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Social and financial efficiency of microfinance institutions: developing markets, macro environment and financial inclusion

by
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Declaration of Authorship

I, Soldatkova Natalie, declare that this thesis titled, 'Social and financial efficiency of microfinance institutions: developing markets, macro environment and financial inclusion' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Title: Social and financial efficiency of microfinance institutions: developing markets, macro environment and financial inclusion

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Abstract: The microfinance industry was established with the main purpose to provide financial services to people who generally have no access to traditional banking because of their low, irregular or unpredictable income. The microfinance industry is expanding rapidly with an annual growth of over 9% in the global portfolio of loans and the number of active borrowers, serving around 123 million customers worldwide (Microfinance Baromoter, 2017).

Financial environments where microfinance institutions operate differ from country to country, from unregulated to highly regulated, from fully digitized to paper-based. One naturally raised question is what is the social efficiency, financial efficiency and relation between both for microfinance institutions when compared across different economies, and to what extent do market conditions and internal strategic decisions impact on this efficiency.

Using the database of financial, operational and social performance indicators of service providers in 38 countries of the Sub-Saharan African region, the first part of this work describes the results of an empirical study of social and financial efficiency. This is based on the Data Envelopment Analysis modelling approach for the period of 2004-2017. Hyperbolic non-oriented DEA models, super-efficiency DEA models, Ray-Desli Malmquist Index and Circular Malmquist Index were employed. Further relation between internal institutional and external environmental factors and efficiency level has been assessed using non-parametric Kruskal–Wallis tests. The internal factors included in the research are the presence of a deposit scheme, gender focus, customer target group and the prevailing term of the loan. The external environmental factors include the presence of legislation, interest rate limitations, presence of a private credit bureau and public registry and presence of microfinance-focused projects run by international organizations providing support to developing countries in their fight with poverty.

The research indicates important findings. For instance, microfinance institutions focusing on lending to small and medium enterprises demonstrate a higher level of efficiency (both social and financial), which is good news for the development of small business in the region. Gender focus of the lending institutions also has a significant influence on the efficiency, with female-focused entities being more efficient than the group mean in the social context and less efficient than the group mean from a financial perspective. The presence of the private credit bureau on a market correlated with significantly higher efficiency levels in both social and financial aspects. Public credit registers, however, are not associated with a positive trend. The presence of microfinance legislation shows no significant influence, although the interest rate cap is indeed associated with a change in the performance. Strong differentiation was indicated for all three efficiency specifications: for overall and financial efficiency, the presence of an interest rate cap was associated with reduced mean efficiency. For social efficiency, efficiency was increased. For all time periods, units operating on the market with an interest rate cap have a higher mean social efficiency than the mean efficiency of the sample.

The frequently discussed question of mutual exclusiveness between social and financial objectives was also studied in this research, and no strong evidence of the mutual exclusiveness was indicated. On the contrary, some countries have shown the ability to balance two objectives over time, which sets a positive example and motivation to other economies. In general, the priority focus of the microfinance industry remains on the achievement of financial objectives, although some movement towards the higher social efficiency has been observed over the most recent years of the observation period, which is a positive sign in a context of poverty reduction.

Keywords: Microfinance Industry, social efficiency, financial efficiency, Data Envelopment Analysis, Malmquist Index.
AMS Classification: 90B50, 90C05
JEL Classification: C67, C61, C43

Nazev: Sociální a finanční účinnost mikrofinančních institucí: rozvíjející se trhy, makro prostředí a finanční začlenění.

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Abstrakt: Odvětví mikrofinancování bylo založeno s hlavním cílem poskytnout finanční služby lidem, kteří nemají přístup k tradičnímu bankovnictví kvůli nízkému, nepravidelnému nebo nepředvídatelnému příjmu. Mikrofinancování se rychle rozšiřuje s ročním růstem více než o 9% globálního portfolia úvěrů a počtem aktivních dlužníků, kteří obsluhují přibližně 123 milionů zákazníků po celém světě (Microfinance Baromoter, 2017).

Finanční prostředí, ve kterém fungují mikrofinanční instituce, se v jednotlivých zemích liší, od neregulovaných po vysoce regulované, od plně digitalizovaných po závislé na manuálních procesech. Hlavní otázkou je, jaká je sociální a finanční účinnost mikrofinančních institucí v různých prostředích a do jaké míry tržní podmínky a vnitřní strategická rozhodnutí ovlivňují jejích účinnost.

Pomocí databáze finančních, provozních a sociálních ukazatelů výkonnosti mikrofinančních institucí v 38 zemích subsaharské Afriky, první část práce popisuje výsledky empirického studia sociální, finanční a celkové účinnosti. Tyto výsledky vychází z aplikace analýzy obalu dat pro období 2004–2017. Byly použity hyperbolické neorientované DEA modely, modely superefektivity, Ray-Desli Malmquistův index a Circular Malmquistův index. Další vztah mezi vnitřními institucionálními a externími faktory vnějšího prostředí a úrovně účinnosti byla hodnocena s použitím neparametrických Kruskal – Wallisových testů. Interní faktory zahrnuté do výzkumu jsou cílová skupina zákazníků, nabídka depositních vkladů, genderové zaměření na určité pohlaví zákazníků, a doba trvání úvěru. Mezi externími faktory vnějšího prostředí patří právní předpisy, omezení úrokových sazeb, přítomnost kreditního byra, státního úvěrového rejstříku a také efekt projektů mezinárodních organizaci zaměřených na podporu mikrofinancování v rozvíjejících zemích v jejich boji proti chudobě.

Výzkum ukazuje na důležitá zjištění. Například, mikrofinanční instituce zaměřené na poskytování úvěrů malým a středním podnikům vykazují vyšší úroveň účinnosti (sociální i finanční), což je dobrá zpráva pro rozvoj malého podnikání v regionu. Genderové zaměření úvěrových institucí má také významný vliv na účinnost, přičemž jednotky zaměřené na ženy jsou v sociálním kontextu účinnější než průměr skupiny ale z finančního hlediska méně efektivní než průměr skupiny. Přítomnost soukromého úvěrového rejstříku na trhu souvisí s výrazně vyšší úrovní účinnosti sociální a také finanční. Veřejné státní úvěrové registry však nejsou spojeny s pozitivním trendem.

Výzkum ukázal, že přítomnost právních předpisů v oblasti mikrofinancování nemá významný vliv, ale strop úrokové sazby je skutečně spojen se změnou výkonu. Výrazná diferenciace byla naznačena u všech tří specifikací účinnosti: pro celkovou a finanční účinnost byla přítomnost stropu úrokových sazeb spojena se sníženou průměrnou účinností. Z hlediska sociální efektivity účinnost byla zvýšena. Ve všech časových obdobích instituce působící na trhu s limitem úrokových sazeb mají vyšší střední sociální účinnost než průměrná účinnost vzorku.

V tomto výzkumu byla také studována často diskutovaná otázka vzájemné výlučnosti mezi sociálním a finančním cílem mikrofinančních instituci a nebyl prokázán žádný silný důkaz o vzájemné exkluzivitě. Naopak, některé mikrofinanční podniky prokázaly schopnost vyrovnat dva cíle v čase, což je pozitivním příkladem a motivací pro ostatní instituce. Obecně platí, že odvětví mikrofinancování se primárně zaměřuje na dosažení finančních cílů, ačkoli v posledních letech sledovaného období byl zaznamenán určitý posun směrem k vyšší sociální účinnosti, což je v kontextu snižování chudoby pozitivním znakem.

Klíčová slova: Odvětví mikrofinancování, sociální efektivita, finanční efektivita, analýza obalu dat, Malmquistův index.

AMS Klasifikace: 90B50, 90C05
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Chapter 1

Introduction - Motivation

1.1 Lack of access to traditional banking

Milton Friedman once said that "the poor stay poor, not because they are lazy, but because they have no access to capital." (Nayak, 2014). The problem Friedman was referring to is just as relevant now as it was in 1976 when the author made the statement in his Nobel Prize acceptance speech. In 1981 more then a half of the developing world's population lived on a daily budget of under 1.25 USD (World Bank report, 2017). During the following decades, the poverty rate declined dramatically to 21% in 2010, which indicates a great success in poverty reduction. Nevertheless, 1.2 billion people living in extreme poverty in 2010 is still a very high figure. The fast development of the Chinese economy has significantly contributed to the reduction of the worldwide poverty rate. In 2010, 12% of Chinese citizens lived under the poverty threshold compared to 84% in 1981. Other Asian regions have also experienced a major decrease in the poverty rate. On the other hand, Latin America and the Caribbean and Sub–Saharan Africa did not witness any real reduction in poverty until 1999, and it was only after entering the new millennium, that poverty rates started to decline. However, despite its falling poverty rates, Sub–Saharan Africa is the only region in the world for which the number of poor individuals has risen steadily and dramatically between 1981 and 2010. There were more than twice as many extremely poor people living in SSA in 2010 (414 million) than there were three decades ago (205 million), according to the report. The latest figures show a further reduction of the poverty rate to 10% in 2015 (World Bank, 2018); however, findings also indicated that decline in poverty rates has slowed, raising concerns about achieving the goal of ending poverty by 2030 and pointing to the need for an increase in pro-poor investments.

