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Margarethe Hattingh, B.A.

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Microfinance and the Macro Scale: A Panel Data Analysis of Countries in the SADC from 1999-2019

Abstract

This paper investigates the relationship between the growth in size of microfinance initiatives (as proxied by growth in the gross loan portfolio per capita) and economic development (as given by growth in gross domestic product per capita) in nine of the lower and middle income countries in the Southern African Development Community from 1999 to 2019. The theoretical literature on the subject suggests an ambiguous relationship between these two interest variables, regional analyses have yielded heterogenous results, and no paper to date has investigated this question in the context of the SADC specifically — hence the motivation for our analysis, which uses panel data techniques. The fixed effects (FE) model specification is selected from four panel model candidates through a battery of tests. It is upon this model that we draw our conclusions. It suggests that there is at best a weak but statistically insignificant contribution of microfinance growth on economic development in this region, and that inflation and government expenditure growth are the best predictors of the outcome variable from all variables considered. These results are useful for policy setting as they imply that economic growth would be better served by setting a low and stable rate of inflation and by supporting already-existing governmental initiatives rather than MFIs. By the same token, the conclusion that MFIs do not have a negative, but rather neutral, impact on economic growth is useful to consider when weighing up the many arguments for and against the use of microloans in this region. It may still have a place in the developmental landscape regardless of its contribution to economic growth.

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1. Introduction

Microfinance institutions (MFIs) are a type of financial intermediary that are characterised by their unique combination of a social and financial logic. The principle behind microfinancing is simple: to provide small[1] loans to people who would likely go unbanked or otherwise be asked exploitatively high interest rates so that they can invest in capital to improve their individual circumstance. Though such a concept has existed informally for centuries — for example, in the form of a “community pot” or other informal credit associations — MFIs began to receive wider attention as a poverty alleviation and developmental tool with the success of the Grameen Bank, which was founded in Bangladesh in 1976 (Dokulilová et al, 2009).

A number of empirical studies exist which aim to determine the extent to which a microloan may be transferred into a macroeconomic effect. It is hypothesised that microfinance may provide a solution to the immature formal financial intermediation often seen in developing nations, thereby promoting economic growth through the power of micro-entrepreneurship. Results along this line of inquiry have been mixed. Indeed, there has been substantial debate surrounding the true impact of MFIs, with some suggesting microloans may have negative consequences for the level of development of the economies in which they are deployed, let alone for the individuals who receive them (Dichter, 2010). Though the original enthusiasm for microfinance has been tempered over the past decades, MFIs nonetheless remain non-negligible financial intermediaries on the global stage (D’Espallier et al., 2017), and the question regarding their efficacy in promoting economic development remains an open one. Keeping in mind this debate, this thesis paper asks: *Has growth in the size of microfinance in the lower and middle income members of the Southern African*

Development Community had a positive and significant effect on economic growth since the turn of the century?

The importance of the inquiry has to do with the urgency of finding ways to promote economic growth in developing economies in order to sustainably improve the quality of life of the citizens in these regions. To the best of our knowledge, no paper exists which addresses this question in the context of the SADC, hence the motivation for our inquiry. For our analysis, we collect data on 9 of the 16 SADC member states from the period 1999-2019 on an annual basis and apply a series of econometric techniques suited to panel data. By considering the possibility of reverse causality and using instrumental variable methods, and by appealing to a body of theoretical literature on the subject, we attempt to draw firm conclusions about the nature of the relationship between our two main variables of interest. Whether we have been able to address the question of causality remains open to debate. This thesis will speak mainly in terms of "effect" in its analysis rather than laying claim to firm conclusions on the matter of the exact nature of the relationship between microfinance size and economic growth.

Ultimately, we find a positive but statistically insignificant effect of the growth in the size of microfinance gross loan portfolio on economic growth for this timeframe. This is to say, controlling for the macroeconomic environment and individual differences between countries, we detect no meaningfully beneficial nor adverse contribution of the growth in microfinance size to economic development. It is possible that more data, which will only come to light with the passing of time, would yield more meaningful results.

To begin the paper, we provide an overview of the history of microfinance and the SADC in section 2; section 3 reviews the theoretical and empirical literature on the subject; section 4 outlines the potential variables considered to construct the fixed effects (FE) model ultimately estimated; section 5 describes the methodology behind the data processing in greater detail; section 6 displays and discusses all relevant results of the data processing (including robustness checks); section 7 provides an analysis of our FE model of interest; section 8 provides a synthesis of all information and results presented; section 9 concludes.

2. Background Information

2.1. Microfinance: A Brief History

Microfinance is broadly defined as the provision of financial services to individuals in low-income groups who are typically excluded from traditional banking. The terms “microfinance” and “microcredit” are often used interchangeably: many microfinance institutions (MFIs) concentrate on providing small loans to their borrowers, where these loans themselves are referred to as micro-loans or microcredit. MFIs may also offer other types of financial services including insurance schemes or savings accounts (FINCA, n.d.).

Though the concept of microcredit existed long before the previous century, Muhammad Yunus, a Bangladeshi social entrepreneur, is credited with its formal institutionalisation through the Grameen Bank model in the 1970s (Muhammad, 2009). The motivating concept behind its institutionalisation was one of entrepreneurship. Yunus envisioned an institution that would allow those who would ordinarily not be considered creditworthy to build or grow their own businesses to escape the cycle of poverty (Morduch, 2011). Thus microfinance is considered a “bottom-up” solution to promote economic growth and development through poverty alleviation and the empowerment of the individual (Banto and Monsia, 2020, p. 1). Yunus originally conceived of microloans as a tool not just to alleviate poverty but also, by targeting women borrowers, as one that could help promote gender equality (Morduch, 2011). Thanks in large part to anecdotal evidence and following the positive reviews made by Grameen Bank about the high payback rate of loans, the use of microcredit saw a huge upswing in popularity around the turn of the century (Bateman, 2014, p. 97). MFIs are currently considered a non-negligible financial intermediary, as evidenced by the voluminous literature detailing their history and evaluating their efficacy.

When MFIs gained popularity as a development and poverty alleviation tool in the 1980s and 1990s, the sector as a whole was characterised by non-profit institutions. Since the turn of the century, commercialised (i.e. profit oriented) micro-banks have come to dominate the scene (Wagner and Winkler, 2013, p. 73). The four key types of MFIs in existence today can be characterised as follows: Banks and Non-bank Financial Institutions (NBFIs) are privately owned and profit-oriented, while NGO-MFIs, Cooperatives (Coops) and Credit Unions (CUs) are not. Of these, the majority of for-profit MFIs are regulated while the majority of non-profit MFIs are not (Soumare et al., 2020).

It is important to note the heterogeneity of the sector as such a granular analysis can help us to interpret our empirical results down the line. Understanding the evolution of the microfinance landscape globally in the past two decades may help us understand the connection between microfinance and economic growth, and how this connection itself may be evolving. The evolution of the sector to comprise mostly profit-oriented MFIs may have important implications for their efficacy in fostering economic growth insofar as this evolution can be considered a “mission drift”. This is a term that the literature has begun to use as euphemism to describe the tension “between the social welfare mission of microfinance and the ever stronger market and profit orientation of MFIs” (Lopatta and Tchikov, 2016, p 1660).

2.2. The SADC

Headquartered in Gaborone, Botswana, the Southern African Development Community (SADC) is an inter-governmental organisation that today comprises the 16 southern-most countries on the African continent. These are, in alphabetical order, Angola, Botswana, Comoros, Democratic Republic of Congo, Eswatini, Lesotho, Madagascar, Malawi, Mauritius, Mozambique, Namibia, Seychelles, South Africa, Tanzania, Zambia and Zimbabwe. Of these member states, Comoros, Seychelles, Mauritius and Madagascar are island nations.

The SADC officially came into being as a legal entity in 1992. It was originally known as the Southern African Development Coordination Conference (SADCC), a loose alliance between nine of the current member states that was formed in 1979 with the objective of minimising economic dependence on the then-Apartheid era South Africa (The African Union Commission, n.d). Since then, it has expanded its network and mission and become known as the SADC. According to SADC's official website, the main objectives of the community are to "achieve economic development, peace and security, and growth, alleviate poverty, enhance the standard and quality of life of the peoples of Southern Africa, and support the socially disadvantaged through regional integration" (2012). As such, it is a Free Trade Area, i.e. a trade bloc where barriers to trade have been largely abolished. The SADC's activities are co-ordinated at annual conferences in which heads of government and a council of ministers from all member states are present (Britannica, 2018).

Poverty alleviation is at the top of the SADC's agenda. According to the International Council on Social Welfare, nearly half of the population in the region live in poverty (as cited in SADC, n.d). And this number is projected to increase in the coming decades (Institute for Security Studies, 2017). Thus an inquiry into potential avenues for economic growth and development, such as that represented in this thesis paper, is of particular relevance to the objectives of the community as these macroeconomic phenomena are negatively associated with poverty's incidence (Zhang, 2017).

3. Literature Review

The following sections review the literature exploring the microfinance and economic growth connection. We distinguish between theoretical and empirical studies in sections 3.1 and 3.2 respectively. In section 3.2, we highlight those studies that have greatest relevance for the SADC — that is, those studies that explicitly differentiate their regions of analysis and/or focus in on African countries. To date, to the best of our knowledge, there is no study in the economic growth and MFI literature that focuses explicitly on the SADC.

3.1. Theoretical Studies

As for the theoretical literature exploring the microfinance and economic growth connection, three papers stand out as worthy of mention, each with slightly different implications for this relationship. In short, taken altogether, the theoretical literature suggests that microloans may be effective in promoting economic development, but not necessarily in all cases.

The first theoretical paper, one by Ahlin and Jiang, builds on the simple neoliberal idea at the core of the Grameen Bank model — that is, a belief in the power of entrepreneurship to positively impact an economy. The model they build borrows heavily from the occupational choice model of Banerjee and Newman (1993). Within it, they consider microcredit as "a pure improvement in the credit market that opens up self-employment options to some agents who otherwise could only work for wages or subsist"

(Ahlin and Jiang, 2005, p. 1). In this framework, entrepreneurship is assumed to be more efficient than self-employment, and self-employment more efficient than subsistence. This gives rise to a hierarchy between production technologies. Ranked in ascending order by productivity and scale, they are subsistence, self-employment, and entrepreneurship (p. 3).

The chief concern of their model is to determine whether microcredit can bring an underdeveloped economy to full development, which they define as "the steady state with only the most efficient technology in use, high wages, and no inequality" (p. 4). Within their model, there are two potential outcomes related to the existence of microcredit in an economy: it can either increase or decrease long-run GDP as it impacts both subsistence and full-scale industrial technologies. To determine microcredit's long-run effects, they look at the so-called "graduation rate" at which the self-employed build up enough wealth to move into the entrepreneurial class. Two avenues for graduation exist — one in which microcredit is viewed as a mechanism to sort "winners" who earn supernormal returns into the entrepreneurial class ("winner" graduation), and another in which anyone can gradually save up enough to make this transition ("saver" graduation).

