zero within variance over time and large outliers must be

unlikely. Lastly, since the fixed effects method already captures time-constant characteristics within the individual-specific effect term, only parameters β and δ are identifiable, and not α and λ.

2.3 Random Effects Model

Whereas the fixed effects model treats parameter β_{it} as a fixed set of constants that differ across institutions, the random-effects model treats parameter β_{it} as a random variable that has a unique value for each institution i. Below are summarized the additional assumptions under which a random effects model holds, labeled *RE1* through *RE3*, in accordance with Schmidheiny (2022). The random effects model establishes tighter assumptions about the individual-specific effect in comparison with the fixed-effects model, namely *RE1* and *RE2*. Moreover, the random effects model can be described as follows:

$$y_{it} = \alpha + \beta x'_{it} + \delta w'_{it} + \lambda z'_{i} + v_{it}, \text{ where } v_{it} = c_i + u_{it}$$

RE1: Unrelated Random Effects

$$E[c_i|X_i, w_i, z_i] = 0$$

Under the first assumption of random effects model, it is implied that the individual-specific effect c_i is a random variable, drawn from a given probability distribution. This unique individual-specific effect must be uncorrelated to the explanatory variables of any past, present, or future time periods t of the same institution.

RE2: Effect Variance

The second assumption of this model infers that there is constant variance of the individual-specific random effect c_i.

RE3: Identifiability

Similarly to *FE1*, the last assumption of the random effects model establishes that the regressors, as well as the constant term, do not display perfect collinearity. Moreover, all regressors must have non-zero variance and large outliers must be unlikely.

In theory, if one can be sure that assumption *RE1* holds, and that the individual-specific effect is in fact unrelated to any explanatory variables, then the random effects estimator is preferred over the fixed effects estimator. Although this is an extremely strong assumption, and difficult to justify, the Durbin-Wu-Hausman test can be used to decide between RE and FE models, under homoskedasticity. This test has been used in comparable literature (Berhane & Gardebroek, 2011; Quayes, 2015; Bibi et al., 2018; El-Nasharty, 2022) in order to select the most appropriate panel data estimator. The Durbin-Wu-Hausman test is rejected if the estimates between random and fixed effects models are sufficiently different and if the fixed-effects

coefficients are sufficiently precise. If there is enough evidence to reject this null hypothesis, then the fixed effects model should be selected over the random effects model. Otherwise, the random effects method is deemed the most appropriate.

Similarly, the Breusch-Pagan Lagrange Multiplier test is widely used in panel data analyses to determine the existence of significant random effects, based on pooled OLS residuals (Breusch & Pagan, 1980). If the null hypothesis of no random effects is rejected when performing the Breusch-Pagan Lagrange Multiplier test, then it is implied that the random effects model is a more appropriate tool to analyze the data than a pooled OLS method. Otherwise, the pooled OLS regression method is deemed more appropriate.

IV. Analysis and Results

The following section is dedicated to the analysis of the data, and presentation of the results. The models employed follow the specifications of the previous section. Table 2 presents the results of a pooled OLS regression, on both outcomes of female empowerment – GII and GDI. Table 3 displays the results of both a fixed effects model and a random effects model regressed on the outcome empowerment proxy GII. Similarly, Table 4 displays the regression results of both a fixed effects model and a random effects model on the empowerment proxy GDI. Tables 3 and 4 also display the Durbin-Wu-Hausman test, as well as its statistical p-value. Tables 5 and 6 summarize the results for the Breusch-Pagan Lagrange Multiplier test.