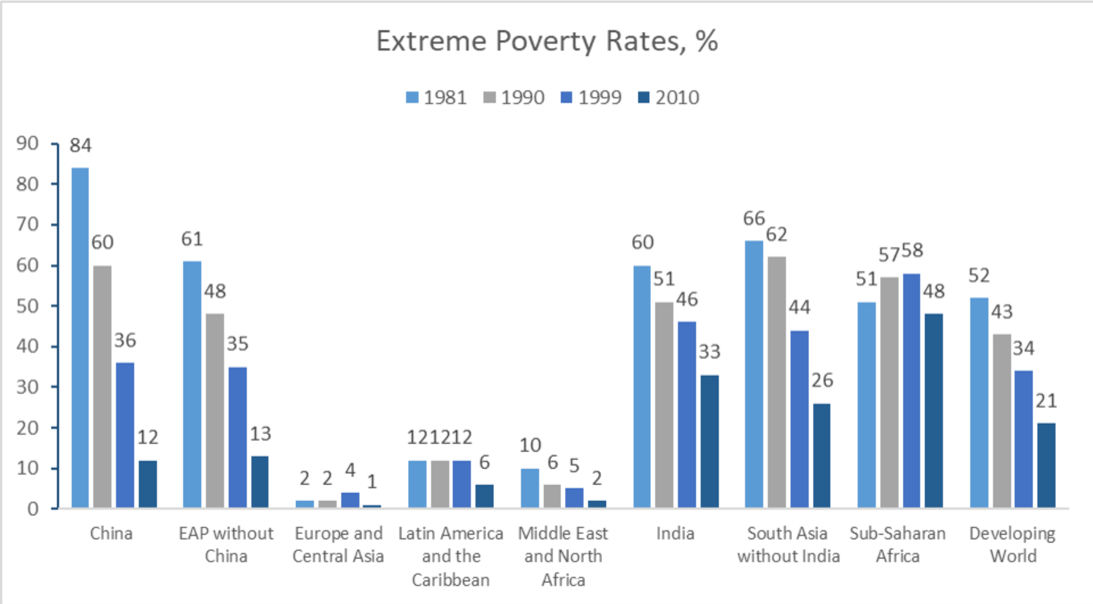

Figure 1.1: Extreme poverty rates

The depth of extreme poverty is commonly measured by the extreme poverty gap. When expressed in dollars based on Purchasing Power Parity (PPP) calculations, the extreme poverty gap represents the average amount of additional daily income needed by the extremely poor to reach the poverty line of $1.25 per day. The average gap of the extremely poor in the world was 38 cents per day or approximately $140 per year in 2005. For conventional banks, most of which in Africa issue loans under the requirement of a collateral guarantee (Cull et al., 2007), this population is considered to be too risky (Chowdhury and Mukhopadhaya, 2012a) and unprofitable to serve (Armendariz and Morduch, 2010). Therefore, a solution was needed for a large group of "unbanked" individuals (Simanowitz and Walter, 2002).

1.2 Microfinance and poverty

The solution, which was introduced in the 1970s and is so popular nowadays, was proposed by Dr Muhammad Yunus, professor of economics at the University of Chittagong. Determined to find a practical solution, Yunus began visiting local villages in Bangladesh. He lent money first from his own pocket and later in cooperation with Grameen, establishing the Grameen Bank project, the "Village Bank", which today works in over eighty-thousand villages with more than six million borrowers. In 2006 both Yunus and Grameen were awarded the Nobel Peace Prize for their contribution to poverty reduction. The success of The Grameen Bank inspired the establishment of many microfinance institutions around the world (Mersland and Strom, 2014; Reichert, 2018). Initially, microloans were granted with zero interest rate. However, with ever-increasing demand, the industry soon realized that it would not be able to grow sufficiently by only relying on grant funding. Therefore, non-for-profit institutions originally started changing their structure to attract commercial investors, which resulted in the transformation of microfinance institutions into formal businesses striving to improve their sustainability. The industry experiences rapid growth every year. According to the latest report (Microfinance Barometer, 2018), at the end of 2017, microfinance institutions (MFIs) reached an estimated 139 million low-income and underserved clients with loans totalling an estimated 114 billion dollars.

1.3 Microfinance in its modifications

The microfinance industry has found its way into various markets worldwide. Often adjusting to the economic and cultural specifics of the market, microfinance services now offer a broad range of loan products.

Group loans, first offered by Grameen Bank Bangladesh, remain a popular form of microlending. A group is formed of several borrowers usually united by business activity. The members then are jointly responsible for each other's loan, and penalty in case of non-repayment is applicable to each member (Widiarto et al., 2017). Postelnicu et al. (2014) conducted research into the impact of network configuration on the amount of social capital pledged as collateral. It shows why the group lending methodology works better in rural areas than in urban areas, namely because rural social networks are typically denser than urban ones, which results in higher social collateral. Group lending is most popular in Latin American and Asian countries. The average size of a group differs according to country, and it could be as small as five members or as large as 50 members as in case of the Kyrgyz Republic.

Microfinance loans for the purpose of household reconstruction are popular in countries on Eastern Europe and North Africa (Matul and Tsilikounas, 2004). Business loans are another popular form of microfinance service (Robinson, 2002), which supports the development of small businesses in countries in West Africa, Latin America and Europe.

In 2005, a Kenyan mobile operator launched a service called M-Pesa: a mobile wallet enabling microcredit borrowers to receive and repay microloans conveniently using their mobile devices. Interestingly, borrowers expanded the use of the product informally to pay for goods and services and even to send money to relatives in other parts of the country (Atikus Report, 2014). As it stands, two-thirds of Kenya's 44 million people subscribe to the service, which opportunities to increase financial service offerings for millions of unbanked Africans.

1.4 Microfinance double objective line and trade-off

The microfinance movement began with a very specific objective, which differentiates microfinance from all other categories of financial services. The objective is to help poor people find a way out of poverty. By providing small value loans to individuals and small businesses lacking access to conventional banking, microfinance gives an opportunity for their customers to become self-sufficient. Because of this fundamental objective of the microfinance industry, studies assessing individual institution performance, include some form of measurement of social impact. Financial sustainability is another crucial performance measurement as it determines the ability of an institution to continue providing services over time. Thus, in modern literature, researchers measure the performance of microfinance institutions focusing on two main objectives: outreach and financial sustainability (Morduch, 1999). Microfinance outreach is the ability to provide poor families with access to financial services (Mersland and Strom, 2014). Outreach is measured in both the number and depth of poverty (Zeller and Meyer, 2002). It is often referred to as a social mission of the microfinance industry. Financial sustainability is the ability of a microfinance institution to pay its employees, lenders, suppliers and to produce a profit from operations. The "microfinance promise" (Morduch, 1999) is that microfinances are able to provide financing to low-income people and at the same time remain profitable. Therefore, besides the outreach and financial sustainability, another important aspect of microfinance performance is the relation between the aforementioned objectives. Some studies find strong evidence that outreach is negatively related to the financial efficiency of MFIs, such us the study of Hermes et al. (2008) for instance. Cull et al. (2007) conducted an empirical study and have indicated "mission drift" phenomenon: higher loan amounts associated with higher profitability, and there is a deliberate move away from serving poor clients to wealthier clients in order to achieve higher financial sustainability. Current research investigates the performance of a microfinance institution on both objectives separately, and compares the results in striving to answer the question of whether the two objectives are mutually exclusive. In other literature on the subject, there were attempts to employ a third objective of microfinance institutions. Zeller and Meyer (2002) argue that microfinance should be measured in three dimensions; financial sustainability, outreach and impact. The term "impact" here means discernible effect upon clients' quality of life as they choose their target clients and create the products they will offer, the loan conditions they will set, and the application procedures they will require. Other authors, however, provide arguments against employing impact as a third objective (Mersland and Strom, 2014), as the impact for customers is to a large extent dependent on market conditions and entrepreneurial efforts, and is to a lesser degree influenced by the MFI. Therefore, in current research, the double objective line is assumed and research is focused on the investigation to what extent microfinances fulfil their social and financial objectives. Due to the double objectives specific to microfinance, the performance of microfinance institutions cannot be measured using only traditional financial indicators, such as profit margin and return on investment (Widiarto and Emrouznejad, 2015). As there is no universal standard approach for microfinance performance measurement, which would account for double objectives, a number of studies (Churchill, 1999; Bhatt and Tang, 2001; Khalily, 2004) in literature assess the performance of microfinances utilizing financial ratios and indicators. Several sets of microfinance oriented financial indicators had been proposed by groups of multilateral development banks, microfinance rating agencies and voluntary organizations (International Finance Corporation) to measure microfinance performance (Abrams and Ivatury, 2003; Jansson et al., 2003) and have been used in studies, e.g. in Koveos and Randhawa (2004), and Nanayakkara and Iselin (2012).