The key finding to highlight from this paper is that "winner" graduation alone cannot bring an economy to full development because as the entrepreneurial class grows, so will labour demand, thus wages, and thus more and more agents will choose to work for wage labor rather than be self-employed. Rather, full development can only come about through the second avenue of "saver" graduation: if "normal returns in self-employment and the saving rate are jointly high enough … an economy [can move] from low output and subsistence wages to full development …" (p. 5). A complementarity thus exists between microcredit and micro-savings services; an important policy implication of their findings is that both these services ought to be provided to enable the possibility of full development for developing economies. Ultimately they conclude that microcredit will typically lower the number of people earning subsistence level-income (i.e. poverty) by either raising the wage or lifting “subsisters” into self-employment.[2]

A paper by Yusupov (2012) finds the aforementioned model too generic and amends it to include an element of predatory competition. Specifically, they construct a model wherein the probability of graduation from being self-employed to the entrepreneurial class depends on the population of micro-entrepreneurs. They make the case that a larger population of entrepreneurs increases the competition among them, which can have a detrimental effect on development in the long run: “the more micro entrepreneurs that emerge the more difficult it gets for them to earn high returns, and consequently to graduate to the upper class” (p. 822). Yusupov, however, does not go so far as to characterise a steady state for the economy within this slightly modified framework.

Lastly, a theoretical paper by Buera et al. (2017) models the redistributive impact of microfinance in partial and general equilibrium. They concentrate on five measures of economic development, namely output, capital, total factor productivity, wages, and interest rates, and the distributional consequences of these measures in response to microfinance initiatives. In contrast to the aforementioned papers, the agents in Buera et al.’s analysis have only two options for occupation: they can either work for a wage as an employee or operate a business as an entrepreneur (p. 9). Microfinance is modelled as a financial technology that allows an agent access to (and requires repayment of) a certain amount that they can use for either consumption or capital rental (p. 11). Their analysis yields different implications for the short and long run.

Their short-run partial equilibrium analysis implies that the positive impact of microfinance on income and capital is non-negligible: TFP decreases as microfinance encourages the entry of low-productivity entrepreneurs and allows them access to capital. Wage and interest rates rise in both the short and long run as the demand for capital is increased by entrepreneurial entry. In a long-run general equilibrium, the availability of microfinance is predicted to lead to increased interest rates, thus reduced demand for capital: TFP increases as only the higher quality entrepreneurs are able to remain in business. Ultimately, the higher TFP and lower capital offset such that microfinance is predicted to have a negligible impact on output in the long run. (Note that this contradicts the more optimistic forecast of long-run economic development predicted by Ahlin et al.). Nevertheless, in this framework, everyone benefits from microfinance from a welfare perspective: marginal entrepreneurs who take out microloans for production and the poor who take out microloans for consumption benefit the most from microfinance initiative; the rest benefit indirectly as higher consumption in the present is enabled by the possibility of taking out microloans in the future.

In conclusion, on the theoretical front, the models relating microfinance initiatives to economic growth highlight that MFIs have the potential to contribute to the output of an economy and improve welfare, even if these improvements are not enjoyed equally by the economy's agents, but that it is not necessarily sufficient to shift a long-run equilibrium. We turn to the empirical studies next to shed further light on the issue.

3.2. Empirical Studies

The empirical studies that investigate the efficacy of microfinance initiatives to contribute to economic growth show mixed but generally positive results. For the most part, studies find either moderately positive or no statistically significant relationship on a global scale; mixed positive and negative results are indicated on the regional level. Further narratives of the potential harms of microfinance initiatives tend to fall into the category of anecdotal or, if empirical, examine the impact of microcredit in a specific context (e.g. on education or women's empowerment) which, while important to consider in assessing MFIs generally, are not directly relevant to a study of the MFI-economic growth connection and have thus been excluded from this section.[3]

To begin our review of the literature, we look at an early study by Woolley, published during the global financial crisis, that conducts a panel data analysis using data from the Microfinance Information Exchange (MIX) to test the resiliency of MFIs to economic change. By looking at both financial and social metrics of performance — namely gross loan portfolio and number of borrowers — controlling for year and country fixed effects, Woolley concludes that there is no significant correlation between GDP growth and microfinance performance. This is taken as evidence for the resilience of MFIs against economic fluctuations. This resilience is, in turn, argued to be something which can assist MFIs in their mission to promote long-run economic growth even in times of economic turmoil. While Woolley takes a global perspective and includes Africa in his data set, he does not distinguish the effect by region (2008).

Where Woolley treats GDP growth as a regressor, Maksudova flips the equation such that the growth rate of microfinance variables (gross loan portfolio and number of clients) appear as regressors and GDP becomes the regressand. Using panel data, they find that there is a significant positive effect of the lagged growth rate of microfinance portfolio size on economic growth for low income countries, but that this effect is not seen with middle income countries. They propose that this is because less developed countries are typically characterised by immature formal financial intermediation, thus leaving more room for microfinance to have a positive effect on economic growth (2010).

As an aspect of their analysis, Maksudova augments their structural equation to control for foreign aid received by developing countries; they find microfinance has no significant effect on economic growth once aid is controlled for. Tangential to this analysis, Lacalle-Caldron et al. inspect the effect of microfinance (MF) *vis-à-vis* official development aid (ODA) and find that microfinance outperforms foreign aid in promoting economic growth: they find that ODA has no significant effect whereas MF has a significant effect through private investment as a transmission mechanism (2015).

Lopatta and Tchikov similarly find that microfinance has a positive and statistically significant effect on economic growth. This is accomplished directly through value added to purchasing power and indirectly through capital accumulation and employment rates. They consider a handful of microfinance performance indicators including breadth of outreach, depth of outreach, loan repayment, financial stability, and efficiency — variables that our own paper also considers in order to capture MFI performance (see section 4.2). Moreover, of relevance to this thesis' analysis, theirs is one of the few studies to provide a regional differentiation for their results. Though they don't examine the impact of MFI initiatives in the SADC specifically, they distinguish North African countries and find that the positive effect is also present here (2015).

Alimi provides one of the few studies recognised in the literature at large that focuses in on African countries in particular — namely Nigeria, South Africa, Lesotho, Malawi, Sierra Leone, Botswana and Kenya — but not explicitly on MFIs. By applying panel data methods he finds that financial development as proxied by domestic credit provided by the banking sector has not led to economic development in these countries. He calls on initiatives like microfinance institutions to act as complements to the traditional banking sector (2015).

More recently, Donou-Adonsou and Sylvester have revisited the question of a microfinance-economic growth connection. Though they find evidence to support its existence, they find the impact is small and that such financial intermediation comes at a high cost to the borrower, with countries in Africa reporting interest rates as high as 85%; the medium interest rate clocks in at just over 30% in this region (p. 31-32). Donou-Adonsou and Sylvester employ a model similar to the popular Levine et al. (2000) model of financial development and growth. To account for potential endogeneity of microfinance in the economic growth equation, they use lags of the microfinance variable of interest (gross loan portfolio) and a system-GMM estimator (2018).

Finally, we review a recent study by Banto and Monsia that contributes to the existing field of literature by considering a wide variety of both social and financial indicators of microfinance performance while also controlling for traditional bank performance. Like many papers before, they take a global perspective and do not distinguish the effect of microfinance by region. Overall they discover a positive and statistically significant relationship between both MFIs' social and financial performance and economic development, "despite their relatively small size" (p. 2). The key implication of their findings is that MFIs ought to pursue both social and financial objectives in order to contribute to economic development — which may be thought of by some as a sort of "economic paradox" (p. 1). The most important channels they identify through which both banks and MFIs affect GDP are investment and household consumption. Interestingly, they also find that an increase in the number of female borrowers from MFIs — a social indicator of MFI performance — is clearly positively associated with economic development, and that female borrowers are more likely to use their loans to consume rather than invest (2020).

It is relevant to note that much of the literature exploring the MFI-economic growth connection take a global perspective and does not differentiate results according to region. One study of note, by Sodokin and Donou-Adonsou, investigates this question in a West African context: contrary to the findings of the globally-oriented analyses, they find that microfinance had a small but significant *negative* effect on economic growth in this region over the 1999-2005 period. They do, however, find that there is a complementary positive relationship between formal financial intermediation (i.e. banks) and MFIs, and therefore suggest closer collaboration between the two may be most helpful in promoting economic growth in the West African Economic and Monetary Union (2010).

This paper, along with a study situated in Arab countries looking at the 1999-2016 period that finds no significant relationship between microfinance and economic growth (Khalaf and Saqfalhait, 2019), gives us reason to believe that the existing literature on the subject may be inadvertently obscuring important regional heterogeneity worth investigating. All in all, studies exploring an MFI-economic growth connection in an African context specifically are lacking, and, to the best of our knowledge, none exist which investigate the SADC in particular. Hence the motivation for this thesis paper.

4. Variable Descriptions

4.1. Dependent Variable

The dependent variable of choice in this investigation is gross domestic product (GDP) per capita as a measure of economic development. This follows the approach of Lopatta and Tchikov (2016) and, more recently, of Banto and Monsia (2020). The data for GDP per capita for each of the SADC countries considered in this paper were obtained from the WDI.

Table 1 Dependent Variable

Code	Definition	Measurement	Source
Dependent Variable			
GDPPC	Gross domestic product per capita (constant 2017 international $)	GDP standardised by midyear population, where GDP = (gross value added by all resident producers in the economy) + (product taxes) - (subsidies not included in the value of the products). For the concept and methodology of 2017 PPP, please refer to https://www.worldbank.org/en/programs/icp.	WDI

4.2. Independent Variables: MFI Indicators

The following section details the particular MFI indicators used in the econometric analysis of the relationship between economic growth and microfinance size in the SADC region. Gross loan portfolio proxies microfinance size as the main independent variable of interest and, as such, is fixed (i.e. included unconditionally) in the model specification; the social and financial indicators for MFI performance are not necessarily fixed in the model specification. For a particular social or financial indicator to be represented in the final model specification it must weigh in favourably in the tradeoff between model fit and model complexity as calculated by the AIC. Such an IC selection method is necessary due to data availability. See section section 5.2 on the empirical approach for further details.

Interest Variable

Gross loan portfolio gives a measure of the size of microfinance. Gross loan portfolio has been standardised by dividing by the population size[4] of each country in order to give an approximation of the actual funds disbursed to households. The value for gross loan portfolio used in this investigation was obtained from the MIX Market, and, as such, is comparable across countries as it is adjusted for write-offs and inflation (Imai et. al, 2012, p. 1676).

It is worth noting that gross loan portfolio represents the size — i.e volume or scale — of microfinance. This is not the same as the performance or quality of microfinance activities. These qualitative aspects are rather captured by social and financial indicators (Banto and Monsia, 2020, p. 4). The particular social and financial MFI indicators considered in the preliminary stages of the analysis are given below.

Social Indicators

Growth in number of active borrowers is a measure of the growth in the number of individuals that have a loan outstanding with an MFI. The **average loan balance per borrower/GNI per capita** (referred to as average loan balance per borrower from hereon) proxies the depth of MFI outreach. **Percent of female borrowers** gives the fraction of female borrowers as a percent of the total number of active borrowers.

These indicators are defined as "social" indicators by the MIX Market because they are reflective of how well an MFI is progressing towards the goal of financial inclusion for otherwise potentially unbanked people, with a special focus on women's financial empowerment. Number of active borrowers and average loan balance per borrower are considered a reflection of extensive growth and intensive growth respectively (Banto and Monsia, 2020, p. 4).

Financial Indicators

The **yield on gross portfolio** gives a measure of an MFI portfolio's ability to "generate cash financial revenue from interest, fees, and commissions." It excludes any revenue that has accrued but has not been paid in cash, or any type of non-cash revenues e.g. unsold collateral (Banto and Monsia, 2012, p. 4). **Return on assets** is interpreted in the same way in the context of an MFI as with any other commercial institution — that is, as a measure of how well assets are put to use in order to generate a return. Return on equity is excluded from the analysis as not all MFIs issue equity. Many rely on grants and/or "soft loans" (Bogan, 2012). The ratio of **operating expense to loan portfolio** can be used to capture the efficiency of MFIs: a higher ratio indicates lower efficiency. **Profit margin,** as an accounting identity, indicates how much revenue remains after various relevant expenses have been paid (financial, loan-loss provisions, operating expenses, and other).