Table 2. Pooled OLS Regression Results for GII and GDI

Variable	*GII (1)*	*GII (2)*	*GII (3)*	*GII (4)*	*GDI (1)*	*GDI (2)*	*GDI (3)*	*GDI (4)*
Panel A: Outcome in terms of outreach measures of MFI								
loan size	4.01E-06	-	1.55E-06	-6.70E-06	-6.05E-06***	-	-1.49E-06	2.37E-06
	(2.95E-06)		(3.43E-06)	(5.14E-06)	(2.07E-06)		(2.73E-06)	(2.57E-06)
borrowers	3.73E-08*	-	3.64E-08	5.00E-09	-3.09E-10	-	1.29E-08	1.64E-09
	(2.13E-08)		(2.41E-08)	(2.71E-08)	(1.50E-08)		(1.92E-08)	(1.76E-08)
Panel B: Outcome in terms of financial performance measures of MFI								
par30days	-	-2.97E-03**	-4.09E03***	-3.18E-03*	-	2.14E-03**	1.89E-03	-3.73E-04
		(9.35E-04)	(1.51E-03)	(1.81E-03)		(8.39E-04)	(1.20E-03)	(1.09E-03)
par90days	-	3.69E-03***	4.73E-03***	4.11E-03**	-	-2.86E-03***	-2.3E-03*	-5.86E-05
		(1.07E-03)	(1.67E-03)	(1.95E-03)		(9.6E-04)	(1.33E-03)	(1.21E-03)
OSS	-	1.41E-04**	1.04E-04	2.97E-05	-	-1.12E-04*	-1.13E-04*	-6.31E-05
		(6.99E-05)	(8.24E-05)	(7.77E-05)		(6.27E-05)	(6.56E-05)	(5.8E-05)
ROA	-	1.68E-05	7.9E-05	-3.85-05	-	-1.96E-04	-3.04E-04	-2.5E-0.4
		(2.08E-04)	(3.17E-04)	(5.99E-04)		(1.87E-04)	(2.53E-04)	(2.27E-04)
ROE	-	1.81E-05*	1.79E-05	1.74E-04	-	-1.69E-05*	-1.86E-05**	-8.91E-06
		(9.67E-06)	(1.1E-05)	(1.38E-04)		(8.68E-06)	(8.78E-06)	(7.83E-06)
Panel C: Control variables								
log_GDP	-	-	-	0.0439***	-	-	-	-0.316***
				(0.0150)				(0.007)
inflation	-	-	-	3E-05	-	-	-	2.21E-03***
				(7.37E-04)				(4.44E-04)
HDI	-	-	-	-1.117***	-	-	-	0.441***
				(0.137)				(0.734)
target_2	-	-	-	0.0352*	-	-	-	2.26E-03
				(0.0181)				(9.42E-03)
constant	0.578***	0.579***	0.581***	0.870***	0.900***	0.895***	0.901***	0.874***
Adjusted R^2	0.0084	0.0390	0.0401	0.4053	0.0160	0.0379	0.0299	0.2653
F-statistic	2.73	4.25	2.47	9.58	4.29	4.16	2.09	9.11
p-value (F)	0.0667	0.0009	0.0181	0.0000	0.0143	0.0011	0.0458	0.0000

Notes: This table analyzes the impact of a set of explanatory variables on two gender empowerment proxies – GII and GDI - by means of a pooled OLS regression. The columns labeled with GII (1) and GDI (1) estimate the outcome in terms of outreach measures (Panel A); columns labeled with GII (2) and GDI (2) estimate the outcome in terms of financial performance measures (Panel B); columns labeled with GII (3) and GDI (3) estimate the outcome in terms of both outreach and financial performance measures (Panels A and B); lastly, columns labeled with GII (4) and GDI (4) estimate the outcome in terms of both outreach and financial performance measures, and add a set of control variables (Panels A, B, and C). See Appendix A for a detailed description of each variable. Due to the small scale of some of the coefficients, these are presented in (exponential) scientific notation. Standard errors follow the same notation and are reported in parentheses.