(Nanayakkara and Iselin, 2012) argue that financial sustainability is not necessarily linked to the profitability of an institution, but rather to the ability of an institution to operate without the threat of bankruptcy in the long-term. As the microfinance industry is composed of non-for-profit and for-profit organizations, only the latter group drive it's operations with an aim to maximize profitability. Fluckiger and Vassiliev (2007) proposed the use of efficiency as a measurement of microfinance performance to account for both financial and social goals. The method thus is applicable to commercially viable institutions and not-for-profit organizations with a prior focus on poverty reduction. Efficiency is a concept which refers to the utilization of input to create output, with the working definition being the optimal utilization of available inputs in the transformation process to produce outputs (Thanassoulis, 2001). Efficiency is measured as a ratio of output production over input usage, and is able to account for the scenario of multiple inputs and multiple outputs. A frontier approach, as proposed by Charnes et al. (1978) is created from best practice in the industry with similar characteristics/attributes to the benchmark performance of a microfinance institution.

1.5 Research gap and study plan

The topic of empirical measurement of social and financial microfinance performance increasingly attracts the attention of researches. However, no standard methodology for the assessment of the double objective performance of microfinances has yet been developed. Various studies attempt to measure the financial performance of microfinance institutions using financial indicators (Churchill, 1999; Bhatt and Tang, 2001; Khalily, 2004; Koveos and Randhawa, 2004; Nanayakkara and Iselin, 2012), although, the social component of the double objective line has rarely been analyzed.

Numerous research has conducted studies of financial and social performance of microfinance industry using data envelopment analysis. The studies cover different geographical regions from a single economy to cross-economy and cross-continental coverage. Currently, this field of study is enriched by following works: Qayyum and Ahmad (2006), where authors investigated efficiency and sustainability of microfinance institutitons in South Asian countries using DEA; Nghiem et al. (2006) employed DEA to measure efficiency of microfinance in Vietnam and built a second stage regression analysis to assess the impact of environmental variables upon the MFI efficiency; Fluckiger and Vassiliev (2007) investigated microfinance efficiency in Peru; Gutiérrez–Nieto et al. (2007) and Gutiérrez–Nieto et al. (2009) presented DEA-based analysis of social and financial efficiency of microfinance using data on 89 MFIs worldwide at that time available at the Microfinance Information eXchange (MIX) (MIX database is also utilized in the current research, however, the data coverage and quality improved significantly since Gutiérrez–Nieto and coauthors used the source for their empirical study); Bassem (2008) investigated efficiency of MFIs in Mediterranean region; Hassan and Sanchez (2009) covered multiple regions of developing economies in their study; Sedzro and Keita (2009) focused on MFI efficiency in West Africa Monetary Union (8 countries of West Africa); Nawaz (2010) conducted a study across 54 world economies; Haq et al. (2010) conducted cross-economy research covering African, Asian and American regions; Pal (2010) conducted research of Indian MFIs and found that efficiency of MFIs differs across regions of India; Gebremichael and Rani (2012) found that improvement of technical efficiency is the main source of MFI productivity growth in Ethiopia; Kipesha (2012) studied MFI efficiency in the East African region and found that NGOs (Non-Governmental Organisations) and Credit Unions have lower technical efficiency than traditional commercial MFIs; Bassem (2014) investigated efficiency of MFIs operating in the Middle East and North Africa; Tahir and Tahrim (2015) studied efficiency of MFIs in Cambodia; Bibi and Ahmad (2015) studied efficiency of MFIs in South Asian Association for Regional Cooperation; Widiarto and Emrouznejad (2015) focused on economies of EAP, MENA and SA regions comparing the performance of Islamic MFIs versus conventional MFIs; Mia and Chandran (2016) conducted a detailed study of MFIs and their efficiency in Bangladesh; Widiarto et al. (2017) conducted cross-continental research covering economies of Africa, EAP, EECA, LAC, MENA and SA; and Efendic and Hadziahmetovic (2017) investigated the efficiency of MFIs in Bosnia and Herzegovine during the economic crisis and post-crisis periods.

There is, however, no detailed study specifically assessing the financial and social performance of microfinances operating in economies of the Sub–Saharan African region.

This indicates a gap in the current literature, which this research attempts to fill.

Significant attention in the subject literature is dedicated to the relation between social and financial performance, and the question of whether these two efficiencies are mutually exclusive. Reichert (2018) indicates there were 3299 articles on the topic written as of 2016, 61 of them are empirical studies. Lebovics et al. (2016), Hudon et al. (2018) and Gutiérrez-Nieto et al. (2009) studied the relationship between financial and social efficiency looking for the evidence of the "mission drift" (Armendariz and Szafarz, 2011; Beisland and Mersland, 2013). In this research, we investigate the relationship between social and financial efficiency in an attempt to answer whether the two objectives are mutually exclusive.

A significant body of research has attempted to identify a relationship between efficiency level and external environmental factors or internal factors of the institution's operating structure. Such research has applied techniques such as regression analysis or nonparametric tests as a second stage after the efficiency analysis. Widiarto and Emrouznejad (2015) analyzed factors such as size, age, profit-orientation, target portfolio and regulation status and found significant dependencies between some of the factors and the efficiency level. Among the other structural factors analyzed by researchers are gender focus, presence of foreign investments and foreign ownership, product composition, deposit scheme and others, such as loan terms, loan types, loan channels. The current research has also investigated the relationship between efficiency level and institution structural factors focusing on four of them: the presence of deposit scheme, borrowers gender prevalence, customer target group and the prevailing term of the loan.

Among the environmental factors investigated in various bodies of research, regulation is frequently analyzed. Research conducted by Hartarska and Nadolnyak (2007) concluded that the presence of regulation does not impact microfinance efficiency. The results are generally consistent across studies and generally contradict the common opinion that regulation highly affects microfinance operations and their efficiency.

In view of this study, the regulation factor requires more in-depth analysis because it consists of multiple components. Instead of representing regulation by a single binary variable, this proposes to separate regulation components and investigate their relationship with microfinance efficiency individually. Current research covers the analysis of two regulation components: legislation and limitations of the interest ceiling. Another factor that this study has separated is the presence of a credit registry or credit bureau. This factor is only partially related to regulations due to the fact that credit registries are public organizations, credit bureaus can be and frequently are operated by private companies (although they need governmental support to operate in a full market scale). Other studies include credit bureau presence in the regulatory factor. However, this study prefers to analyze its relation to efficiency individually. Finally, the current research analyzes the relationship between efficiency and presence of microfinance-focused projects run by international organizations providing support to developing countries in their fight with poverty. As I have not indicated DEA studies with a similar composition of environmental factors, I believe this analysis is one of the unique contributions of this research to current literature in this subject.

1.6 Study questions

The study addresses the main twelve questions formulated as the following:

Question 1. What is the financial and social efficiency of microfinance institutions across developing countries of the Sub–Saharan African region? Do most institutions operate close to the efficiency frontier or away from it? This is important for understanding the extent to which static equilibrium is a good approximation of the real economy.

Question 2. What is the productivity change over time? What is the change in the time of external shocks such as the 2008 global financial crisis?

Question 3. Social and financial objectives - are they mutually exclusive?

Question 4. Has the microfinance industry witnessed a mission drift over time?

Question 5. Does the composition of products offered by microfinance institutions impact efficiency? Where do the institutions focusing on support of small and medium enterprises (SME) stand on the efficiency scale? The answer to this question is important, as the SME sector is a major contributor to the world economy in terms of growth and in terms of employment. Improvement of SME access to finance is crucial for economic development, especially in the emerging markets.

Question 6. Are microfinance institutions which provide deposit products in addition to lending products more efficient then the ones providing only lending products?

Question 7. Does gender orientation matters? Are female-financing microfinance institutions more efficient comparing to the overall sample?

Question 8. What could be the increase in the number of consumers if all microfinance institutions in the study were operating relatively efficiently?

Question 9. Do regulations have an impact on the efficiency of the microfinance industry? Are institutions operating in more regulated markets also more efficient? Answers to these questions are useful from the regulatory policy perspective.

Question 10. Do infrastructural components such as credit registry and credit bureaus matter? Are institutions operating on markets with credit bureaus more efficient compared to the institutions operating on the markets with no credit bureaus?

Question 11. Does presence of international funding projects focused on improvement of the microfinance environment bring about higher efficiency?

Question 12. Does the microfinance industry contribute to the improvement of consumer access to traditional banking services? Is there a dependency between social or financial efficiency of microfinance institutions and consumer transition from unbanked portfolio to a traditional banking portfolio?

1.7 Study contribution

This research contributes to the current body of literature with its in-depth analysis of social and financial efficiency of microfinance institutions operating on 38 markets of the Sub–Saharan African region. The empirical study covers the period of 2004 — 2017 and therefore provides an opportunity to observe efficiency trends and their relation to external factor over time. The research employs a Data Envelopment Analysis and thus contributes to so far limited literature on microfinance efficiency measurement using the nonparametric methodology. Several separate studies to ensure the robustness of the DEA model were conducted within this research and therefore contribute the literature on solving the missing data issue according to DEA specification, and impact of model orientation on the DEA model results. This research studies the relationship between social and financial efficiencies across 14 time periods, helping to answer the question of whether a trade-off exists between the two objectives. Furthermore, the relationship between efficiency levels and internal institutional structure is analyzed (including gender focus, SME focus, loan term prevailing, deposit scheme) to access what operational specifics of an institution relate to achieving a high level of efficiency. The relation between environmental factors (legislation, limitation of interest rate, credit bureau presence and presence of international projects) and efficiency levels is analyzed, indicating what macroeconomic changes contribute to an increase in efficiency. The results are important for investors, international organizations, regulatory entities and all stakeholders contributing to the development of the microfinance industry and poverty reduction. For these stakeholders, this research indicates the areas which need development and worthy of additional attention, as they are associated with the high efficiency level.