Table 2 MFI Indicators

Code	Definition	Measurement	Source
MFI Size			
GLPPC	Gross loan portfolio per capita (USD)	All outstanding principals due for all outstanding client loans standardised by population size. This measure includes current, delinquent, and renegotiated loans, but not loans that have been written off.	MIX Market
Social Indicators			
NoABgr	Growth in number of active borrowers per annum (%)	Per annum growth in the number of individuals who currently have an outstanding loan balance at a particular MFI or are primarily responsible for repaying any portion of the GLP. Individuals who have multiple loans at an MFI are only counted once.	MIX Market
AvgLBB	Average loan balance per borrower / GNI per capita (%)	Average Loan Balance per Borrower / GNI per Capita	MIX Market
PFem	Percent of female borrowers (%)	Number of active female borrowers / Number of Active Borrowers	MIX Market
Financial Indicators			
YGP	Yield on gross portfolio (real) (%)	(Yield on Gross Portfolio (nominal) - Inflation Rate) / (1 + Inflation Rate)	MIX Market
ROA	Return on assets (%)	(Net Operating Income - Taxes) / Average Total Assets	MIX Market
OELP	Operating expense / loan portfolio (%)	Operating Expense / Average Gross Loan Portfolio	MIX Market

PMar	Profit margin (%)	Net Operating Income / Financial Revenue	MIX Market

4.3. Independent Variables: Macroeconomic and Political Controls

The following section details the particular macroeconomic and political controls used in the econometric analysis of the relationship between economic growth and microfinance size in the SADC region. As with the social and financial indicators, for a particular macroeconomic or political control variable to be represented in the final model specification it must weigh in favourably in the tradeoff between model fit and model complexity as calculated by the AIC. Such an IC selection method is necessary due to data availability. See section 5.2 on the empirical approach for further details.

Macroeconomic and Political Control Variables

The consideration of the macroeconomic and political control variables listed in Table 3 is inspired by the literature at large on the subject (see the literature review for specific studies). However, this thesis paper follows closely in the footsteps of the most recent paper on the subject by Banto and Monsia (2020). While theirs takes a global approach and furthermore considers the interaction of traditional banking services with MFIs, our study is focused on the SADC and microfinance.

A few words on each potential control variable: The share of **domestic credit** to the private sector in GDP gives an indication of the overall development of the financial sector (Zhang, 2017, p. 5).[5] Distinguishing the domestic credit to the private sector from the size of microfinance in our regression model will allow us to capture the potentially different effects of the development of these sectors on economic growth. **Democracy** is considered a political control variable[6] in the model specification as it proxies for the strength of a country's institutions: it is controversial whether democracy directly impacts economic growth, but there is nonetheless robust evidence that it indirectly facilitates it (Doucouliagos and Ulubasoglu, 2008). **Education** proxies the level of human capital; **government expenditure** has been shown to lead to higher steady-state growth (Devarajan et al., 1996); **inflation** controls for macroeconomic conditions; the **trade** variable captures the degree of openness of an economy (Zhang, 2017, p. 5-6). Levine et al. (2000) and Adonsou and Sylwester (2015) consider education an input to the growth equation while government expenditure, inflation, and trade openness are classified as policy factors.

Table 3 Macroeconomic and Political Control Variables

Code	Definition	Measurement	Source
Control Variables			
DC	Domestic Credit to private sector by banks (% of GDP)	Financial resources provided to the private sector by deposit taking corporations that are not central banks. These may be through loans, purchases of non-equity securities, trade credits and other accounts receivable	WDI
Demo	Democracy (point scale)	An additive 11 point scale with measurements ranging from 0 to 10, where 10 represents a full institutional democracy. Data available from 1999 to 2018. Exceptions processed as described in section 2.4 here http://www.systemicpeace.org/inscr/p5manualv2018.pdf	The INSCR PolityV Project[7]
Educ	Education participation (%)	(Number of students enrolled in secondary education) / (population of the age group which officially corresponds to secondary education) x 100.	WDI
GovExp	Government Expenditure (constant 2010 USD)	General government final consumption expenditure includes all government current expenditures for purchases of goods and services and most expenditures on national defense and security. It excludes government military expenditures that are part of government capital formation	WDI
Infl	Inflation (%)	Inflation is measured by the consumer price index (CPI). It 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	WDI

Trade	Trade (% of GDP)	Trade is the sum of the value of exports and imports of goods and services measured as a share of gross domestic product	WDI

5. Methodology

5.1. Data

Description of Panel Data

The dataset used in this econometric analysis was uniquely compiled by the author from the WDI and MIX Market databases: these are public datasets hosted on the World Bank's server. The dataset constitutes an 'unbalanced panel'. Panel data -- which is also sometimes referred to as longitudinal data -- has both a time-series and cross-sectional dimension (Wooldridge, 2016, p. 403) .[8] In the case of this particular analysis, the time frame chosen is 1999-2019, observations are taken on an annual basis, and the individuals considered are 9 of the 14 lower and middle income SADC countries. (Refer to Appendix B for a classification of each country by income group).

This particular time-frame was chosen based on data availability: the key microfinance indicators needed for this analysis are reported by the MIX Market for these two decades only. Similarly, 5 of the total of 16 SADC countries (namely, Botswana, Comoros, Eswatini Lesotho and Namibia) were not included because of the insufficiency of available data, while the other 2 of the total (Mauritius and Seychelles) were excluded as there is no data whatsoever available on them. This is likely because these latter two island nations are considered upper income countries (World Bank, World Development Indicators); microfinance initiatives are typically grounded in poorer countries with the intention of poverty alleviation.

The dataset is considered 'unbalanced' because, despite the selection of data on the basis of data availability, there are nevertheless gaps in the time series used. This is a common problem in studies based in poorer regions because of the expense involved in collecting data on measures most relevant to poverty and economic development (Zhang, 2017, p. 4). Econometric methods can still be reliably applied to unbalanced panels so long as the reason that data is missing for any particular individual is not correlated with the idiosyncratic error for this individual over time (Wooldridge, 2016, p. 440). Considering that all cross-sectional units (i.e. countries) in this analysis are taken from the geographical, political, and economic region of the SADC, a strong case can be made for the reliability of the application of panel data methods to this sample because we are able to infer that the data missing for every country does not systematically differ from country to country. The 'missingness' of data leads to problems when the reason for the incompleteness of the dataset is non-random. For example, this is the case in studies of the effect of the size of microfinance on poverty reduction on a global level, where countries of all income brackets are considered[9]: in these studies, the relatively wealthier countries are likely to report more comprehensively on poverty measures in their country for reasons such as resource availability (Zhang, 2017, p. 3).

Details regarding the specific number of observations available for each variable are given in section 6.1 on descriptive statistics. No outliers were removed. The MIX Market database is itself adjusted to limit their influence (Soumaré et al., 2020, p. 5).

Databanks and Data Quality

As mentioned, the dataset used in this analysis draws most heavily from the World Development Indicators as well as the Microfinance Information Exchange (MIX) Market.

The WDI is compiled from officially recognised international international sources and is widely considered to be one of the most current and reliable sources of development data (UNCDD Knowledge Hub, 2016).

The majority of country-specific data have been drawn from the WDI and all microfinance data (that is, data on all social and financial indicators) have been drawn from the MIX Market. The MIX Market was a service provided by MIX that aimed to support initiatives for financial inclusion by addressing information asymmetries (Ahlin et al., 2011, p. 107). The data hub collated the reports of MFIs annually based on predetermined formats and reporting standards; information reported therein has been validated and standardised (Imai et al., 2012, p. 1676). During its time of independent operation, MIX was considered the “leading global data resource for inclusive finance”. MIX was integrated into the Center for Financial Inclusion in 2020, but its data continues to be hosted on the World Bank’s website along with the WDI (CFI, n.d.).

Though it is widely used and trusted, it is important to keep in mind that MIX is not able to send questionnaires to all MFIs in all countries (particularly if the MFIs are small and recent), that not all MFIs that MIX has been able to reach would necessarily respond to the surveys, introducing a self-selection bias, and that errors may nonetheless be present in the data because of MIX’ reliance on self-reporting by MFIs (Imai et al., 2012, p. 1676).

The democracy index (coded ‘Demo’) is noteworthy in that it was taken from neither the WDI nor MIX Market, but from the The INSCR Polity5 Project, whose objective it is to uphold a research tradition of “coding authority characteristics of states in the world system for purposes of comparative, quantitative analysis.” The Polity5 project covers all major independent states from 1800-2018. It is described as a “living data collection effort” as it is continually updated thanks to the watchfulness and criticism of the intelligence community (Center for Systemic Peace, n.d.).

5.2. Empirical Approach

In order to address the research question put forth by this thesis paper, four separate specifications of panel models were considered to fit the multiple linear regression model below:

$$y_{it} = c + X_{it}'B + u_i + e_{it} \quad (1)$$

The notation is such that y_{it} represents the dependent variable, c is a constant, X_{it}' is the vector of time-varying explanatory variables, B is the column vector of parameters to be estimated, u_i is the individual-specific effect (unobserved heterogeneity), and e_{it} is the error term.

The first model specification considered is the **pooled OLS model**. This is essentially an application of the ordinary least squares method of econometric estimation to a dataset which ignores the panel structure of the data. In other words, the time-series and cross-sectional dimensions of the dataset are disregarded as the data is ‘pooled’ together. For pooled OLS estimation to be useful, we must assume that the relationship between the dependent variable y_{it} and at least some of the independent variables in the X_{it}' vector remain constant over time (Wooldridge 2010, p. 403). Furthermore, in order to produce unbiased and consistent parameter estimates, a handful of assumptions must be met, including that of exogeneity, homoskedasticity, no multicollinearity and non-autocorrrelation of error terms.

It is important to note that these assumptions are unlikely to realistically be met in any given panel dataset taken from the real world. In particular, the likely existence of an individual-specific effect u_i, which captures characteristics specific to the individual countries which are not represented by the X_{it}' vector, may lead to a violation of these three assumptions. Thus, the pooled OLS model specification is included in this analysis for the sake of completeness; this first regression gives us a naive intuition of the overall relationship between economic growth and gross loan portfolio per capita growth in the SADC region for the entire time period considered while acting as a robustness check against our other model specifications.

The second model specification considered is the **fixed effects model.** The fixed effects model assumes there is indeed correlation of unknown form between the entity error term, u_i and the explanatory variables, X_{it}. It furthermore assumes that there is no correlation between the composite error terms ($u_i + e_{it}$) for the different entities i considered — in our analysis, countries. In a fixed effects model, the goal is essentially to eliminate the unobserved heterogeneity, u_i, for example through the use of dummy variables or otherwise by taking deviations from the group means. The parameter estimate for a dummy variable is a part of the intercept in the fixed effects model. If an intercept is reported, it usually represents the average of the individual-specific intercepts (Wooldridge 2010, p. 439).