** Indicates statistical significance at the 10% level (p-value<0.10)*

*** Indicates statistical significance at the 5% level (p-value<0.05)*

**** Indicates statistical significance at the 1% level (p-value<0.01)*

Table 3. Fixed Effects and Random Effects Regression Results for GII

Variable	*FE (1)*	*FE (2)*	*FE (3)*	*FE (4)*	*RE (1)*	*RE (2)*	*RE (3)*	*RE (4)*
Panel A: Outcome in terms of outreach measures of MFI								
loan size	-1.21E-05***	-	-1.3E-05***	-8.25E-06***	-1.15E-05***	-	-1.2E-05***	-8.18E-06***
	(1.57E-06)		(1.99E-06)	(1.62E-06)	(1.57e-06)		(1.98E-06)	(1.62E-06)
borrowers	-6.71E-08***	-	-3.93E-08**	2.76E-08*	-5.99e-08***	-	-3.16E-08*	2.60E-08*
	(1.71E-08)		(1.89E-08)	(1.56E-08)	(1.68e-08)		(1.84E-08)	(1.53E-08)
Panel B: Outcome in terms of financial performance measures of MFI								
par30days	-	-1.34E-03***	-5.82E-04	-5.38E-04	-	-1.36E-03***	-6.78E-04	-4.79E-04
		(3.89E-04)	(5.78E-04)	(4.53E-04)		(3.9E-04)	(5.82E-04)	(4.59E-04)
par90days	-	9.68E-04**	3.03E-04	6.13E-04	-	1.01E-03***	4.07E-04	5.85E-04
		(4.28E-04)	(6.23E-04)	(4.88E-04)		(4.30E-04)	(6.28E-04)	(4.95E-04)
OSS	-	1.46E-05	-1.82E-06	-1.36E-05	-	1.91E-05	4.68E-06	-2.27E-05
		(2.82E-05)	(2.93E-05)	(2.33E-05)		(2.83E-05)	(2.95E-05)	(2.34E-05)
ROA	-	-4.34E-04***	-2.78E-04**	6.64E-05	-	-4.19E-04***	-2.61E-04*	7.68E-05
		(8.84E-05)	(1.2E-04)	(1.12E-04)		(8.86E-05)	(1.4E-04)	(1.13E-04)
ROE	-	-3.02E-06	-6.12E-06	-3.87E-06	-	-2.46E-06	-5.08E-06	-3.50E-06
		(3.66E-06)	(3.90E-06)	(3.01E-06)		(3.68E-06)	(3.92E-06)	(3.06E-06)
Panel C: Control variables								
log_GDP	-	-	-	-0.0338	-	-	-	0.0157
				(0.0228)				(0.0152)
inflation	-	-	-	2.42E-04	-	-	-	3.62E-04*
				(2.01E-04)				(2E-04)
HDI	-	-	-	-0.531***	-	-	-	-0.721***
				(0.104)				(0.0788)
target_2	-	-	-	*ommitted*	-	-	-	0.0516***
								(0.0195)
constant	0.599***	0.594***	0.605***	1.09***	0.596***	0.590***	0.602***	1.09***
R^2 *(within)*	0.1674	0.1096	0.2453	0.5594	0.1673	0.1093	0.2444	0.5489
F-statistic	36.28	8.46	9.66	26.03	-	-	-	-
p-value (F)	0.0000	0.0000	0.0000	0.0000	-	-	-	-
Wald χ^2	-	-	-	-	64.92	40.10	59.83	254.48
p-value (χ^2)	-	-	-	-	0.0000	0.0000	0.0000	0.0000
Rho	0.936	0.896	0.917	0.967	0.926	0.884	0.901	0.916
Hausman test (p-value)	-	-	-	9.06 (0.1705)	-	-	-	-

Notes: This table analyzes the impact of a set of explanatory variables on GII by means of fixed effects (FE) and random effects (RE) regressions. The columns labeled with FE (1) and RE (1) estimate the outcome in terms of outreach measures (Panel A); columns labeled with FE (2) and RE (2) estimate the outcome in terms of financial performance measures (Panel B); columns labeled with FE (3) and RE (3) estimate the outcome in terms of both outreach and financial performance measures (Panels A and B); lastly, columns labeled with FE (4) and RE (4) estimate the outcome in terms of both outreach and financial performance measures, and add a set of control variables (Panels A, B, and C). See Appendix A for detailed variable description. Due to the small scale of some of the coefficients, these are presented in (exponential) scientific notation. Standard errors follow the same notation and are reported in parentheses. In column FE (4), the target coefficient is omitted because this is a time-invariant variable. The last row reports the chi-squared value of the Durbin-Wu-Hausman test, and its p-value in parentheses. This test was only calculated for models FE (4) and RE (4).