Chapter 2

Methodology framework - productivity and efficiency

2.1 Productivity

The theory of production was proposed by Cobb and Douglas in 1928 and has been used ever since by economists to study the production of manufacturing units. The function proposed by authors represents the technological relationship between the amounts of two or more inputs and the amount of output that can be produced by those inputs. The production process is then an economic process of converting a set of inputs into outputs (Cobb and Douglas, 1928) and the production firm is a decision-making unit. As described by Ray (2004), any decision-making agent faces a problem with three main features: production variables, or rather selection of their values (decision variables); certain limitations defining the feasibility set of decision variables; and criterion functions, which defines outcome level based on the decisions made by a unit. Thus, the firm decides on the levels of inputs and outputs, and the input-output combination selected by the firm must be feasible in a way that a selected amount of outputs can be produced from the selected amount of inputs. The goal is then to maximize the amount of outputs produced. On the other hand, it is essential to utilize input resources efficiently. Thus, the double objectives faced by firms are a) to produce as many outputs as possible from a specified amount of inputs and b) to utilize minimum input resources to produce a specified amount of outputs.

2.2 Production possibility set

Limitations faced by a decision-making unit (DMU) when selecting input-output combination in literature is referred to as production possibility set (PPS). PPS is a set of all input-output combinations feasible under the restrictions of a specified technology. Let's consider DMU which utilizes input $x \in \mathbb{R}_+^n$ to produce output $y \in \mathbb{R}_+^m$. The production process is defined by a production function $y = f(x), f : R_+^n \Rightarrow R_+^m$.

$$PPS = \{(x,y) : y \leq f(x),\ x \in \mathbb{R}_+^n,\ y \in \mathbb{R}_+^m\}. \tag{2.1}$$

For the simple economy of one input and one output, production possibility set is illustrated in the figure 2.1.

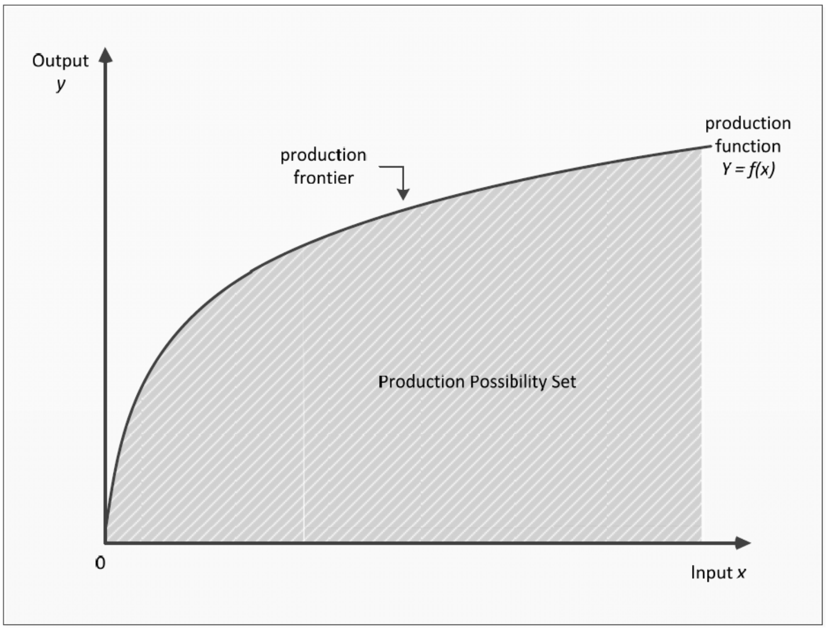

Figure 2.1: Production possibility set for economy with one input and one output

PPS is bounded by the production function. The boundary of the production set is a production possibility frontier (PPF).

$$PPF = \{(x,y) : (x,y) \in PPS,\ \forall \sigma_x > 0,\ \forall \sigma_y > 0 : (x - \sigma_x, y + \sigma_y) \notin PPS\} \tag{2.2}$$

The output combinations on the frontier of this set correspond to the Pareto-optimal allocation of factor inputs, i.e. the allocation at which it is not possible, given the total factor endowment, to increase the production of one good without decreasing the production of some other good (Stiglitz, 1981). Converting the statement into an input-output allocation context, in a production process with the objective of maximising output, an allocation is considered to be Pareto-optimal if it is not feasible to increase the production level of any outputs without decreasing the production level of at least one other output and/or increasing level of at least one input. For units functioning with the objective of minimising inputs, Pareto-optimality is defined as a situation whereby is not possible to further reduce the level of any of its inputs without increasing the level of at least one of its other inputs and/or decreasing the level of any of its outputs (Thanassoulis, 2001). Later in this research, the concept applied in the performance evaluating methodology.

2.3 Efficiency concept

Two concepts are used to access the units utilization performance, and these are productivity and efficiency. It is important for our research to state the difference between these two concepts. If the production function is defined for a certain process, two identical firms using the same amounts of inputs should produce the same amounts of outputs. However, in practice, this is not always true and therefore other factors, which are relevant to the production process and can explain the difference in output level, are not included in the production function. Let's consider decision-making units A and B and the case of a single input - single output scenario. Let's assume unit A consumes x_A amount of input x to produce y_A amount of output y. The same notation is for the unit B: x_B is consumed to produce y_B. The productivity of each unit is then assessed as $AP^A = y_A/x_A$ for the unit A and $AP^B = y_B/x_B$ for unit B. Let's further assume, there is a production function defined as $y^* = f(x)$. Then, $y_A^* = f(x_A)$ is the maximum output which could be produced using input x_A. $y_B^* = f(x_B)$ will be then maximum possible output from the input x_B. The technical efficiency of units A and B are measured as follows: $TE^A = y_A/y_A^*$, and $TE^B = y_B/y_B^*$. Here, the efficiency is measured as a productivity index of an actual firm's production against the production of a hypothetical company, which produces maximum possible output from the same amount of input. Such a set-up is an output-oriented measure of efficiency.

This is visualized in the figure 2.2, where points P_A and P_B represent actual input-output combination of firms A and B. These two points belong to a feasible production set as these input-output combinations are observed. The curve $OP_A^*P_B^*$ defines the boundary of the production possibility set. In other words, it defines the efficiency frontier, which will be discussed further in this chapter. The technical efficiency of the firm A is then obtained as $TE_O^A = y_A/y_A^* = P_Ax_A/P_A^*x_A$ and for the firm B as $TE_O^B = y_B/y_B^* = P_Bx_B/P_B^*x_B$. As we are using single input – single output example here, either input or output orientation can be assumed here, the resulting efficiency levels would have the same values and efficiency frontier would be the same. As in the figure 2.2 we assess technical efficiency by using vertical projections on the frontier to measure the distance from the frontier, we assume here output orientation.

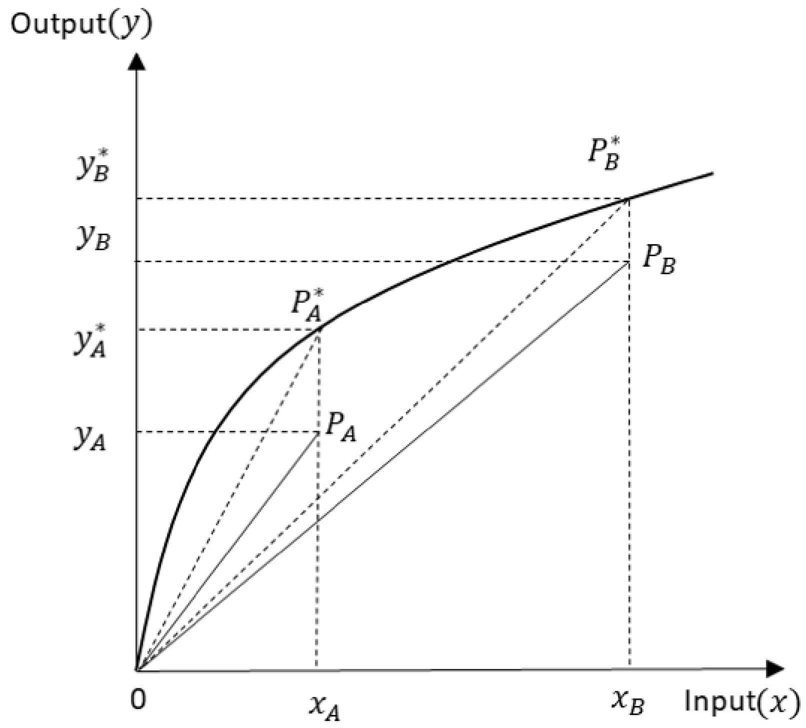

Figure 2.2: Technical efficiency - example of calculation using vertical projection (output-orientation)

The alternative approach is to apply a horizontal projection on the frontier and use the utilization of production inputs as a measure of technical efficiency. The approach is, therefore, input-oriented. The figure 2.3 visualizes units A and B and the efficiency assessment under the input-oriented scenario. Positions of the A and B input-output combination and frontier remains unchanged; however, the units now reach the frontier by minimizing the amount of input used as oppose to the maximizing output production when the output-oriented approach is used. The technical efficiency of the unit A is calculated as $TE_I^A = x_A^*/x_A = P_A^* y_A/P_A y_A$ and for firm B as $TE_I^B = x_B^*/x_B = P_B^* y_B/P_B y_B$.