The third model specification considered is the **random effects model.** Unlike the fixed effects model, the random effects model assumes there is no correlation between the entity error term, u_i and the explanatory variables, X_{it}. In this sense, the individual-specific effect is treated as a random variable and thus as a component of the error term. A random effects model is essentially an application of fGLS to panel data.[10]

Finally, we fit an **IV model** using **2SLS.** Please refer to the subsequent section on model selection criteria for more information on how the foundation of FE or RE model is chosen to build the IV specification. The rationale behind considering an IV model specification is that the size of gross loan portfolio is potentially endogenous in the economic growth equation. Whether this is actually the case remains an open question that will be assessed via the Durbin-Wu Hausman test, which is also explained in greater detail in the subsequent section.

Endogeneity is a term broadly used to refer to a situation where an explanatory variable may be correlated with the error term (Wooldridge 2010, p. 77). Three possible sources of endogeneity are omitted variables, measurement error, and simultaneous causality.[11] The possibility of a measurement error is not dealt with by the estimation techniques mentioned here, though it ought not to be discarded and we will come back to it in our final analysis of the results; the fixed effects estimation technique already mentioned offers a way of addressing omitted variable bias so long as the omitted variables do not affect both the dependent variable and variable of interest, but only the dependent variable; the question of simultaneity in our economic growth equation remains an open one.

In the literature on the subject of the relationship between microfinance initiatives and poverty, it is cited that reverse causality may arise between the size of microfinance and the severity of poverty in a particular nation as development agencies are likely to channel more funds to those countries where poverty is most rampant (see, for example, Zhang, 2017; Imai et al., 2012). Insofar as economic growth is a determinant of poverty, we can postulate that reverse causality may arise between economic growth and the size of microfinance loans (GLP) as, for example, development agencies with a social mission in mind may channel more funds to a particular country in times of an economic recession. Thus we do not rule out the potential endogeneity of MFI gross loan portfolio size.

The affair of finding a suitable instrument for the potentially endogenous microfinance variable in our economic growth equation is complex. In order to be considered a viable candidate, the instrument must not be correlated with the error term (a property which cannot be tested) but must be correlated with the endogenous variable we are seeking to account for (which can be theorised as well as tested). In the case of this particular analysis, this means that the instrumental variable/s (IV/s) used must correlate with the size of microfinance GLP but not have a direct causal effect on economic growth.

In practice, in empirical studies using observational data where the identification of an appropriate instrument is difficult, lagged explanatory variables are commonly used. Indeed, when lagged explanatory variables have no direct causal effect on the dependent variable or on the unobserved confounding variables, the "lagged IV" method has been reliably shown to mitigate the endogeneity problem (Bellemare and Wang, 2019). Accordingly, the IV model that is set to work here uses two instruments: firstly, a one-period lag of the GLPPC growth variable; secondly; the lag of the 5-year average of gross loan portfolio weighted by the number of MFIs in each country, adjusted for stationarity. This second microfinance instrument was originally used in the context of a study on the potential link between microfinance size and poverty reduction. It is nonetheless useful in the context of our study as it intends to account for the extent of institutionalisation of microfinance in a particular country, which may in turn help account for the potential problem of reverse causality. It is hypothesised that the greater the extent of institutionalisation (proxied here by a larger number of pre-existing MFIs) the more likely foreign investors would be willing to invest in an MFI in that country (Imai et al., 2012, p. 1681).

It should be noted here that the case to be made for reverse causality in the context of the study of the relationship between microfinance size on economic growth is weaker than that to be made in the context of the relationship between microfinance size and poverty. Nonetheless, as economic growth has been extensively documented[12] to directly interact with both financial development and poverty, we thought it prudent to also consider such an IV model as a potential candidate for analysis.

Data Preparation and Preliminary Tests

To begin, we run the **Fisher-type test for a panel unit root** on our choice dependent variables: this type of test is selected because it allows for gaps in the time series considered. The Fisher-type approach essentially tests for a unit-root in each panel individually and then combines the p-values from the individual tests into an overall assessment of the composite panel. The null hypothesis of this unit root test is that there is a unit root present in all panels (Choi 2001 as cited in StataCorpLLC). If the null hypothesis is rejected, this means that the data is stationary. If the null hypothesis is *not* rejected, we cannot conclude that the data is non-stationary, and in this case we take a log first difference of the series in question. This transformation approximates a growth rate.

After we have made the appropriate transformations to ensure the stationarity of our data, we examine the level of correlation between the regressors in our equation. This is done using **Pearson's correlation coefficients**, and the results of this test are displayed in table Table 4. It is important to observe the level of correlation because, if two variables are highly positively or negatively correlated, we could run into the problem of multicollinearity in our data analysis.

The results of the unit root tests and the PCCs are discussed in section 6.2.

Model Selection Criteria

After accounting for potential multicollinearity problems, we use the Akaike Information Criteria (AIC) for our model selection. The AIC, in essence, selects a model from all potential variables mentioned based on the tradeoff each variable presents with regards to model fit and model complexity (see section 4 for descriptions of all potential variables). As we are only dealing with 9 cross-sectional units and our panel is unbalanced, it is not technically possible to estimate an equation which includes all candidate regressors put forth in sections 4.2 and 4.3, which is why such an IC selection method is employed. It accounts for the fact that each additional independent variable in the X_{it}' vector brings with it the risk of 'overfitting': each additional variable included in the model is associated with a penalty term. The model selected by the AIC is the one that explains the greatest amount of variation in the data using the fewest independent variables. For the sake of this analysis, both 'specific to general' and 'general to specific' methods are considered. In both, we keep our variable of interest — microfinance size as measured by gross loan portfolio per capita — fixed (i.e. it is included unconditionally in the model specification).

After determining which variables to include in our specification based on the AIC, we analyse the **F-test on the fixed effect model** to determine if unobserved heterogeneity can indeed be said to be present, and consequently whether a fixed effect model is preferred to a pooled OLS model. To understand this test better, observe again the panel data model specification in equation (1). The null hypothesis of the F-test is that all u_i equal zero, and the alternative is that at least one of these unobserved fixed (i.e. time invariant) effects is non-zero.

In a similar vein, we use the **Breusch-Pagan Lagrange Multiplier test** to determine if there is a significant random effect in the model, and consequently if a random effect approach is preferred to pooled OLS. The LM test examines the variance of u_i . Its null hypothesis is that the variance of u_i terms is zero — that is, that there is no significant difference across entities in our panel.

The above two tests tell us if a FE or RE model is preferred to a pooled OLS model. We use the **Hausman test** to decide between a FE and a RE model. Its null hypothesis is that the individual effects are not correlated with the other regressors. The favoured model is used for the next step of data processing — building and testing the IV-2SLS model.[13]

Once the IV model is set up we perform the **Durbin-Wu Hausman test** for endogeneity. A rejection of the null hypothesis would indicate that the endogenous regressors' effects on the estimates are meaningful and consequently that IV techniques are appropriate.

As a preliminary to these model selection tests, we perform the **Breusch-Pagan test** for heteroskedasticity, with a null hypothesis of homogeneity. If potential heteroskedasticity is indicated, we cluster standard errors at the institutional level to address it.

6. Results

6.1. Descriptive Statistics

Table 5 provides an overview of the mean of the variables most relevant to the macroeconomic conditions of each country as well as the average level of institutional democracy in each. This data allows us a rudimentary overview of key between the countries in our sample. We do not observe the change in each of these variables over time, but we can conclude that, for our sample period, on average, South Africa is the wealthiest country as measured by GDPPC with Angola in second place, while Mozambique, Malawi, and the DRC rank last; South Africa and Tanzania have the highest GLPPC coming to just over 9 USD per capita, while Angola, Zambia, and Zimbabwe enjoy less than half a dollar per capita; Angola and Zimbabwe also are reported to have incredibly low levels of institutional democracy (below 3 on the 11 point scale), along with Tanzania, while South Africa is reported to have the highest level of institutional democracy. It is furthermore worth noting that the countries with the greatest wealth are also those with the highest level of government expenditure (GovExp), and that South Africa, while also being the country with the greatest GDPPC, GLPPC, and highest level of institutional democracy, has the most developed financial sector as proxied by domestic credit (DC).

Table 5 Mean of Key Variables by Country over 1999-2019

Variable	Angola	Congo. Dem. Rep.	Madagascar	Malawi	Mozambique
GDPPC	6777.80	886.72	1573.98	904.14	990.28
GLPPC	0.43	1.45	2.77	2.39	1.07
MFI	2	33	20	11	11
Pop	2.30E+07	6.39E+07	2.08E+07	1.44E+07	2.32E+07
DC	12.47	3.70	9.86	8.26	17.90
Infl	57.71	73.13	8.99	16.74	8.15
Educ	22.14	42.21	33.13	34.63	20.16
Trade	96.73	60.88	56.07	61.67	79.92
Demo	1.70	3.45	5.90	5.95	5.30
GovExp	1.48E+10	1.21E+09	1.42E+09	8.96E+08	2.42E+09

Variable	South Africa	Tanzania	Zambia	Zimbabwe
GDPPC	11897.89	1975.27	2835.57	2752.38
GLPPC	9.98	9.66	0.49	0.41
MFI	18	26	13	9
Pop	5.10E+07	4.39E+07	1.35E+07	1.28E+07
DC	68.11	9.76	9.70	24.84
Infl	5.29	7.05	13.67	2.13
Educ	93.23	29.30	n.a.	46.38

Trade	58.35	39.45	68.25	70.43
Demo	9.00	2.40	5.75	2.60
GovExp	7.06E+10	3.22E+09	1.90E+09	3.70E+09

Table 6 below displays the key summary statistics of each variable considered in the preliminary stages of the analysis. Descriptions of each variable are found in section 4. As much of the information provided herein is self-evident, we will only verbally describe noteworthy observations.

With relation to data quality, it is worthwhile to note that the education panel (Educ), as proxied by gross secondary school enrolment, contains the highest number of missing data points.[14] The remaining variables have a comparable number of observations, and the regressand (GLPPC) is the most complete series.

It is interesting to observe that the mean level of institutional democracy in the SADC region over the time period of 1999-2019 clocks in at just below 5, indicating moderately weak institutional democracy in this region.[15] From table 5 above and the standard deviation, we know the spread of this variable is rather large. The implications of this observation will be explored in the analysis section of the thesis paper.

With respect to MFIs specifically, we look at the bottom half of the table, where the social and financial indicators are displayed. These numbers tell a story. From here we observe that, on average, growth in number of active borrowers has been strong at 37.45% (NoABgr), but that the variation over time and between countries is substantial, as evidenced by the standard deviation of 135.68%. Though these figures may seem large at first glance, if we consider that MFIs serve clients in the tens and maximally up to hundreds of thousands in these countries (according to the original NoAB data collected from the MIX Market), a growth of 100% in a year does not necessarily represent many clients in absolute terms. The average loan balance per borrower comes to circa 278 USD, but an average loan balance as small as 2.09 USD has also been seen.[16] Encouragingly, it seems as if the majority of MFI clients are female (a PFem of 58.09% on average). These are all considered social indicators.