** Indicates statistical significance at the 10% level (p-value<0.10)*

*** Indicates statistical significance at the 5% level (p-value<0.05)*

**** Indicates statistical significance at the 1% level (p-value<0.01)*

Table 4. Fixed Effects and Random Effects Regression Results for GDI

Variable	*FE (1)*	*FE (2)*	*FE (3)*	*FE (4)*	*RE (1)*	*RE (2)*	*RE (3)*	*RE (4)*
Panel A: Outcome in terms of outreach measures of MFI								
loan size	5.93E-06***	-	3.12E-06*	3.53E-07	5.11E-06***	-	2.58E-06	2.83E-07
	(1.48E-06)		(1.75E-06)	(1.31E-06)	(1.46E-06)		(1.72E-06)	(1.31E-06)
borrowers	4.26E-08***	-	3.25E-08*	-2.87E-08**	3.64E-08**	-	2.82E-08*	-2.43E-08**
	(1.61E-08)		(1.66E-08)	(1.26E-08)	(1.54E-08)		(1.59E-08)	(1.24E-08)
Panel B: Outcome in terms of financial performance measures of MFI								
par30days	-	5.09E-04	2.69E-04	-1.43E-04	-	5.4E-04	3.42E-04	-1.12E-04
		(3.55E-04)	(5.07E-04)	(3.65E-04)		(3.59E-04)	(5.08E-04)	(3.72E-04)
par90days	-	-9.21E-05	5.44E-05	1.24E-04	-	-1.55E-04	-3.15E-05	9.9E-05
		(3.9E-04)	(5.47E-04)	(3.93E-04)		(3.95E-04)	(5.48E-04)	(4.01E-04)
OSS	-	1.11E-05	-1.9E-05	1.78E-05	-	5.54E-06	-2.4E-05	1.25E-05
		(2.57E-05)	(2.57E-05)	(1.88E-05)		(2.6E-05)	(2.57E-05)	(1.89E-05)
ROA	-	3.69E-04***	3.48E-04***	1.86E-06	-	3.45E-04***	3.13E-04**	9.9e-06
		(8.06E-05)	(1.23E-04)	(9.04E-05)		(8.14E-05)	(1.22E-04)	(9.16E-05)
ROE	-	9.68E-07	1.43E-06	1.25E-07	-	3.48E-07	4.38E-07	-5.01e-08
		(3.34E-06)	(3.42E-06)	(2.43E-06)		(3.39E-06)	(3.42E-06)	(2.48e-06)
Panel C: OControl variables								
log_GDP	-	-	-	-0.0581***	-	-	-	-0.0452***
				(0.0184)				(0.0121)
inflation	-	-	-	8.13E-06	-	-	-	8.02e-06
				(1.62E-04)				(1.62E-04)
HDI	-	-	-	0.862***	-	-	-	0.789***
				(0.0838)				(0.0631)
target_2	-	-	-	*ommitted*	-	-	-	5.15E-04
								(0.154)
constant	0.887***	0.880***	0.888***	0.853***	0.890***	0.884***	0.892***	0.853***
R^2 *(within)*	0.0580	0.0908	0.1125	0.5620	0.0580	0.0905	0.1115	0.5607
F-statistic	11.11	6.87	3.77	26.30	-	-	-	-
p-value (F)	0.0000	0.0000	0.0007	0.0000	-	-	-	-
Wald χ^2	-	-	-	-	17.47	29.55	23.09	252.71
p-value (χ^2)	-	-	-	-	0.0002	0.0000	0.0016	0.0000
Rho	0.878	0.964	0.890	0.936	0.861	0.870	0.876	0.911
Hausman test (p-value)	-	-	-	29.55 (0.0000)	-	-	-	-

Notes: This table analyzes the impact of a set of explanatory variables on GII by means of fixed effects (FE) and random effects (RE) regressions. The columns labeled with FE (1) and RE (1) estimate the outcome in terms of outreach measures (Panel A); columns labeled with FE (2) and RE (2) estimate the outcome in terms of financial performance measures (Panel B); columns labeled with FE (3) and RE (3) estimate the outcome in terms of both outreach and financial performance measures (Panels A and B); lastly, columns labeled with FE (4) and RE (4) estimate the outcome in terms of both outreach and financial performance measures, and add a set of control variables (Panels A, B, and C). See Appendix A for detailed variable description. Due to the small scale of some of the coefficients, these are presented in (exponential) scientific notation. Standard errors follow the same notation and are reported in parentheses. In column FE (4), the target coefficient is omitted because this is a time-invariant variable. The last row reports the chi-squared value of the Durbin-Wu-Hausman test, and its p-value in parentheses. This test was only calculated for models FE (4) and RE (4).

** Indicates statistical significance at the 10% level (p-value<0.10)*

*** Indicates statistical significance at the 5% level (p-value<0.05)*

**** Indicates statistical significance at the 1% level (p-value<0.01)*

Table 5. Breusch-Pagan Lagrange Multiplier test for GII

	Variance
GII	0.0028
e	0.0002
u	0.0017
Chi-squared (p-value)	740.34 (0.0000)

Notes: The result of the chi-squared Breusch-Pagan test is reported in the last row, and its p-value is displayed in paratheses. The rows above report variances.