In practice, the choice of input or output orientation of efficiency measurement depends on the goal of the study as well as on the specifics of the production process. If the production process uses a constant amount of inputs, then the output-oriented approach will present an appropriate option. If the study focuses on the optimization of the utilization of inputs, then input orientation fits the purpose. This study pays attention to the question of the input and output orientation as it is particularly essential for our

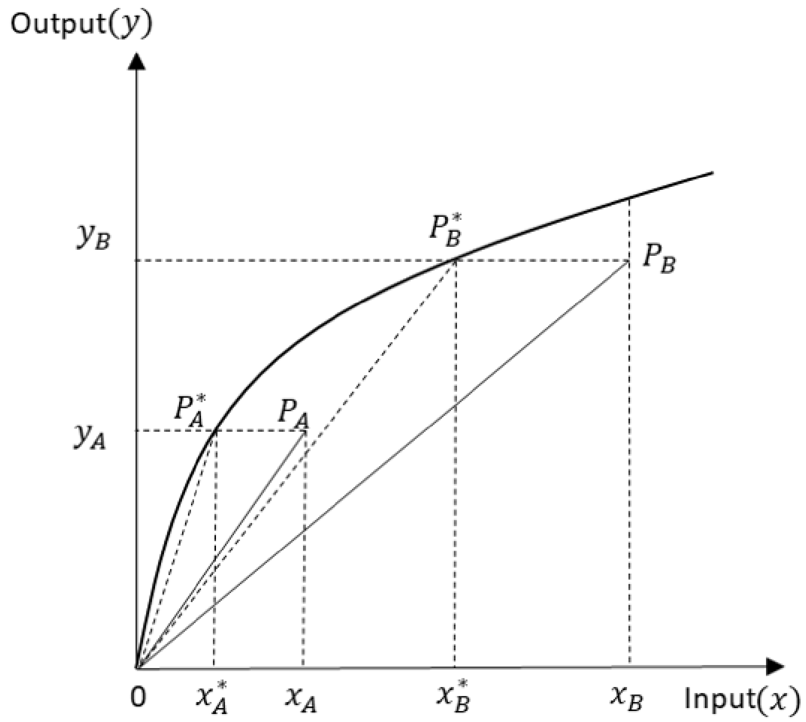

Figure 2.3: Technical efficiency - example of calculation using horizontal projection (input-orientation)

research. Discussion on this topic is held in chapter 4, and arguments are presented leading to the utilization of a non-oriented approach among the other models.

2.4 Returns to scale

Returns to scale indicate the rate of increase in production to the associated increase in the factors of production in the long run. There are constant returns to scale and variable returns to scale, which are further divided into increasing returns to scale and decreasing returns to scale. When constant returns to scale are assumed, the level of outputs increases at an equal proportion to the increase in inputs. When variable returns to scale are assumed, the increase in outputs has a different proportion than the level of proportional change of inputs. Under increasing returns to scale, outputs increase at a higher proportion, than the change in all inputs. This is a situation of decline in marginal production costs. Under decreasing returns to scale, the proportional increase in inputs results in a lower proportional increase of outputs (marginal production costs increasing).

As per Ray (2004), let's consider single input and single output production with a production possibility set:

$$T = \{(x, y) : y \leq f(x);\ x \geq a\} \tag{2.3}$$

Denote maximum quantity of output y produced from an input x as $y^* = f(x)$. Denote $a \geq 0$ is a minimum input scale below which production function is not defined. At point (x, y), the average productivity on the production function is $AP = f(x)/x$. Increasing returns to scale are defined locally if a small increase in x results in an increase in AP. In the same way, if a small increase of x results in a decline in AP, decreasing returns to scale are present. Under constant returns to scale, AP stays unchanged regardless to any change in x. Thus, dAP/dx is positive under increasing returns to scale, negative under decreasing returns to scale and 0 under constant returns to scale. If the production function is differentiable,

$$\frac{dAP}{dx} = \frac{xf'(x) - f(x)}{x^2} = \frac{f(x)}{x^2}\left[\frac{xf'(x)}{f(x)} - 1\right] \tag{2.4}$$

If average productivity reaches a maximum at a finite level of x, dAP/dx equals 0 at that point and the first-order condition for maximum is satisfied. If the production function is concave, then $f''(x) < 0$ for the entire range of x and the second-order condition for maximum is satisfied as well:

$$\epsilon = \frac{xf'(x)}{f(x)},\quad \frac{dAP}{dx}\frac{f(x)}{x^2}(\epsilon - 1). \tag{2.5}$$

$\epsilon > 1$ implies increasing returns to scale,
$\epsilon = 1$ implies constant returns to scale,
$\epsilon < 1$ implies decreasing returns to scale.

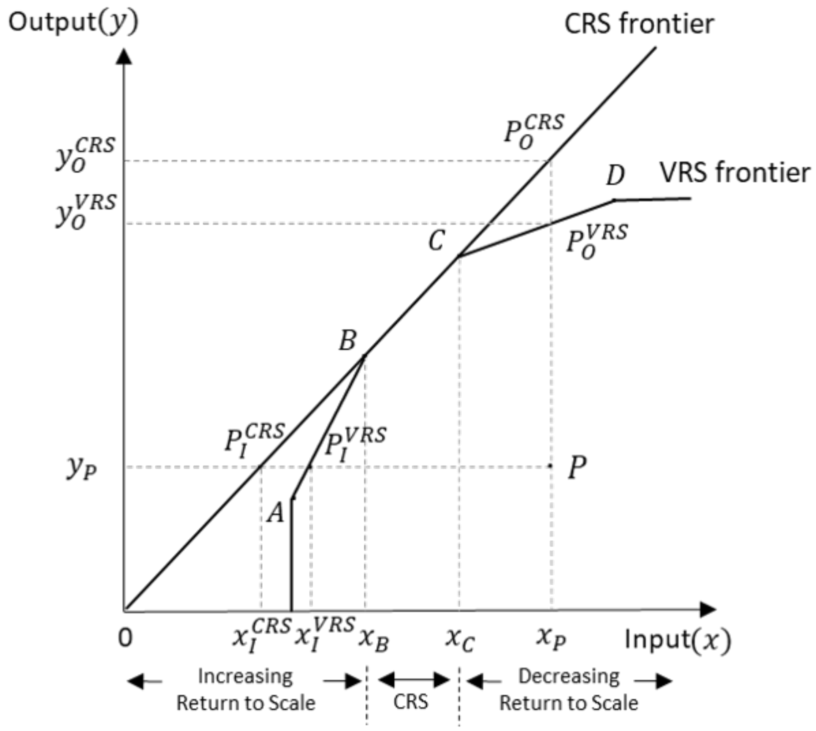

Figure 2.4: CRS production frontier versus VRS production frontier

Figure 2.4 visualizes construction of the efficiency frontiers under CRS assumption and under VRS assumption. Five data points (A, B, C, D and P) are used to estimate the efficient frontier and the level of capacity utilization under both scale assumptions. The frontier defines the full capacity output given the level of fixed inputs. With constant returns to scale, the frontier is defined by points B and C for all points along the frontier, with all other points falling below the frontier (hence indicating capacity underutilization). With variable returns to scale, the frontier is defined by points A, B, C and D, and only point P lies below the frontier i.e. exhibits capacity underutilization. The distance to the frontier for the point P is smaller under the VRS assumption than under CRS assumption.

Returns to scale discussion for the microfinance industry is held further in the sections 3.3 and 4.3.2.

2.5 Efficiency frontier

As discussed in the previous section, the efficiency measure compares the actual input-output proportion of a firm against the maximal possible proportion specified by production technology. The measure relies on how the production frontier is defined. Under the scenario of the available production function, the question is solved by the use of the production function. Another option is an empirically derived production function from the available observations of the input-output data.

There are deterministic and stochastic methodologies for building a desirable frontier. However, each one has some shortfalls. Besides, when using the econometric approach, a specific functional form must be selected, which limits the flexibility of the frontier.

Data envelopment analysis is an alternative approach, which utilizes non-parametric techniques instead of regression. This advantage allows a relatively flexible form of the frontier, as no specific function form needs to be selected. The approach was first proposed in 1978 by Charnes et al. (1978). However, the linear programming model for measuring the technical efficiency of a unit in comparison to benchmark technology had already been developed by Farrell in 1957 (Farrell, 1957). The benchmark technology, which serves as a frontier, is built using an input–output combination of the observed units in a sample. The other authors contributed to the theory with relative methodologies, such as Shephard publishing the distance function in 1953 (Shephard, 1953) and Debreu in 1951, proposing coefficient of resource utilization (Debreu, 1951).