As far as the financial indicators go, the real yield on gross portfolio (YGP) is usually positive and large, with an average of 43.90% reported. This is consistent with the high interest rates typically charged by MFIs. Operating expense to loan portfolio is, on average, high as well (64.08%), which reflects the level of inefficiency of the MFIs (Banto and Monsia, 2020, p. 4). We observe an average negative return on assets (ROA) and a negative profit margin (PMar): both are indicators of a bank's profitability. That both these measures are negative is not surprising as MFIs are often subsidised (Banto and Monsia, 2020, p. 7)

Table 6 Summary Statistics by Variable over 1999-2019

Variable	Obs. Count	Mean	Std. Dev.	Minimum	Maximum
GDPPC	189	3,399.34	3,528.39	630.70	12,884.06
GLPPC	161	3.40	8.17	0.00	64.06
DC	182	18.43	20.28	0.45	84.05
Infl	168	22.36	61.42	-2.43	513.91
Educ	101	43.03	26.51	5.29	109.44
Trade	185	65.84	21.80	23.98	152.55
Demo	180	4.67	2.56	0.00	9.00
GovExp	150	1.31E+10	2.43E+10	2.64E+08	8.89E+10
NoABgr	156	37.45	135.68	-89.87	1100.89
AvgLBB	155	278.43	1,916.02	2.09	23,895.46
PFem	151	58.09	21.08	7.98	100.00
YGP	118	43.90	21.97	5.81	123.20
ROA	149	-3.94	14.03	-71.02	27.97
OELP	147	64.08	38.63	0.55	238.40
PMAR	158	-42.08	138.23	-949.96	200.06

6.2. Data Preparation

Unit Root Tests

To lay the stage for our econometric regression analysis, we must evaluate the stationarity of all panels of variables described in section 4. If a particular time series in a panel is non-stationary, this implies that its mean and variance are not constant over time, which in turn entails that we cannot make reliable predictions with the data using our standard econometric methods. "For example, if a series is consistently increasing over time, the sample mean and variance will grow with the size of the sample" such that mean and variance of future periods will be underestimated (Duke University, n.d.). Stationarity of our variables is thus induced in the panels where we have sufficient evidence to believe that it is not already present. This is done so that we may reliably analyse our regression results of a later stage.

In order to evaluate if the time series in a particular panel is stationary, we used the Fisher-type test for a unit root (results available upon request) and transformed each panel until we had sufficient evidence to deduce it had been rendered stationary. In the case where the null hypothesis for a unit root was not rejected on the first instance of testing, the panel of the variable in question was subjected to a log transformation such that each data point for variable x was replaced with log(x) in the panel. The log-transformed panel for the variable was then tested again for a unit root. If the null hypothesis of the Fisher-type test was not rejected a second time, after the log(x) transformation, the difference of the log(x) panel data was taken such that each data point was represented by $\log(x_t) - \log(x_{t-1})$. These log-differenced series were tested once more (a third time) for a unit root: all panels were rendered stationary by such "log-differencing". The following variables were all transformed in this manner: GLPPC, GDPPC, DC, Educ, Trade, GovExp, PFem, and YGP.

An advantage of the log-differencing transformation to induce stationarity (i.e. taking a first difference of log-transformed variables) is that it allows us to interpret these variables in terms of a growth rate. The log-difference provides an approximation for percentage change in a discrete time framework which "is almost exact if the percentage change is small." (Duke University, 2007). Thus the GLPPC, GDPPC, DC, Educ, Trade, GovExp, PFem, YGP variables are interpreted in terms of a growth rate in the further stages of analysis. To distinguish the growth rate approximation from calculation according to the discrete-time framework, we flag the transformation with the words "growth as per diff-log". Note that, if we observe only the time series of these differenced logarithmic values, we would need to multiply by 100 to interpret each value in terms of a percentage change: this step is not relevant in a regression context. (See section 6.4 for a robustness check of our results where the growth rates for selected variables are calculated according to the discrete-time framework formula, $(x_t - x_{t-1}) / (x_{t-1})* 100$.)

Pearson Correlation Coefficients

As the next step in our data preparation, we analyse the Pearson Correlation Coefficients between all variables. This is an important step as we are thereby able to rule out potential multicollinearity, which would be indicated by either a highly positive or highly negative correlation coefficient. What's more, though, is that we are able to observe from the PCCs what relationship the regressand, economic growth, has to our various potential regressors.

As far as the macroeconomic controls go, from table 4 below, we observe a low but positive and signifiant correlation between GLPPC growth (the measure of the growth in the size of microfinance) and GDPPC growth; a low but positive and significant correlation of

GDPPC growth with domestic credit growth, education growth, democracy, and government expenditure growth; a low (in absolute value) but negative and significant correlation of GDPPC growth with inflation. The result regarding inflation is perhaps surprising from a theoretical perspective as moderate levels of inflation are typically positively associated with economic growth. In this context, as the descriptive statistics of section 6.1 reveal, inflation in the SADC region (for the countries in our sample) has not been moderate but at times countries in the sample have experienced hyperinflation. The corrosive association between inflation and GDPPC growth is thus consistent with standard economic theory.

GLPPC growth, our variable of interest, is itself positively associated with domestic credit growth, which may suggest a complementary relationship between MFIs and more traditional banks. It is furthermore positively associated with government expenditure and trade growth, the latter relation being unsurprising considering trade growth is included as a variable to capture the degree of openness of the economy and that MFIs are generally highly dependent on foreign investment (Bogan, 2012). It is intuitive that GLPPC growth would be positively correlated with average loan balance per borrower: as the size of the gross loan portfolio increases, holding number of borrowers approximately constant, the average loan balance per borrower would logically increase. The same logic is applicable to the slight positive correlation of GLPPC with the growth in number of active borrowers.

In general, the social and financial indicators of MFI performance which are grouped in the lower portion of the table are not significantly correlated with any other variables over and above what would be expected from a mathematical and definitional standpoint (as with, for example, the positive correlation between ROA and PMar). Given the insignificance of their correlation, it is therefore perhaps not surprising that no social or financial indicator was selected by the AIC model selection method when modelling GDPPC growth as a function of

GLPPC growth and other variables. The AIC selection method and its results are explained in greater detail in the following section.

Table 4 Pearson Correlation Coefficients

Variable	GLPPC growth as per diff-log (annual %)	GDPPC growth as per diff-log (annual %)	DC growth as per diff-log (annual %)	Educ growth as per diff-log (annual %)	Infl (annual %)	Trade growth as per diff-log (annual %)	Demo
GLPPC growth as per diff-log (annual %)	1						
GDPPC growth as per diff-log (annual %)	0.1414**	1					
	(0.0853)						
DC growth as per diff-log (annual %)	0.2102**	0.2689***	1				
	(0.0109)	(0.0004)					
Educ growth as per diff-log (annual %)	0.1288	0.345***	0.117	1			
	(0.2775)	(0.0014)	(0.3015)				
Infl (annual %)	0.001	-0.2864***	-0.1782**	0.2214*	1		
	(0.9904)	(0.0002)	(0.0256)	(0.0546)			
Trade growth as per diff-log (annual %)	0.152**	-0.0077	0.1039	0.1236	-0.2167***	1	

	(0.0652)	(0.919)	(0.1802)	(0.2746)	(0.0062)		
Demo	-0.0404	0.1555**	-0.0692	-0.1655	-0.4066***	0.0353	1
	(0.6246)	(0.0422)	(0.3785)	(0.1422)	(0.000)	(0.6483)	
GovExp growth as per diff-log (annual %)	0.184**	0.4862***	0.2461**	0.1288	-0.2601***	0.0791	0.043
	(0.0399)	(0.000)	(0.0037)	(0.2844)	(0.0025)	(0.3512)	(0.6207)
NoABgr	0.2174***	-0.0134	0.0829	0.0875	0.0705	-0.0055	0.1438***
	0.0078	0.8669	0.3097	0.4618	0.4059	0.9451	0.0715
AvgLBB	0.2235***	0.0184	0.0156	0.0706	0.0308	-0.0217	-0.1304
	(0.0071)	(0.8222)	(0.8503)	(0.5555)	(0.7186)	(0.7923)	(0.1058)
PFem growth as per diff-log (annual %)	0.0423	-0.0462	-0.1119	-0.1219	0.0523	-0.0689	0.0317
	(0.6264)	(0.5947)	(0.1997)	(0.3219)	(0.5689)	(0.429)	(0.7155)
YGPgrowth as per diff-log (annual %)	-0.1552	0.0867	-0.0085	0.1195	0.0437	0.2058	0.0115
	(0.1139)	(0.3792)	(0.9316	(0.3589	(0.6598	(0.0361	(0.9073)
ROA	-0.1441**	0.03	0.0236	-0.1118	0.1019	-0.012	-0.1403**
	(0.0837)	(0.7193)	(0.7788)	(0.3499)	(0.2411)	(0.8861)	(0.0878)
OELP	0.0694	-0.065	-0.1093	0.2813**	0.0641	0.1117	0.0708
	(0.4103)	(0.4388)	(0.1952)	(0.0167)	(0.4654)	(0.1839)	(0.3941)
PMar	-0.0568	-0.0582	0.0549	-0.1716	0.0464	-0.0114	-0.1613**
	(0.4961	(0.473)	(0.5032)	(0.1411)	(0.5834)	(0.8892)	(0.0429)

Variable	GovExp growth as per diff-log (annual %)	NoABgr	AvgLBB	PFem growth as per diff-log (annual %)	YGP growth as per diff-log (annual %)	ROA	OELP

GovExp growth as per diff-log (annual %)	1						
NoABgr	0.0066	1					
	(0.9401)						
AvgLBB	0.0184	-0.0796	1				
	(0.8391)	(0.3381)					
PFem growth as per diff-log (annual %)	-0.0226	0.1259	-0.0145	1			
	(0.8119)	(0.1456)	(0.868)				
YGP growth as per diff-log (annual %)	0.178	-0.0639	-0.0089	-0.0939	1		
	(0.0895)	(0.5171)	(0.9284)	(0.3603)			
ROA	0.0254	0.0688	0.0598	-0.0142	0.0446	1	
	(0.7814)	(0.4110)	(0.4735)	(0.8701)	(0.6512)		
OELP	0.0869	0.0069	-0.12	-0.0246	0.1648**	-0.6714***	1
	(0.3452)	(0.9344)	(0.1519)	(0.7784)	(0.093)	(0.000)	
PMar	-0.0027	0.0570	0.037	0.0247	-0.0197	0.3529***	-0.2139***
	(0.9755)	(0.4884)	(0.6511)	(0.7768)	(0.842)	(0.000)	(0.0095)

Robust Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

6.3. Model Selection

AIC Selection Process

The AIC selection process is used such that we construct and fit a model whereby the greatest variation in the data is explained using the fewest independent variables. Such an IC selection method is used because of the limitations of available data: as we are only dealing with 9 cross-sectional units and our panel is unbalanced, it is not technically possible to estimate an equation which includes all candidate regressors put forth in sections 4.2 and 4.3.

For the AIC selection process, we consider both 'specific to general' and 'general to specific' methods as each acts as a robustness check for the other, keeping our variable of interest — microfinance size as measured by gross loan portfolio per capita (in growth terms, after our stationarity transformation) — fixed in the model specification, i.e. we include it unconditionally. Specific to general means we start with just our dependent variable of interest and our independent microfinance size variable and systematically add in and test whether the addition of each new potential variable improves the ratio of model fit to complexity. For the general to specific method of selection, we start with all potential dependent variables on the right-hand side of the equation and systematically remove and test the affect of the removal of variables on the AIC (all except GLPPC growth). The model which minimises the AIC is selected. Both the forward and backward selection methods agree on the same model.[17]

Formally, to repeat, the model selected is given by:

$$y_{it} = c + X_{it}'B + u_i + e_{it} \quad (1)$$

According to the AIC selection, y_{it} represents GDPPC growth; c is a constant; X_{it}' is the vector of time-varying explanatory variables that comprises GLPPC growth, education (participation) growth, inflation, trade growth, and government expenditure growth; B is the column vector of parameters to be estimated, u_i is the individual-specific effect (unobserved heterogeneity), and e_{it} is the error term.