Table 6. Breusch-Pagan Lagrange Multiplier test for GDI

	Variance
GDI	0.0018
e	0.0001
u	0.0011
Chi-squared (p-value)	591.94 (0.0000)

Notes: The result of the chi-squared Breusch-Pagan test is reported in the last row, and its p-value is displayed in paratheses. The rows above report variances.

Starting from the pooled OLS regression in Table 2, it is evident from an initial analysis that the results are notably different depending on the outcome variable used. This indicates that the explanatory variables have, in general, different effects on GII when compared to GDI, although they are both used as female empowerment proxies. Models GII (1) and GDI (1) do not produce many significant results, and it is plausible to assume that these are biased estimators, due to the lack of control variables and possible violation of the strict exogeneity assumption (PLO3). Models GII (2) and GDI (2), however, suggest that almost every financial performance variable, on average, impacts GII significantly. However, it is still uncertain that these are unbiased estimators to be taking definitive conclusions. Models GII (3) and GDI (3) merge all these explanatory regressors and, for some variables of financial performance, show enough statistical evidence to reject the hypothesis of no effect on female empowerment. However, for a more complete and unbiased analysis, GII (4) and GDI (4) show the closest approximation of the true effect of MFI. As for GII, we see that this index is only significantly associated with values of portfolio at risk. The outcome shows a negative significant correlation with PaR30 and a positive significant correlation with PaR90. Regarding GDI, the model does not produce any significant coefficients for the explanatory variables, suggesting no evidence of effects between social and financial performance measures of MFI and this proxy of female empowerment. This can be the case for several reasons, discussed further below.

As anticipated, the simple pooled OLS regression model did not produce significant enough results to draw a realistic conclusion. Following the methodological discussion from before, Tables 3 and 4 summarize the results of two slightly more elaborate statistical methods – fixed and random effects models. Table 3 reports the results for GII as an outcome variable of empowerment, and Table 4 reports the results for GDI as a

dependent variable. In Table 3, we observe again that through models (1), (2) and (3), both for fixed (FE) and random effects (RE) models, some variables of outreach and financial performance are statistically significant when explaining the outcome – namely average loan size, average number of borrowers, portfolio at risk for 30 and 90 days, and return on assets. Nevertheless, it is inappropriate to believe that these estimators are unbiased, due to the likely existence of omitted variables. For this reason, models FE(4) and RE(4) are the most appropriate for analysis, as these include a set of relevant control variables. In these models, only outreach variables are statistically significant when explaining GII. Depth of outreach is negatively related to GII, and hence beneficial for female empowerment, and breadth of outreach is positively associated with GII, thus detrimental for female empowermen. When control variables are added, there is no sufficient evidence of an effect of financial performance indicators on the proxy of female empowerment. Lastly, the bottom row of Table 3, reports the value obtained for the Durbin-Wu-Hausman test, which is not statistically significant (p-value > 0.05). This suggests that, for the case of GII, there is not enough evidence to accept that a fixed effects model is preferred over a random effects model. Hence, the random effects model is more appropriate to analyze this dataset.

Following this, Table 4 summarizes comparable results for the second proxy of female empowerment – GDI. Comparably to previous analyses, models (1), (2), and (3) for both fixed (FE) and random effects (RE) models produced some statistically significant results – namely average loan size, average number of borrowers, and return on assets. However, the least biased models are FE (4) and RE (4), and here only the average number of borrowers is considered statistically significant at 5% level. This coefficient is significantly and negatively correlated to female empowerment. This does not indicate that there are no effects of other outreach and financial performance measures of MFI on this outcome – GDI -, but rather that there is no evidence of any effects in the present dataset. Finally, the last row of Table 4 reports a statistically significant value of the Durbin-Wu-Hausman test at 1% confidence level. Having enough evidence to reject the Durbin-Wu-Hausman null hypothesis indicates that coefficients between random and fixed effects models are sufficiently different and that the fixed-effects coefficients are sufficiently precise. Hence, the fixed effects model is the most appropriate method to choose in this analysis.

Lastly on the statistical analysis, Tables 5 and 6 summarize the results for the Breusch-Pagan Lagrange Multiplier test, which tests for presence of random effects – both for GII and GDI. The chi-squared value is reported as statistically significant at a 1% confidence level for both cases. This provides evidence that there is presence of random effects, and that a random effects model is appropriately used over a pooled OLS model.