Data envelopment analysis makes very few assumptions about production technology. The production function has no specific form except the assumption that it is a quasi-concave function.

Assume a production set includes n inputs and m outputs. There are N production units. Denote vectors $x^j \in \mathbb{R}^n_+$ and $y^j \in \mathbb{R}^m_+$ are input and output vectors of the unit $j, (j = 1, 2, ..., N)$.

Ray (2004) summarizes the following four assumptions initially presented in Banker et al. (1984) and utilized in the technology function:

Assumption 1. All input-output combinations presented in an observed dataset of production units are feasible. Therefore for every input-output pair (x, y) it should be true that the output amount y can be produced from the amount x.

$$\forall (x^j, y^j),\ j = 1, 2, ..., N,\ (x^j, y^j) \in PPS. \tag{2.6}$$

Assumption 2. The production feasibility set is convex.

$$(x^A, y^A) \in PPS, (x^B, y^B) \in PPS \Leftrightarrow (\bar{x}, \bar{y}) \in PPS, \bar{x} = \lambda x^A + (1-\lambda)x^B,$$
$$\bar{y} = \lambda y^A + (1-\lambda)y^B,\ \forall \lambda,\ 0 \leq \lambda \leq 1. \tag{2.7}$$

Assumption 3. Inputs are freely disposable.

$$(x^0, y^0) \in PPS \Rightarrow \forall x, x \geq x^0,\ (x, y^0) \in PPS \tag{2.8}$$

Assumption 4. Outputs are freely disposable.

$$(x^0, y^0) \in PPS \Rightarrow \forall y, y \leq y^0,\ (x^0, y) \in PPS \tag{2.9}$$

Now, consider pair $(\hat{x}, \hat{y})$, where $\hat{x} = \sum_{j=1}^{N} \mu_j x^j$, $\hat{y} = \sum_{j=1}^{N} \mu_j y^j$, $\sum_{j=1}^{N} \mu_j = 1$, for $\mu \geq 0, (j = 1, 2, ..., N)$. According to the Assumption 1 and Assumption 2, the pair $(\hat{x}, \hat{y})$ is feasible. If constant returns to scale are assumed, the following is true: $\forall k \geq 0, (k\hat{x}, k\hat{y})$ is feasible. If we define $\tilde{x} = k\hat{x}, \tilde{y} = k\hat{y}$ and $\lambda_j = k\mu_j$ Then $\sum_{j=1}^{N} \lambda_j = k$ and $\lambda \geq 0$. Since there is only restriction on values of k to be non-negative, there are no additional restrictions on values of λ. The production possibility set (denote is here T^C) under the assumption of constant returns to scale is then defined as

$$T^C = \left\{ (x, y) : x \geq \sum_{j=1}^{N} \lambda_j x^j;\ y \leq \sum_{j=1}^{N} \lambda_j y^j;\ \lambda_j \geq 0;\ j = 1, 2, ..., N \right\} \tag{2.10}$$

Having a definition of the production possibility set, we can define the output-oriented and input-oriented technical definition of a unit.

Consider unit t with input-output pair (x^t, y^t). Denote ϕ^* is a maximum value of a parameter ϕ, that $(x^t, \phi y^t)$ belongs to the production possibility set. $y^* = \phi^* y^t$ is the maximum feasible output produced from the input x^t. Output-oriented efficiency of the unit is $TE_O^t = TE_O(x^t, y^t) = 1/\phi^*$.

For the input-oriented efficiency, the goal is to identify what is the minimal amount of inputs needed for the production of output y^t. Thus, $\theta^* = min\theta : (\theta x^t, y^t) \in T^C$ is the input-oriented technical efficiency of the unit t.

2.6 Data Envelopment Analysis - CRS

In 1978 Charnes, Cooper and Rhodes formulated the first DEA model utilizing constant returns to scale. They proposed broadening the definition of units under analysis to include not only production firms but also agencies such as schools, hospitals and courts. All of them have a common characteristic of producing measurable outputs from measurable inputs, but generally lacking market prices of outputs, inputs or both to assess performance. Therefore, the term decision-making unit (DMU) used in DEA, refers to units under investigation, not necessarily assuming that they are production firms.

Let's consider an environment with N operating DMUs, each producing m outputs from n inputs. DMU t uses the input vector $x_t \in \mathbb{R}^n_+$ and $y_t \in \mathbb{R}^m_+$ The authors use "shadow" prices to emphasise the relation to the market price comparison. Define $u_t \in \mathbb{R}^n_+$ as the shadow price vector for inputs and $v_t \in \mathbb{R}^m_+$ as the shadow price vector for outputs and average productivity of a DMU t :

$$AP_t = \frac{\sum_{r=1}^{m} v_{rt} y_{rt}}{\sum_{i=1}^{n} u_{it} x_{it}} = \frac{v^{t\prime} y^t}{u^{t\prime} x^t} \tag{2.11}$$

The shadow prices vary across the firms with restrictions to have non-negative values and the condition that, when aggregated, no firms input-output set results in average productivity greater than unity. Thus,

$$\begin{aligned} AP_j = \frac{v^{t\prime} y^j}{u^{t\prime} x^j} = \frac{\sum_{r=1}^{m} v_{rt} y_{rj}}{\sum_{i=1}^{n} u_{it} x_{ij}} \leq 1;\ (j = 1, 2, ..., N); \\ u_{it} \geq 0;\ (i = 1, 2, ..., n); v_{rt} \geq 0;\ (r = 1, 2, ..., m). \end{aligned} \tag{2.12}$$

Denote $w_t = ku_t$, and $p_{rt} = kv_{rt}$, $k \in R^1_+$ The optimization problem is then

$$max \frac{p^{t\prime} y^t}{w^{t\prime} x^t} \quad s.t. \frac{p^{t\prime} y^t}{w^{t\prime} x^t} \leq 1;\ (j = 1, 2, ..., N);\ p^t \geq 0;\ w^t \geq 0. \tag{2.13}$$

Denote $k = 1/\sum_{i=1}^{n} u_{it}x_{it}$ and $w^{t\prime}x^{t} = 1$. The CCR model is then formulated as

$$\begin{aligned}
& max \sum_{r=1}^{m} p_{rt}y_{rt} \\
& s.t. \sum_{r=1}^{m} p_{rj}y_{rj} - \sum_{i=1}^{n} w_{ij}x_{ij} \leq 0; \quad (j = 1,2,...,N) \\
& \sum_{i=1}^{n} w_{it}x_{it} = 1 \\
& p_{rj} \geq 0; \quad (r = 1,2,...,m), \quad (j = 1,2,...,N) \\
& w_{ij} \geq 0; \quad (i = 1,2,...,n), \quad (j = 1,2,...,N).
\end{aligned} \tag{2.14}$$

2.7 Data Envelopment Analysis - VRS

As discussed in the previous chapter, production technology satisfies the following assumptions: (i) the production possibility set is convex; (ii) inputs are freely disposable; (iii) outputs are freely disposable. Assume the production possibility set T. If input-output pairs (x_0, y_0) and (x_1, y_1) are feasible, then pair $(\bar{x}, \bar{y})$, where $\bar{x} = \lambda x_0 + (1-\lambda)x_1$ and $\bar{y} = \lambda y_{0j} + (1-\lambda)y_1$, $0 \leq \lambda \leq 1$. If $(x, y) \in T$, then $(\hat{x}, y) \in T$, when $\hat{x} \geq x$ and $(x, \hat{y}) \in T$ when $\hat{y} \leq y$. For set of N firms, denote their input-output pair as $(x_j, y_j), (j = 1,2,...,N)$. As discussed in the assumption 1 of the previous section, we assume all pairs are feasible,

$$(x_j, y_j) \in T, \quad i = 1,2,...,N. \tag{2.15}$$

There are indefinitely many production possibility sets satisfying assumptions $(1)-(4)$, the smallest of these sets is further selected (denote a superscript V to indicate variable returns to scale)

$$\begin{aligned}
T^{V} = (x, y) : x \geq \sum_{j=1}^{N} \lambda_j x^{j}; \quad y \leq \sum_{j=1}^{N} \lambda_j y^{j}; \quad \sum_{j=1}^{N} \lambda_j = 1; \\
\lambda_j \geq 0; \ (j = 1,2,...,N).
\end{aligned} \tag{2.16}$$

The input-oriented measure of technical efficiency of any firm t utilizing n input and producing m outputs under VRS requires the solution of the following LP problem as proposed by Banker (1984):

$$\begin{aligned}
& min\ \theta \\
& s.t. \sum_{j=1}^{N} \lambda_j x_{ij} \leq \theta x_{it},\ i = 1,2,...,n; \\
& \quad \sum_{j=1}^{N} \lambda_j y_{rj} \geq y_{rt},\ r = 1,2,...,m; \\
& \quad \sum_{j=1}^{N} \lambda_j = 1 \\
& \lambda_j \geq 0;\ (j = 1,2,...,N).
\end{aligned} \tag{2.17}$$

The optimal solution of the model is $(\theta^*; \lambda_1^*, \lambda_2^*, , ..., \lambda_N^*,)$. Denote $x_t^* = \theta^* x_t$, then (x_t^*, y_t) is an efficient input-oriented radial projection of (x_t, y_t) onto the frontier and $TE_I^V(x_t, y_t) = \theta^*$.