Notice that X_{it}' largely comprises macroeconomic indicators. This in itself is worthy of analysis as it implies that neither the social nor financial performance of MFIs are well-able to explain economic growth *vis-à-vis* the tradeoff of model fit to model complexity. As mentioned in the previous section on the Pearson Correlation Coefficients, we find few of the social and financial microfinance indicators are correlated with economic growth at a statistically significant level and thus find it unsurprising that they do not feature in the final model selected.

Model Specification

The results of the battery of tests geared towards our ultimate model selection are displayed in the lower quadrant of Table 7. In summary, the Breusch-Pagan test indicates potential heteroskedasticity, thus we cluster standard errors at the institutional level to address it. Robust standard errors for each model specification are reported in parentheses. The null hypothesis of the F-test, that all u_i equal zero, is rejected in favour of the alternative that at least one of these unobserved fixed effects is non-zero: thus the fixed effects model is preferred to the pooled OLS model specification. The Breusch-Pagan Lagrange Multiplier test, which examines the variance of u_i, does not indicate the presence of a random effect.

At this stage our analysis indicates that a FE model is preferred to a pooled OLS model, but that a RE model is not necessarily preferred to a pooled OLS model. The results of the Hausman test, which could potentially corroborate a preference for a FE over a RE model were inconclusive. Thus we turn to econometric theory for further guidance.

Williams writes on the econometric intuition behind FE and RE models. RE models, he summarises, are best if we have reason to believe that the omitted variables in our model specification are *uncorrelated* with the explanatory variables we have chosen, while a FE model should be preferred if we have reason to believe the opposite is true (2018). In our case, an examination of the PCCs (reported in Table 4) give us reason enough to believe that the FE model is most appropriate. In particular, we observe a statistically significant, strong and negative correlation of -0.4066 between inflation and democracy; also, statistically significant correlations can be observed between ROA and GLPPC and between AvgLBB and GLPPC. Thus we know from the PCCs that at least democracy, ROA, and AvgLBB — potential explanatory variables that were nonetheless omitted from our ultimate model specification — are correlated with our regressors. It is possible that other relevant variables have been omitted which we did not consider in our PCC calculation. As mentioned in the methodology section, a FE model gives us a way to control for this particular type of endogeneity.

Considering the results of the F-test, the Breusch-Pagan Lagrange Multiplier test, and the input of economic theory, we conclude that the fixed effects model is preferred to both the pooled OLS and random effects specifications. Next we examine the IV model, which we build using the FE model as scaffolding. Using two instrumental variables for GLPPC growth (a one-period lag of the GLPPC growth variable and the lag of the 5-year average of gross loan portfolio weighted by the number of MFIs in each country, adjusted for stationarity) we run the Durbin-Wu Hausman test. The null hypothesis of the Durbin-Wu Hausman test was not rejected. Thus we do not have sufficient evidence for the relevance of the use of IVs. Taken altogether, the results of the statistical tests and the econometric intuition give us strong reason to believe that a FE model is most appropriate for our analysis. This makes sense especially if we consider that the limitations of available data necessitated an IC selection method of variables. Thus we work solely with this model (model (2) in Table 7) from hereon out. Please refer to Appendix C for a visualisation.

Table 7 Model Selection

GDPPC growth as per diff-log (annual %)	(1) Pooled OLS	(2) FE Model	(3) RE Model	(4) IV Model
GLPPC growth as per diff-log (annual %)	-0.0009	0.0018	-0.0009	-0.011
	(0.0014)	(0.0016)	(0.0019)	(0.0113)
Educ growth as per diff-log (annual %)	0.0422**	0.0377	0.0422***	0.0402*
	(0.0167)	(0.0217)	(0.014)	(0.023)
Infl (annual %)	-0.0005**	-0.0006*	-0.0005***	-0.0005*
	(0.0002)	(0.0003)	(0.0001)	(0.0003)
Trade growth as per diff-log (annual %)	0.0145	0.0172	0.0145	0.0174*
	(0.0098)	(0.0138)	(0.0114)	(0.0099)
GovExp growth as per diff-log (annual %)	0.0251**	0.0133***	0.0251***	0.0156
	(0.0116)	(0.0034)	(0.0048)	(0.0112)
Cons	0.0108***	0.0123***	0.0108***	0.0112***
	(0.0018)	(0.0018)	(0.0021)	(0.003)
N	65	65	65	64
R-sq	0.261	0.217	0.261	0.115
Breusch-Pagan test		F-test	Breusch-Pagan LM test	Durbin-Wu Hausman test

Chi-sq (6) = 21.8 Prob>chi-sq = 0.0013	F(5,7) = 23.22 Prob > F = 0.0003	Chi-sq(01) = 0.00 Prob>Chi-sq=1.00	F(1,7) = 2.73 Prob > F = 0.1422

Robust Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

6.4. Robustness Checks

Microfinance Size and Economic Growth in the Discrete-time Framework

The regressions represented in Table 7 Model Selection rely on variables that have been transformed, with the exception of the inflation rate, to growth rates with a log-difference approximation. The log-differencing of a variable (i.e. taking the first difference of a logarithm-transformed variable) gives an approximation to percentage change in a discrete time framework that "is almost exact if the percentage change is small" (Duke University, 2007). Recall that a log-difference transformation was imposed on certain relevant variables likely possessing unit roots, as described in section 6.2 on data preparation, to induce stationarity of these variables. Stationarity of variables is necessary to reliably analyse regression results (Duke University, n.d.).

As a robustness check to our results, we run the fixed effects model using the variables of microfinance size growth and economic growth calculated according to the discrete-time framework formula. In other words, for our robustness check, the growth rates for GDPPC, GLPPC, Educ, Trade, and GovExp are calculated according to the formula $(x_t - x_{t-1}) / (x_{t-1})* 100$, with each variable denoted by x in turn. These growth rates were each tested for stationarity using the Fisher-type test described in section 6.2: the results of the Fisher-type tests indicated sufficient evidence to support the hypothesis of the overall stationarity of all time series for each panel variable. Thus no further transformations were made.

A further robustness check that uses discrete increments of each variable was considered (i.e. taking only a first-difference of each variable in question). However, the Fisher-type tests of the first-differenced variables suggested the presence of a unit root in all panels. Thus we present only the results for the robustness check using the discrete-time framework growth rates. These results are presented in Table 8 below.

Table 8 FE Model in Discrete-time Framework

GDPPC growth (annual %)	FE Model
GLPPC growth (annual %)	0.0000
	(0.0001)
Educ growth (annual %)	0.0022
	(0.0251)
Infl (annual %)	-0.1682***
	(0.0294)
Trade growth (annual %)	0.0360
	(0.0279)
GovExp growth (annual %)	0.0867**
	(0.0336)
Cons	3.3908***
	(0.3195)
F-test	F(5,7)=44.36
	Prob > F =0.00
N	95
R-Sq	0.277

Robust Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

The results of the discrete-time framework robustness check are analogous to those obtained by the FE model, where the growth rates of relevant variables are calculated as per the diff-log transformation. On a macro level, the R-squared values of 0.217 of the FE model in section 6.3 and 0.277 of this robustness check indicate that a comparable amount of variation in the outcome variable is explained by the regressors of each respective model. On a more granular level, we observe that the only statistically significant contributors to economic growth in this regression, as with the FE model in 6.3, are inflation, government expenditure growth, and the constant. As with the FE model presented in section 6.3, the results of which will be analysed at greater length in the subsequent section, the growth in the size of microfinance as measured by gross loan portfolio can not be said to be a statistically significant determinant of economic growth in the context of this regression: moreover, the coefficient estimated in the robustness check is essentially zero, while in the FE model of section 6.3 a very slight positive coefficient of 0.0018 is estimated (albeit also not at a statistically significant level). The coefficient estimated on inflation in the robustness check is -0.1682 as opposed to -0.0006 of the FE model of 6.3; it is 0.0867 as opposed to 0.0133 on government expenditure growth; and it is 3.3908 as opposed to 0.0123 on the constant. In other words, each statistically significant variable explains a greater amount of the overall variation in the outcome variable in the discrete-time framework estimation. The last observation regarding the value of the constant estimated represents the greatest difference in the value of the statistically significant estimated coefficients between the robustness check and the FE model of section 6.3.

The constant of a FE model represents the average of the intercepts specific to each individual subject (Wooldridge 2010, p. 439).[18] It does not, however, estimate the average effect of those variables that do not change across time (Williams, 2018, p. 2). Rather, observing that its estimated value is statistically significant is itself useful as this implies that there are omitted variables in our specification which significantly explain our outcome variable of GDPPC growth. Put another way, the fact that the constant estimated is positive and statistically significant is more informative than the absolute value estimated. Thus we can conclude that the results of the robustness check align closely with those of the FE model of the previous section, lending support to its analysis in the following section. We also observe that the presence of fixed-effects is indicated by the F-test in the discrete-time framework regression presented here, lending further support to our choice to analyse the FE model of section 6.3 in greater detail out of all candidate models.

Microfinance Size, Economic Growth, and the Global Financial Crisis

As a second robustness check to our results, we considered dividing the data into sub-samples by subject (country) and excluding one country at a time from the FE model. The motivation behind dividing the data by country is that we would be able to glean, by fitting an econometric model for the dataset with one country missing at a time, which particular countries might be driving the relationship between economic growth and GLPPC growth.

Unfortunately this country-by-country analysis was not possible due to the insufficiency of data; a year-by-year analysis was not possible for the same reason. Thus, as an extension to the model specification detailed in section 6.3, we decided to split our data along the lines of a key global event. Specifically, we examine whether there is any statistically significant influence of the aftermath of the 2007-2008 global financial crisis of on economic growth in the SADC region, controlling for MFI initiatives.

The implicit interest in introducing a crisis variable is to see if the relationship between economic growth and microfinance size is indirectly impacted: it is not possible to examine an interaction effect between the crisis and microfinance size with this data set because of collinearity issues. The rationale behind why MFI initiatives may have been impacted by the global financial crisis has to do with the increased vulnerability of MFIs to fluctuations in global financial markets (Wagner and Winkler, 2013; Soumare et al., 2020). Thus it is possible that controlling for the crisis may affect the estimated coefficient on annual GLPPC growth.

To conduct this analysis, we introduce a dummy variable to our data set which takes on the value of 1 for each year post-2008, and 0 otherwise (i.e. 1999-2007 are coded 0 and 2007-2019 are coded 1). Then, we run the regression as before according to the fixed effects model corresponding to column (2) in Table 7, including the new 'crisis' dummy variable as a regressor. What this dummy variable allows us to do is to interpret whether the global financial crisis had an impact on the economies represented in our particular sub-sample of the SADC.

From table 9 below we can see that the FE model estimates a coefficient of -0.0067 on the crisis dummy variable that is significant at a 5% level. This indicates that the crisis, did indeed have a statistically significant negative impact on economic growth in this region overall, with every year post-2008 associated with 0.0067% lower economic growth (holding all other regressors fixed).

Table 9 Effect of the Global Financial Crisis

GDPPC growth as per log-diff (annual %)	FE Model
GLPPC growth as per log-diff (annual %)	0.0012
	(0.0021)
Educ growth as per log-diff (annual %)	0.0205
	(0.0206)

Infl (annual %)	-0.0005*
	(0.0002)
Trade growth as per log-diff (annual %)	0.0156
	(0.0126)
GovExp growth as per log-diff (annual %)	0.0109**
	(0.0037)
Crisis	-0.0067**
	(0.0022)
Cons	0.0177***
	(0.0019)
F-test	F(6,7)=8153.54
	Prob > F =0.00
N	65
R-Sq	0.37

Robust Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

As with model (2) represented under section 6.3, this model formulation including the crisis variable finds inflation, government expenditure growth, and the constant to be the only significant predictors of economic growth in the region, where we can recall from the explanation in section 5.2 that the constant reported here represents the average of the individual-specific intercepts. The effect of our MFI variable of interest, the growth in the size of the gross loan portfolio per capita, has remained small and statistically insignificant even when factoring the potential miscellaneous effects of the global financial crisis into the equation.