V. Discussion

This thesis aimed to identify the existence of an effect of outreach and financial performance measures of microfinance institutions on female empowerment proxies across 18 countries in Sub-Saharan Africa,

during the period of 2008 – 2018. Based on a quantitative analysis of this relationship, employing pooled OLS, fixed effects, and random effects statistical methods, it can be concluded that some of the variables of interest do have a significant statistical relationship with female empowerment. Some other variables did not provide enough evidence of associated effects. Ultimately, the results gathered through the fixed and random effects models, particularly in models FE(4) and RE(4) for both GII and GDI, suggest that only outreach measures of MFI have a significant impact on proxies for female empowerment. These results reject the null hypothesis (H_0) of no effect of either outreach or financial performance on female empowerment across the selected countries. However, these same results only support the first alternative hypothesis (H_1) of significant effect of outreach measures on proxies for female empowerment across the selected countries.

More specifically, for the GII proxy of women's empowerment, both the fixed effects and the random effects model suggest a negative significant relationship between average loan size and female empowerment, at 1% significance level, and a positive significant relationship between average number of borrowers and female empowerment, at a 10% significance level. In other words, this paper's main conclusion indicates that greater average loan sizes are associated, on average and for the selected sample, with a lower and hence more equal GII value. Contrarily, an increase in the average number of borrowers is correlated, on average and for the selected sample, with a higher and hence more inequal index value.

The first relationship is supported by the literature of Imai et al. (2011), whose econometric results indicate that the average size of MFI loans is significantly and negatively correlated with poverty levels in the country. Similarly, Miled and Rejeb (2015) used panel data of over 1000 MFI in 57 developing countries to show that countries where institutions record higher average gross loan figures tend to have lower poverty levels, measured by the poverty head count ratio. As previously established, poverty levels are tightly related to the GII, hence why these empirical results support the relationship found in this paper.

The second relationship is again obtained in the models using GDI as an empowerment proxy. Results in Table 4 also suggest a negative significant relationship between the average number of borrowers and the empowerment proxy index, at a 5% significance level, both under fixed and random effects. Here, the interpretation is that, on average, an increase in number of borrowers is associated with a bigger gap between male and female measures of empowerment. Although possibly counterintuitive, previous studies have shown that microfinance outreach measures may not only generate additional income for women, but also perpetuate inequalities and reconfirm gender-specific division of labor and household tasks, which widens the gender gap (Haile et al., 2012). The same authors hypothesize that women's borrowing can cause increased workloads, followed by health problems and less quality time spent with their families, which can have an opposite, undesired effect on empowerment measures. Moreover, Lopatta et al. (2017) argued, through a transitional panel and country-specific data, that outreach and profitability measures of MFI can be negatively associated to development figures. One possible reason presented in this study is that of higher risk of over-indebtedness due to missing financial education and lack of information. Last but not least, since the outreach measures used in the present analysis refer to the whole population and are not gender-specific, it is possible that a larger number of borrowers is not associated with a proportional increase of female borrowers. This would mean that

instead of empowering women, institutions could be increasing relatively more opportunities for male individuals and widening the gender empowerment gap.

Regarding the inconclusive results obtained for the impact of financial performance measures on gender empowerment proxies, these could happen for several reasons, mainly associated to the limitations of the model. As aforementioned, these results do not imply that there are no effects, but rather that the study does not offer evidence of any effects in the sample. In these cases, if the confidence interval of the estimator is too small, and the model is correctly specified, precise zeros are sufficient evidence of a null effect. However, in this context, the confidence intervals are relatively wide and hence nothing can be assured about the effects, due to lack of statistical power. The main limitation associated with this lack of power is constrained data availability for the selected countries. In the context of developing economies, the reliance on a small sample size is likely to have compromised the statistical power of the models, which impeded the identification of significant effects. Additionally, restricted data availability can further exacerbate the presence of multicollinearity among the set of variables, which makes individual effects of correlated predictors harder to define. In this context, it is likely that the different financial performance measures are correlated with each other, which may yield unstable estimates. Moreover, the inherent high variability and imprecise measurements prevalent in the dataset may have possibly hindered genuine relationships, resulting in imprecise estimates. Furthermore, it is not possible to discard the violation of some assumptions of the fixed and random models, which introduces another potential source of bias to the estimates, and a reason for the arousal of statistically insignificant results. These limitations were further described by Allison (2009), and previous studies such as those of Khandker (2005) and Lopatta et al. (2017) have encountered similar challenges regarding their results.