The output-oriented measure of technical efficiency is obtained from the solution of the following program:

$$\begin{aligned}
& max\ \phi \\
& s.t. \sum_{j=1}^{N} \lambda_j x_{ij} \leq x_{it},\ i = 1,2,...,n; \\
& \quad \sum_{j=1}^{N} \lambda_j y_{rj} \geq \phi y_{rt},\ r = 1,2,...,m; \\
& \quad \sum_{j=1}^{N} \lambda_j = 1 \\
& \lambda_j \geq 0;\ (j = 1,2,...,N).
\end{aligned} \tag{2.18}$$

The optimal solution is $(\phi^*; \lambda_1^*, \lambda_2^*, , ..., \lambda_N^*,)$. Define $y_t^* = \phi^* y_t$, then (x_t, y_t^*) is an efficient output-oriented radial projection of (x_t, y_t) onto the frontier and $TE_O^V(x_t, y_t) = 1/\phi^*$.

2.8 Hyperbolic non–oriented DEA

Most DEA models are either input oriented or output oriented. When input orientation is used, the model standardizes input-output sets to the common output value, and only utilization of inputs is further investigated in the model. Similarly, when output orientation is used, the standardized input level is used and efficiency is then estimated based on output production. An interesting concept which allows us to remove the necessity of orientation in the model was proposed by Fare (Färe et al., 1985, 1994). The proposed model is a hyperbolic non-oriented DEA model under VRS assumption.

The model enables output expansion and input reduction at the same time and offers more flexibility for decision-making units when selecting an input-output combination. The formulation of the model is as follows:

$$\begin{aligned}
& min\ \theta \\
& s.t.\ \sum_{j=1}^{N} \lambda_j x_{ij} \leq \theta x_{it},\ i = 1,2,...,n; \\
& \sum_{j=1}^{N} \lambda_j y_{rj} \geq \phi y_{rt},\ r = 1,2,...,m; \\
& \sum_{j=1}^{N} \lambda_j = 1,\ j = 1,2,...,N; \\
& \lambda_j \geq 0; \\
& \phi = 2 - \theta; \\
& \theta, \phi \geq 0
\end{aligned} \tag{2.19}$$

where x_{ij} and y_{rj} are the ith input and the rth output of the jth DMU respectively. θ is the input-minimizing efficiency for the DMU under investigation and ϕ is output maximizing efficiency of the DMU under investigation. Constraint $\phi = 2 - \theta$ is the first order linear approximation of the constraint $\theta * \phi = 1$, which is tangent line to the hyperbola $\theta * \phi = 1$ at any point. Convexity constraint $\sum_{j=1}^{N} \lambda_j = 1$ represents VRS assumption.

Graphical visualization of the hyperbolic DEA is provided in the figure 2.5.

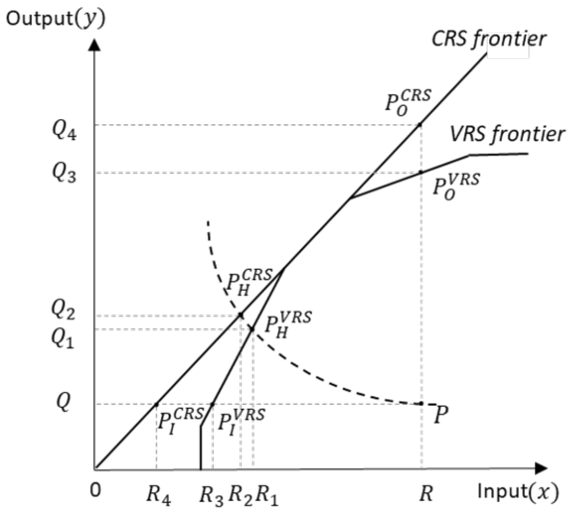

Figure 2.5: Hyperbolic non-orientated technical efficiency

A single input – single output scenario is considered, a DMU P have the input-output vector (R, Q). The figure visualizes the efficiency of DMU under CRS assumption and under VRS assumptions. In an input-oriented approach, the technical efficiency of the

DMU P will be accessed against its benchmarks on the frontiers: $P_I^{VRS}(R_3, Q)$ and $P_I^{CRS}(R_4, Q)$ depending on what returns to scale are assumed. In the output-oriented approach, the DMU would be evaluated against $P_O^{VRS}(R, Q_3)$ and $P_O^{CRS}(R, Q_4)$.

In a hyperbolic non-orientated approach, reduction of input pursued by DMU P is matched by an increase in output, thus its benchmarks now are projected toward VRS and CRS frontiers in a hyperbolic pathway to $P_H^{VRS}(R_1, Q_1)$ and $P_H^{CRS}(R_2, Q_2)$.

2.9 Super-efficiency

In this section, we introduce a super-efficiency model proposed by Andersen and Petersen (1993). Super-efficiency models are used to rank order the efficient units and this is obtained by eliminating data on evaluated DMU from the solution set.

The Empirical part of the current study employs super-efficiency models when dealing with outliers (discussed more in the sections 3.8 and 4.4.5) and therefore we provide the methodological background in this section.

We use two approaches as follows:

Input-oriented variable returns to scale model

$$\begin{aligned}
&min\ \theta \\
&s.t.\ \theta x_{it} \geq \sum_{j=1,\neq t}^{N} \lambda_j x_{ij},\ i = 1, 2, ..., n; \\
&y_{rt} \leq \sum_{j=1,\neq t}^{N} \lambda_j y_{rj},\ r = 1, 2, ..., m; \\
&\sum_{j=1,\neq t}^{N} \lambda_j = 1; \\
&\lambda_j \geq 0\ (\forall j).
\end{aligned} \tag{2.20}$$

Output-oriented variable returns to scale model

$$\begin{aligned}
& min\ 1/\eta \\
& s.t.\ x_{it} \geq \sum_{j=1,\neq t}^{N} \lambda_j x_{ij},\ i = 1,2,...,n; \\
& \quad \eta y_{rt} \leq \sum_{j=1,\neq t}^{N} \lambda_j y_{rj},\ r = 1,2,...,m; \\
& \quad \sum_{j=1,\neq t}^{N} \lambda_j = 1; \\
& \quad \lambda_j \geq 0\ (\forall j).
\end{aligned} \tag{2.21}$$

2.10 Productivity Growth and Malmquist Index

This section covers a DEA-based measurement of total factor productivity growth (TFPG). The section describes three forms of the Malmquist productivity index: CRS based Malmquist Index introduced by Fare, Grosskopf, Norris, and Zhang and known as the FGNZ model (Färe et al., 1994), the VRS-based Ray and Desli modification model (Ray and Desli, 1997), and Circular Malmquist Index.

2.10.1 Malmquist Productivity Index - FGNZ Model

The Malmquist productivity index (MI) is a commonly used method in the measurement of total productivity change over time in an empirical study. It was first introduced in the studies of Caves et al. (1982a and 1982b). Later Färe et al. (1992) developed a DEA model that measures the Malmquist Index. Per Ray (2004), the MI concept based on the construction of a production frontier to which different distance function efficiencies with different input-output combinations are compared. The value of MI and productivity change is measured as a proportion between DMU locations with regards to the frontier in the time periods 0 and 1.

Caves et al. (1982a and 1982b) defines MI from the perspective of output distance function as $MI_0^o = \frac{D_0^o(x_1,y_1)}{D_0^o(x_0,y_0)}$.

If the frontier is static, $D_0^o(x_0, y_0)$ and $D_0^s o(x_1, y_1)$ represent the output distance function of (x_0, y_0) and (x_1, y_1) respectively, relative to frontier at time 0. In the MI context, the output distance function is equivalent to the maximum radial outputs expansion of the assessed DMU holding inputs constant. As under assumption of constant returns to scale, DEA models produce the same results for input and output orientations. The model equation above also holds for input distance function. Denote MI_0^o as MI_0^{CRS}.