Note that the F-test run here indicates that a fixed effects model is preferred to the pooled OLS formulation; also note that the R-squared value of 0.37 is higher than the value of 0.217 reported for model (2), indicating that the crisis-augmented model fits the observed data with a greater degree of accuracy. The interaction of crisis events with an MFIs ability to fulfil its social and financial missions may be a promising avenue for further research.

7. Analysis

In this section, we decode the results of the previous section, focusing our attention on the fixed effects model selected as the most viable candidate for analysis through our battery of tests as set forth in section 5.2. on the empirical approach. To directly address our research question, as can be observed from table 7, the FE model indicates that the growth in the size of microfinance as measured by gross loan portfolio per capita has no statistically significant effect on economic growth in the sub-sample of the SADC analysed here for the years 1999-2019. The variables that are indicated to have a statistically significant effect are inflation (-0.0006), government expenditure growth (0.0133), and the constant (0.0123). As the estimated coefficients on the remaining variables are not statistically significant, we conclude that these variables (including growth in microfinance size) do not significantly predict the outcome variable of economic growth.

Regarding the viability of the model as a whole we look at the R-squared and F-test. The R-squared value of 0.217 may seem low to an untrained eye — R-squared being a statistic that captures how much variation in the outcome variable is explained by our regressors — but this is comparable to the R-squared coefficient on many empirical studies using real world data (see, for example, the studies mentioned in the literature review). Furthermore, as the F-test value for the FE model is statistically significant, we are able to conclude that the model explains a significant amount of variance in GDPPC growth. For a visualisation of these results, please refer to Appendix C.

For inflation, we interpret the estimated coefficient in the following way: keeping all other variables constant, a 1 percentage point increase (decrease) in inflation is associated with a -0.0006 percent decrease (increase) in GDPPC. In layman's terms, this means that a relative increase in the average price levels in this sub-sample of the SADC is associated with a relative decrease in the average level of household wealth. Indeed, the SADC region as a whole has experienced historically high and volatile rates of inflation, which has the potential to harm developing countries by eroding the value of savings and the purchasing power of the population (SADC, 2012). This finding is consistent with the observation of historically high and highly dispersed levels of inflation for our SADC sub-sample reported in section 6.1.

For government expenditure growth, we interpret the estimated coefficient in the following way: keeping all other variables constant, a 1 percentage point increase (decrease) in government expenditure growth is associated with a 0.0133 percent increase (decrease) in GDPPC. Again we can observe that this general trend is consistent with the snapshot our descriptive statistics provide. Recall from table 5 that the wealthiest countries in our sample are, on average, those with the greatest level of government expenditure. It is interesting to see how this rudimentary observation bears out in our more sophisticated econometric analysis.

To interpret the constant it is useful to once more recall the form of the multiple linear regression equation (1). Remember y_{it} represents the dependent variable, c is the constant, X_{it}' is the vector of time-varying explanatory variables, B is the column vector of parameters to be estimated, u_i is the individual-specific effect (unobserved heterogeneity), and e_{it} is the error term.

Recall that the fixed effects model assumes there is correlation of unknown form between u_i and variables X_{it} but no correlation between the composite error terms ($u_i + e_{it}$) for countries i.[19] This correlation of the error term with the variables vector represents endogeneity which may arise, for example, if there are omitted variables. The fixed effects model accounts for this type of endogeneity problem by letting each subject act as its own control. Thus we treat the unobserved heterogeneity, u_i, as "fixed" parameters to estimate for each subject — hence the name "fixed effects" model. The overall intercept reported for the FE model (2) thus represents the average of the individual-specific intercepts (Wooldridge 2010, p. 439).[20] This, however, does *not* imply that we have estimated the average effect of variables whose values do not change across time. Rather we have "partialled them out" through the use of a FE model (Williams, 2018, p. 2).

On a basic level, from a mathematical standpoint we can interpret the constant as the value y_{it} would assume if all other variables took on the value zero: in this case, the constant 0.0123 indicates that GDPPC growth would be 0.00123% if all other variables in our model were set to zero. This is, however, abstracted from the real world. Though the value of the constant itself does not tell us very much about what exactly is driving the behaviour of our system, the fact that it is significant in our regression is itself informative. In essence, the significance of the constant implies that there are omitted variables which significantly explain our outcome variable. Moreover, as we are operating in the context of a fixed effects model and as fixed effects are positively indicated by our battery of preliminary tests (see section 5.2 for the description and section 6.3 for the results of these tests), this implies that these omitted variables which are, on average, statistically significant, have time-invariant values and time-invariant effects (Williams, 2018, p. 1).

In layman's terms this means that non-negligible drivers of economic growth are variables that do not show up as regressors in model (2) which are themselves specific to each country in the sample, do not change in value over time, and do not change in the way in which they impact economic growth. Without further information on the particularities of each country in the region, it is not possible to say what exactly these omitted variables might rightly be. We can hypothesise that one may be related to the level of development of the underlying infrastructure. Infrastructure generally takes a long time to advance in any country (thus approximating a time-invariant variable), and infrastructure in the SADC is heterogeneously developed (SADC, n.d.). Another may have to do with the level of corruption in the respective nation states, a notoriously intractable problem, which affects resource allocation to such things as development of infrastructure as well as the likelihood of foreign investment, which in turn affect economic development. That this may be the case is hinted at by the large spread in the level of institutional democracy in the region, as observed in relation to the 'demo' variable in section 6.1. Though not a regressor in the final model selected, the 'demo' variable nonetheless does exhibit a positive and statistically significant correlation with GDPPC growth (see Table 4).

We unpack the implications of our econometric findings for the MFI-economic growth connection further in the next section.

8. Synthesis

Applying econometric techniques appropriate to panel data to a sub-sample of the SADC for the years 1999-2019 that was chosen on the basis of data availability from the WDI and MIX Market databases, we found that growth in the size of microfinance has no statistically significant impact on economic growth for the countries in this sample. The following section will situate this finding in the literature at large while highlighting and examining potential drivers for this outcome.

Let us revisit the literature reviewed and examine possible reasons as to why we do not observe a statistically significant positive effect between our outcome and interest variables of GDDPC and GLPPC growth. Recall that, in Ahlin and Jiang's model, microfinance had the possibility to promote full economic development only through an avenue of "saver graduation" — that is to say, if both the increased returns from self-employment that microloans facilitate are complemented with savings services (2005). It is possible that we do not see economic growth in the SADC with a growth in the size of microfinance loans because, according to the logic of this model, the loans are not being put to effective use to generate a return and/or returns are not being saved. Indeed, previous research has shown that while microloans are ostensibly granted only for investment purposes, recipients tend to use the loans to smooth consumption streams, especially if they are living on the edge of subsistence (Morduch, 2011).

Donou-Adonsou and Sodokin postulate something similar in attempting to make sense of the negative and statistically significant coefficient they observe on the equation considering microfinance size and economic growth in the West African Economic and Monetary Union for the period 1999-2005. They hypothesise that the low level of credit supplied via a microloan makes it more feasible for a recipient to consume rather than invest. They also hypothesise that the high interest rates which characterise many microloans may prevent such a loan from being seen as a viable credit option for recipients over a long period of time (2010, p. 506).

Another possible reason for the lack of a statistically significant positive coefficient on our interest variables is that it may be that the predator/prey dynamic that Yusupov warns of has emerged between microentrepreneurs in the SADC. Recall that Yusupov postulates a growth in available funds for microloans may undermine a development mission as competition increases between microentrepreneurs, making it difficult for any one entrepreneur to earn sufficient returns and “graduate” to a higher class (2012). Our results do not demonstrate a directly adverse effect of GLPPC growth on development, but, as they neither evidence a positive effect, it is possible that such a predator/prey dynamic may be at play in our sub-sample to an indeterminate extent, nullifying what might otherwise have been a positive result. Our findings are consistent with the Buera et al.’s theory that the long-run general equilibrium effects of MFI loan provision on economic growth will be negligible — though it is worth reiterating their model suggests MFI initiatives are nonetheless typically associated with welfare improvements for all agents in the economy (2017).

It may also be the case that we do not observe a statistically significant positive coefficient on GLPPC as a non-negligible portion of the countries in our sample (4 of 9) belong to the class of middle-income countries — albeit, of these, mostly to the class of lower middle income countries (see Appendix B for specifics). The lack of significance in the coefficient we observe may be partially due, as Maksudova, who only found a significant positive effect of the lagged growth rate of microfinance portfolio size on economic growth for low income countries, postulates, to there simply not being much “space” for MFI initiatives to have a positive effect on economic growth as compared to formal financial intermediation in middle income countries (2010). The fact that domestic credit growth was eliminated as a potential regressor via the AIC selection method in the preliminary stages of our own analysis throws some doubt on this theory in the context of the SADC, however, as does the observed positive correlation between GLPPC and DC growth and between GDPPC and DC growth in Table 4, which suggests there may be complementarity rather than an implicit rivalry between the two types of intermediation.

Another possibility to consider that was alluded to in section 2 of this thesis paper is that the evolution of the microfinance sector to comprise largely profit-oriented MFIs may be undermining the possibility of MFIs to aid economic development. It is still an open debate whether a profit orientation undermines an MFI’s ability to fulfil a social mission, with some going so far as to say as increased commercialisation of MFIs may actually aid the efficiency and sustainability of MFIs in the long run (Bogan, 2012), and with others pointing out that increased commercialisation has resulted in an increased vulnerability of MFI lending behaviour to turmoil in international financial markets (Samara et al., 2020; Wagner and Winkler, 2013). Without further information on this particular issue, it is not possible to know what direction the effect lies in for the SADC, but it is nonetheless likely that the changing MFI landscape has had implications for its efficacy in promoting economic growth in the region.

Finally, we should also consider that it may actually be the case that an underlying positive relationship does exist between the growth in the size of the gross loan portfolio and economic growth in this region. Indeed, the estimated coefficient on GLPPC growth in our candidate model (2) is positive at 0.0018, but it is not statistically significant. Statistical significance essentially tells us is the probability that our estimated coefficient is significantly different from zero: in other words, it gives us a measure of how confident we can be that our results are meaningful. Currently, we cannot interpret this positive GLPPC coefficient as meaningful. However, it is possible that its statistical significance would improve with more data, which we could only gather for the SADC as more time passes. Along the same vein, it is possible that data quality has impacted the results (see section 5.1 for more details), but it is not possible to say to what extent this might be the case.

9. Conclusion

This thesis paper set out to shed light on the possibility of microfinance initiatives to promote economic growth in the SADC. Specifically, it began by asking the question: *Has growth in the size of microfinance in the lower and middle income members of the Southern African Development Community had a positive and significant effect on economic growth since the turn of the century?* The motivation for this inquiry has to do with the urgency of uncovering effective tools for economic development. While MFI initiatives have shown promise on a global scale, regional analyses have yielded mixed results. An inquiry at the economic growth and microfinance nexus for the SADC in particular has hitherto, to the best of our knowledge, not been made. This paper's aim has been to address that gap.