Besides the methodological weaknesses covered, this study deals with a set of different limitations that go beyond statistical analysis. The most prominent limitation is that of defining female empowerment. As highlighted by Cheston & Kuhn (2002), empowerment is a complex concept of change that is experienced differently by everyone. The biggest issue with measuring empowerment with a country-specific index is that one fails to recognize that providing a strong financial base through microfinance may not benefit every woman in the same proportions. Moreover, since the impact of microfinance was measured using national-level indices, it is possible that the true, community-level effect of microfinance was significantly underestimated. Additionally, the data collected was very limited, and the analysis' design forced all MFI-specific data within the same country to be paired with the same country-specific empowerment proxies. Consequently, the model failed to address the different characteristics of MFI within the same country and assumed the same effect for all institutions that operated within the same borders. This represents another limitation of the study, as ideally one would either use household-level data for empowerment or control for more MFI-specific characteristics, if available.

VI. Conclusion

All in all, the main conclusion supports the use of a random effects model when testing for the GII outcome, and the use of a fixed effects model when testing for the GDI outcome, based on the output of the Hausman test. Essentially, these results support that greater depth of outreach (average loan size) is beneficial for female empowerment and, contrarily, greater breadth of outreach (average number of active borrowers) is detrimental for female empowerment.

Although not all the results presented in this study are fully conclusive, this empirical analysis still provides valuable insights that can be used to support several meaningful policy implications. Firstly, the diverse outcomes observed in the study suggest that a one-size-fits-all approach to microfinance might not be equally effective in all Sub-Saharan countries. Given the complex and distinct dynamics found in each of the countries analyzed, policymakers and MFI representatives must always consider and understand local dynamics when deciding to implement microfinance programs. This has been acknowledged by the scientific community and inclusively assessed in several works, at a country-specific level. An example is the work of Gobezie (2010), which reviews the different contribution of two microfinance models to empower women in rural Ethiopia. It goes to show that different applications of microfinance yield different impacts on the empowerment of women, especially in Sub-Saharan countries which are so rich in rooted traditions and community dynamics.

Moreover, this study serves to understand that although there is great transformative potential of microfinance in developing areas, this tool alone is not enough to drive significant empowerment in the long-term. It must be paired with a supportive ecosystem and hence policymakers should primarily focus on developing a sustainable infrastructure that promotes a strong educational system, accessible healthcare, and legal support to enhance the impact of microfinance interventions, not only for women but to the whole population of these countries. Hand in hand, comes the need to promote financial literacy programs and network strategies for building social capital among borrowers. Additionally, when addressing this, one must highlight the importance of facilitated collaboration between MFI, non-governmental organizations, government agencies, and local communities in order to maximize the positive impact of microfinance. In this line of thought, the authors Cheston & Kuhn (2002) provide an extensive review on how women can be targeted and empowered through microfinance and add to the research a list of promising best practices that can serve as inspiration for policymakers to better extract the benefits of microfinance programs. Essentially, the authors cover a set of initiatives that encourage future researchers and policymakers to adopt different approaches that combine quantitative data with qualitative insights.

Last but not least, this thesis brings out the necessity of developing more holistic empowerment metrics. One of the main limitations of this paper was that of defining and accurately measuring female empowerment. Country-specific proxies were used due to the lack of a concrete index that measures the empowerment of women. With this being an increasingly important and prominent topic, it is desirable for the

scientific community that there is a measure able to better capture the multidimensional nature of empowerment, not only at a country-specific level, but also at a household- or community—specific level. It is plausible to assume that the collection of such data would be an important tool to better assess and monitor the real effects of microfinance in developing economies. Such metric should assess female empowerment beyond purely economic indicators and include factors of maternal and child health, education, labor market, and decision-making power. Ewerling et al., (2017), and Sharma and Das (2011) agreed, based on an exploratory factor analysis of household-level data of 54 African countries, that these are key dimensions to define female empowerment in rural, developing areas.

In closing, the following section is dedicated to suggestions for further research on this topic. The first suggestion refers back to the necessity of a more holistic metric of female empowerment. A possible, yet more exhaustive and complex analysis, could include the creation of a household-level index created using factors of health outcomes, educational attainment, financial literacy, and decision-making power in order to better capture the multidimensional nature of female empowerment. This has in fact been attempted by authors such as Ewerling et al. (2017), and Malubay and Yaoyao (2022) using principal component analysis (PCA), but still has room for innovative research. PCA is an appropriate and realistic approach in this context, as it can account for the underlying dimensions of women's empowerment, while keeping the individual principal components (PCs) uncorrelated (Sharaunga et al., 2019). Implementation of this method would likely solve the issues of ambiguous and multicollinear definition of female empowerment, and possibly provide more conclusive results and better insights into community-specific policy implications. Alternatively, a very recent publication by the United Nations expands empowerment measures and introduces twin indices of empowerment – the Women's Empowerment Index (WEI) and the Global Gender Parity Index (GGPI) (UNDP & United Nations Entity for Gender Equality and the Empowerment of Women [UN Women], 2023). Had it been published earlier on, the WEI would have likely been a closer proxy to employ in this study, as it specifically measures the power and freedom of women across dimensions of female health, education and knowledge, labor and financial inclusions, participation in decision-making, and freedom from violence. Although this new index could not be employed yet in this study, its recent development shows the increasing importance given by the United Nations to the empowerment of women and eradication of gender disparity. In the future, it is essential that these indices continue to be developed as tools to track the pathway to equality, as described by the UN Sustainable Development Goals.

Another suggestion for further research would be, provided data availability, the use of a time series vector autoregressive (VAR) model. This type of statistical analysis has been used in similar studies, yet, for the selected countries, data was too limited to proceed with the time series analysis. Authors such as Sultan & Masih (2016), Barguellil & Bettayeb (2020), and Chikwira et al. (2022) have conducted macro-level analysis of the impact of microfinance on economic growth, economic development, and poverty alleviation of developing countries, respectively. Essentially, these authors have highlighted the advantages of time series analysis compared to cross-sectional approaches. According to Sultan & Masih (2016), the latter is not appropriate in capturing the dynamics in lead-lag relationships because cross-sectional studies assume that the

parameters across countries remain constant. Logically, in the case of developing economies, this is an unrealistic assumption and hence time series studies would be more appropriate to investigate temporal effects. Again, for the intended analysis, this would require a more extensive and complete database to work with.

Lastly, future research could extend the list of countries analyzed in the developing region and, provided data availability, extend the number of MFI analyzed in each area. Ideally, this would increase sample size and hopefully provide more significant results that could be used in assessing and improving the effectiveness of microfinance schemes in developing economies. As seen throughout the present thesis, the complexity and diverse outcomes obtained highlight the need for continued investigation within the scientific community. By building upon the insights gained in this study, future efforts can and must be driven towards implementing the most efficient and impactful interventions, using data and empirical research as its main monitoring and policy advisory tool. Essentially, it is important that the scientific community recognizes the potential transformative power of microfinance to empower women across Sub-Saharan Africa and other developing economies.

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Appendix A: Variable Description

Panel A: Outreach measures of MFI	
loan size (Average loan balance per borrower) (US$)	Gross Loan Portfolio / Number of Active Borrowers
borrowers (Number of active borrowers)	The number of individuals who currently have an outstanding loan balance with the financial institution or are primarily responsible for repaying any portion of the gross loan portfolio. Individuals who have multiple loans with a financial institution should be counted as a single borrower.
Panel B: Financial performance measures of MFI	
par30days (Portfolio at risk > 30 days) (%)	Outstanding balance, portfolio overdue > 30 Days + renegotiated portfolio / Gross Loan Portfolio
par90days (Portfolio at risk > 90 days) (%)	Outstanding balance, portfolio overdue > 90 Days + renegotiated portfolio / Gross Loan Portfolio
OSS (Operational Self-Sufficiency) (%)	Financial Revenue / (Financial Expense + Net Impairment Loss + Operating Expense)
ROA (Return on Assets) (%)	(Net Operating Income - Taxes) / Average Total Assets
ROE (Return on Equity)(%)	(Net Operating Income - Taxes) / Average Total Equity
Panel C: Control variables	
log_GDP (Logarithm of GDP per capita) (constant 2015 US$)	GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in the logarithm of GDP per capita.
Inflation (Inflation, consumer prices) (annual %)	Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. The Laspeyres formula is generally used.
HDI (Human Development Index)	The Human Development Index (HDI) is a summary measure of human development. It measures the average achievements in a country in three basic dimensions of human development: a long and healthy life, access to knowledge and a decent standard of living. The HDI is the geometric mean of normalized indices measuring achievements in each dimension.

Notes: Variable Descriptions are in accordance with the metadata provided by The World Bank. Panels A and B refer to dataset MiX Market *(The World Bank, 2021(a)) and Panel C refers to dataset* World Development Indicators *(The World Bank, 2023).*