To answer this question, in the tradition of many papers before, microfinance size was measured by gross loan portfolio. Specifically, following a series of transformations, the growth rate in gross loan portfolio per capita (GLPPC) was used as the main variable of interest as it gives a measurement in the growth of funds disbursed to households. Growth in gross domestic product per capita (GDPPC) was used as our measure of economic development, interchangeably referred to as economic growth. In addition to our interest variable, we considered a handful of macroeconomic control variables and a variety of social and financial indicators of microfinance performance as potential regressors. After a battery of tests and by applying the AIC model selection method, the final model specification was given by a fixed effects model that included GLPPC growth, education (participation) growth, inflation, trade growth, and government expenditure growth as regressors: we found no statistically significant effect of the growth in gross loan portfolio per capita on growth in gross domestic product per capita. Rather, inflation, government expenditure growth, and the constant were the only coefficients that could be interpreted as meaningful explanatory variables for economic growth in our model.

The implications of these results are, firstly, that in order to promote sustainable economic growth, countries in the SADC ought to prioritise maintaining a low and stable rate of inflation. Secondly, considering the positive impact of government expenditure on economic growth, it would be worthwhile for international agencies working to promote development in the region to work more closely with individual governments to streamline and support already-existing governmental initiatives.

In relation to microfinance, while it cannot be said that a growth in its size has contributed to economic growth in the region, this is not to say that it does not have its place in the developmental landscape. Indeed, the literature detailing both its potential harms and potential utility on a variety of fronts — including poverty alleviation, women's empowerment, education, nutrition, and more — is vast. The key result presented here (i.e. the finding of an essentially neutral impact of MFI growth on economic growth) is but one piece of the puzzle that policy makers, NGOs, and other invested parties ought to consider when making decisions on how best to allocate funds to meet their particular developmental objectives.

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Footnotes

[1] 'Micro'

[2] However, an exceptional case exists within this model where poverty and inequality may be exacerbated by microcredit. For more on this exceptional case, please see the paper by Ahlin and Jiang

[3] See "The Impact of Microfinance in Sub-Saharan Africa: A Systematic Review of the Evidence" by Van Rooyen et al. for a detailed overview of microfinance's impact on financial as well as non-financial indicators (like nutrition, eductation, women's empowerment etc.) in SSA. The evidence is that microfinance can have both positive and negative impacts on these various indicators

[4] Population size of each country for the years 1999-2019 was obtained from the World Development Indicators Database

[5] Note the role of domestic credit is complex as the development of the financial sector may be both a cause and a consequence of economic growth (Imai et. al., 2012, p. 1676)

[6] It is worth noting that, in addition to democracy as a political control variable, the World Bank's CPIA property rights and rule-based governance rating as well as their CPIA transparency, accountability, and corruption in the public sector rating were considered for this regression. However, they were ultimately not used for the IC selection methods as only very limited data is available for the particular timeframe and countries under analysis here

[7] See section 2.1 on democracy http://www.systemicpeace.org/inscr/p5manualv2018.pdf

[8] Panel data differs from what is known as independently pooled cross-sectional data as it follows the *same* individuals across time, while pooled cross-sectional data reports on potentially different individuals over time

[9] See, for examples, the studies by Imai et. al. (2012) and Zhang (2017), and the corresponding econometric methods employed to account for the missing data. To account for the problems that arise with non-randomly missing data Zhang employs a Heckman two-step model in her analysis of the years 1998-2013. The Heckman two-step model simultaneously also accounts for endogeneity of regressors. Imai et. al., in contrast, consider only the years 2003 and 2007 in their analysis because the majority of countries globally have poverty statistics available for these years

[10] See Wooldridge, 2016, ch. 14 for more details on fixed and random effects models

[11] I.e. X may be causing Y but Y may also simultaneously be causing X

[12] See, for example, Zhuang et al. (2009) for a review of the complex relationship between financial sector development, economic growth, and poverty reduction.

[13] Note that a limitation of the Hausman test is that it cannot be performed when robust standard errors are integrated into the FE and RE models

[14] Alternate proxies were considered but they exhibited similar degrees of incompleteness

[15] "Democracy is conceived as three essential, interdependent elements. One is the presence of institutions and procedures through which citizens can express effective preferences about alternative policies and leaders. Second is the existence of institutionalized constraints on the exercise of power by the executive. Third is the guarantee of civil liberties to all citizens in their daily lives and in acts of political participation" (see section 2.1. of http://www.systemicpeace.org/inscr/p5manualv2018.pdf)

[16] The large AvgLBB maximum of 23 895.46 USD belongs to the DRC for the year 2018. This does not seem to be an accounting error as the Congo also saw an exponential increase in their GLP in this year

[17] The actual AIC values for the model selected are not reported as an AIC value has relevance only with relation to the all other models tested i.e. an internal relevance to the algorithm

[18] This is the case for the statistical package used for the bulk of the econometric analysis in this thesis paper (namely, Stata). See https://www.stata.com/support/faqs/statistics/intercept-in-fixed-effects-model/ for details

[19] Pooled OLS, in contrast, assumes there is no correlation between unobserved, independent variables and the regressors included in the model specification

[20] This is the case for the statistical package used for the bulk of the econometric analysis in this thesis paper (namely, Stata). See https://www.stata.com/support/faqs/statistics/intercept-in-fixed-effects-model/ for details

Appendix A

German-language Abstract

Diese Abhandlung nimmt die Beziehung zwischen Mikrofinanzinitiativen und der wirtschaftlichen Entwicklung in neun Ländern mit niedrigem und mittlerem Einkommen in der ‚Southern African Development Community' (SADC) von 1999 bis 2019 in Betracht. Die Literatur zu diesem Thema ist nicht eindeutig, regionale Analysen haben heterogene Ergebnisse geliefert, und bisher wurde diese Frage im Kontext der SADC noch nicht untersucht — daher die Motivation für unsere Analyse, die Paneldatentechniken verwendet. Die Modellspezifikation mit festen Effekten (FE) wird aus vier Panelmodellkandidaten ausgewählt. Aus diesem Modell ziehen wir unsere Schlussfolgerungen. Es deutet darauf hin, dass das Mikrofinanzwachstum bestenfalls einen schwachen und statistisch unbedeutenden Beitrag zur wirtschaftlichen Entwicklung in dieser Region leistet, und dass Inflation und Wachstum der Staatsausgaben von allen betrachteten Variablen die besten Prädiktoren für die Ergebnisvariable sind. Diese Ergebnisse sind für die Politikgestaltung nützlich, da sie darauf hindeuten, dass dem Wirtschaftswachstum besser gedient wäre, wenn eine niedrige und stabile Inflationsrate festgelegt würde, und zusammen mit bereits bestehende Regierungsinitiativen statt MFIs unterstützt würden. Auch die Schlussfolgerung, dass MFIs keinen negativen, aber neutralen Einfluss auf das Wirtschaftswachstum haben, ist bei der Abwägung der vielen Argumente für und gegen den Einsatz von Mikrokrediten in dieser Region sinnvoll. Sie kann unabhängig von ihrem Beitrag zum Wirtschaftswachstum immer noch einen Platz in der Entwicklungslandschaft haben.

Appendix B

Income Groups of SADC Sub-sample

Table 10 Income Groups of SADC Sub-sample

Code	Long Name	Income Group
AGO	People's Republic of Angola	Lower middle income
COD	Democratic Republic of the Congo	Low income
MDG	Republic of Madagascar	Low income
MWI	Republic of Malawi	Low income
MOZ	Republic of Mozambique	Low income
ZAF	Republic of South Africa	Upper middle income
TZA	United Republic of Tanzania	Lower middle income
ZMB	Republic of Zambia	Lower middle income
ZWE	Republic of Zimbabwe	Lower middle income

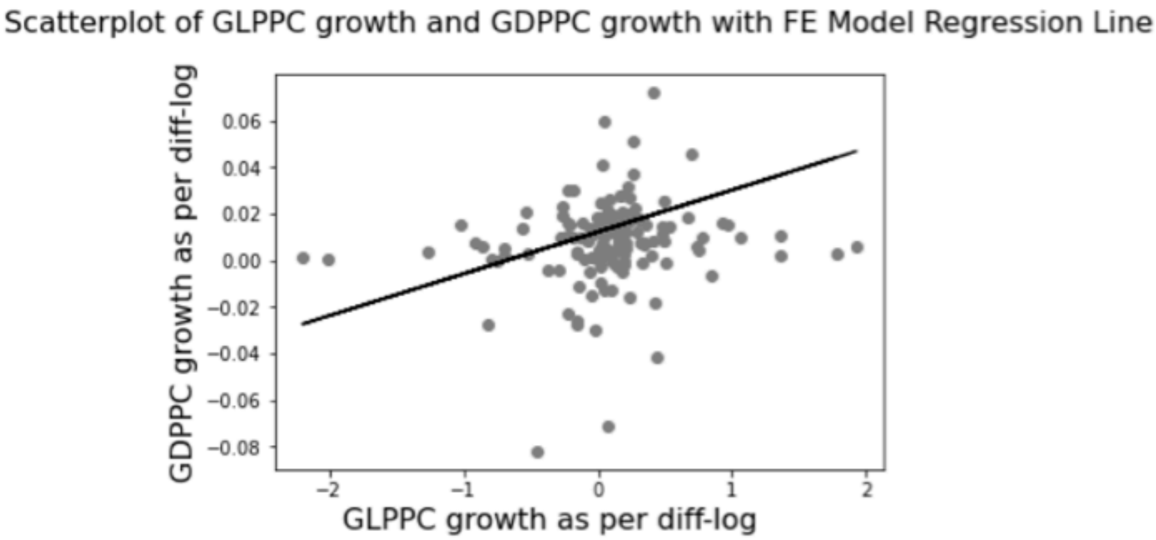
(Source: WDI Metadata)

Appendix C

FE Model Visualisation

For the sake of rendering the above results more tangible, we have included a scatterplot of GDPPC growth against GLPPC growth below using the coefficient for GLPPC growth and the constant from the FE Model (2) as the slope and intercept parameters for the regression line respectively.

For ease of visibility and to remain a useful visualisation, the scatterplot ignores the panel structure such that each grey point represents the data of a particular country at a particular point in time. As you can see, the majority of points are clustered around the centre of the chart, and there is the suggestion of an upward trend as captured by the FE model regression line. Remember from section 6.2 that one must multiply the values of “growth as per diff-log” by 100 to interpret them in terms of a growth rate as in a discrete-time framework.



Considering that one of the main challenges in this investigation stems from lack of data or incomplete data sets, we decided not to remove the points represented in the nether regions of the chart. In other words, we do not consider them "outliers" but instead treat them as valuable sources of information for our regression analysis. The relative symmetry of these points around the central cloud further motivates their treatment as such.

Nonetheless, it is useful to note which countries contribute the most salient outliers visible in the graph above. Taking the (0,0) co-ordinate as our central point along which we divide the graph into quadrants, looking first along the y-axis, we observe from our data set that Angola and Zambia demonstrated high year-on-year growth in GDPPC of circa 6-7% between the years 2004 and 2009 (Angola) and the years 2009-2010 (Zambia); the Democratic Republic of Congo, Malawi, and Zimbabwe exhibited markedly negative GDPPC growth rates in the early 2000s. Next, along the x-axis, we can identify that South Africa had a relatively high growth rate in GLPPC of circa 192% in 2001, and a contraction in GLPPC of 220% in 2014; Zimbabwe exhibited strong growth in GLPPC of 178% in 2014 preceded by a -201% contraction in 2013; Tanzania had a similarly high growth in 2012.