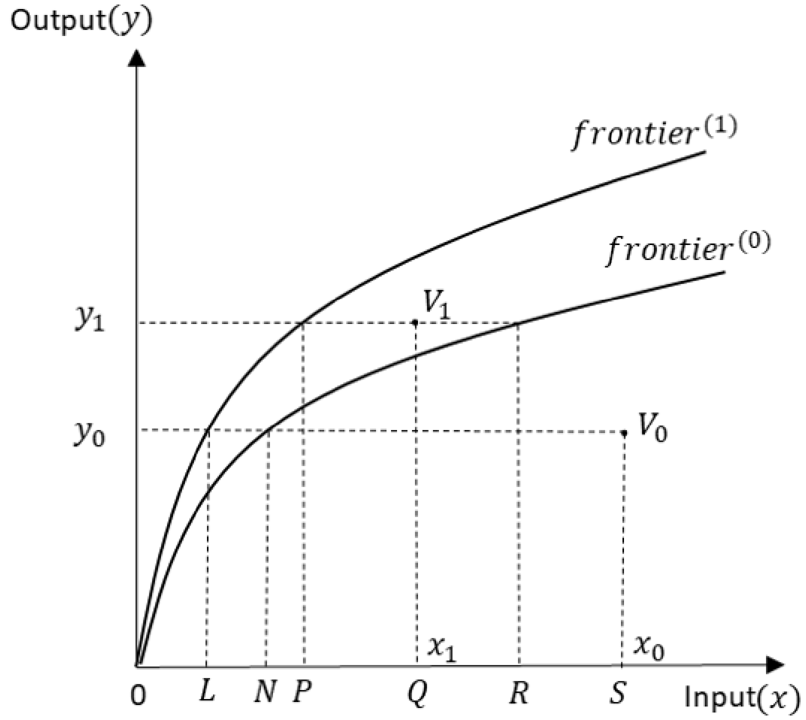

Figure 2.6: Efficiency change and frontier shift over time. Example of single input - single output.

This concept is illustrated in the figure 2.6, where a production frontier representing the efficient level of output (y) that can be produced from a given level of input (x) is constructed for time periods 0 and 1. V_0 represents the position of the analysed DMU V at time 0 and V_1 represents position of the DMU V at time 1 and we measure efficiency change of DMU V by examining its efficiency in time periods 0 and 1, but also by taking into account the technology shift from time period 0 to time period 1. The shift from frontier$^{(0)}$ to frontier$^{(1)}$ represents a change in general industry-level technology. When inefficiency is assumed to exist, the relative movement of any given financial institution over time will, therefore, depend on both its position relative to the corresponding frontier (technical efficiency) and the position of the frontier itself (technical change). If inefficiency is ignored, then productivity growth over time will be unable to distinguish between improvements that derive from a decision making unit catching up to its own frontier or those that result from the frontier itself shifting up over time (Paleckova, 2017). For a DMU V in period 0, represented by the input/output bundle V_0 an input-based measure of efficiency can be deduced by the horizontal distance ratio ON/OS. That is a ratio, by which the input can be reduced in order to make production technically efficient in period 0 (i.e. movement onto the efficient frontier). By comparison, in period 1 inputs should be multiplied by the horizontal distance ratio $0R/0Q$ in order to achieve comparable technical efficiency to that found in period 0.

Since the frontier has shifted, $0R/0Q$ exceeds unity, even though it is technical inefficient when compared to the period 1 frontier.

Färe et al. (1992) have reformulated MI as a geometric average of the distance change, such that:

$$MI = \left(\frac{D_0^{CRS}(x_1, y_1)}{D_0^{CRS}(x_0, y_0)} \times \frac{D_1^{CRS}(x_1, y_1)}{D_1^{CRS}(x_0, y_0)} \right)^{1/2} \tag{2.22}$$

This formulation enables the decomposition of the source of the productivity change: as frontier and efficiency can both change over time, it is then important to understand whether the productivity change measured is due to frontier shift, efficiency change, or both. Thus the authors proposed the following decomposition:

$$MI_{FGNZ} = \frac{D_1^{CRS}(x_1, y_1)}{D_0^{CRS}(x_0, y_0)} \times \left(\frac{D_0^{CRS}(x_1, y_1)}{D_1^{CRS}(x_1, y_1)} \times \frac{D_0^{CRS}(x_0, y_0)}{D_1^{CRS}(x_0, y_0)} \right)^{1/2} \tag{2.23}$$

In the composition, the first component of measures changes in technical efficiency of the DMU under investigation over time. This is referred to as the catch-up component or efficiency change ("EC"):

$$EC = \frac{D_1^{CRS}(x_1, y_1)}{D_0^{CRS}(x_0, y_0)} \tag{2.24}$$

The second component of the MI_{FGNZ} expression measures the shift in industry-level technology. It is referred to as the boundary shift component or technological change ("TC"):

$$TC = \left(\frac{D_0^{CRS}(x_1, y_1)}{D_1^{CRS}(x_1, y_1)} \times \frac{D_0^{CRS}(x_0, y_0)}{D_1^{CRS}(x_0, y_0)} \right)^{1/2} \tag{2.25}$$

Thus, the decomposition of MI in FGNZ is $MI_{FGNZ} = EC \times TC^{CRS}$.

MI is thus a calculation of a combination of DMU efficiency change and the technological change at the industry level. Values of the MI index greater than 1 indicate improvement in productivity level, values of the MI index lower than 1 indicate a decline in productivity level.

The Current formulation of the Malmquist Index constructed under the assumption of CRS, which implies that DMU is an operation on its most productive scale efficiency.

Under the assumption of VRS, the formulation was adopted to account for the scale efficiency change:

$$MI_{FGNZ}^{VRS} = \frac{D_1^{VRS}(x_1,y_1)}{D_0^{VRS}(x_0,y_0)} \times \frac{S_1(x_1,y_1)}{S_0(x_0,y_0)} \times \left(\frac{D_0^{CRS}(x_1,y_1)}{D_1^{CRS}(x_1,y_1)} \times \frac{D_0^{CRS}(x_0,y_0)}{D_1^{CRS}(x_0,y_0)} \right)^{1/2} \tag{2.26}$$

$$MI_{FGNZ}^{VRS} = PEC \times SC_{FGNZ} \times TC^{CRS} \tag{2.27}$$

In this formula the EC part is decomposed into two parts: pure efficiency change ("PEC") and scale efficiency change ("SC"). PEC herein represents the change in efficiency under VRS and SC change in scale efficiency over time, i.e. the scale efficiency of the assessed DMU in time 1 relative to that in time 0.

2.10.2 Malmquist Productivity Index - RD Model

Ray and Desli (1997) noticed that the FGNZ model provides internally inconsistent measurement for DMU under VRS. This is due to the fact that the TC component accounts for the CRS frontier movement, whilst the PEC and SEC account for movement in efficiency under the VRS frontier and scale efficiency. Authors thus proposed an alternate MI decomposition to amend the FGNZ model as follows:

$$\begin{aligned} MI_{RD} = & \frac{D_1^{VRS}(x_1,y_1)}{D_0^{VRS}(x_0,y_0)} \times \left(\frac{D_0^{VRS}(x_1,y_1)}{D_1^{VRS}(x_1,y_1)} \times \frac{D_0^{VRS}(x_0,y_0)}{D_1^{VRS}(x_0,y_0)} \right)^{1/2} \times \\ & \times \left(\frac{S_0(x_1,y_1)}{S_0(x_0,y_0)} \times \frac{S_1(x_1,y_1)}{S_1(x_0,y_0)} \right)^{1/2} \end{aligned} \tag{2.28}$$

$$MI_{RD} = PEC \times TC^{VRS} \times SC_{RD} \tag{2.29}$$

The drawback of such a formulation is that it requires cross-period distance function for both technological change and scale efficiency change, which could be problematic in a case where some of the observed input-output combinations in one period can not be fully enveloped by a frontier from another period. As a result, an unfeasible solution can occur for separate DMUs in a sample.

2.10.3 Circular Malmquist Index

An alternative model for the productivity change assessment was introduced by Pastor and Lovell (2005) and developed further in its decomposition by Portela and Thanassoulis (2008). The main difference proposed in the model of the circular Malmquist Index is that instead of comparing distances to different frontiers, distance to a meta–frontier is assessed. Under the assumption that feasible technology in the base period stays feasible in the future period, the meta–frontier envelops observations from different time periods into one production set, which enables us to make direct comparisons of unit performance across different time periods.

For the analysed DMU_j, denote θ_{jt}^{T} efficiency at time t relative to the original frontier T. Portela and Thanassoulis (2008) meta–frontier efficiency as $\theta_{jt}^{m} = \theta_{jt}^{T} \times TG_{jt}$, where TG_{jt} is the distance between frontier T at time t to meta-frontier m. Productivity change of DMU_j from time t to time $t+1$ can be measured as $MI_C = \theta_{jt+1}^{m} / \theta_{jt}^{m}$.

The Circular Malmquist Index is thus

$$MI_C = \frac{\theta_{jt+1}^{T}}{\theta_{jt}^{T}} \times \frac{TG_{jt+1}}{TG_{jt},} \tag{2.30}$$

where the first component is the efficiency change and the second component is the technological gap change (TGC). The last equation assumes CRS and Portela and Thanassoulis (2008) proposed a modified version to account for VRS:

$$MI_C^{CRS} = \frac{\theta_{jt+1}^{T(CRS)}}{\theta_{jt}^{T(CRS)}} \times \left(\frac{\theta_{jt+1}^{m(CRS)}}{\theta_{jt+1}^{T(CRS)}} \right) \left(\frac{\theta_{jt}^{m(CRS)}}{\theta_{jt}^{T(CRS)}} \right) \tag{2.31}$$

$$MI_C^{VRS} = \frac{\theta_{jt+1}^{T(VRS)}}{\theta_{jt}^{T(VRS)}} \times \frac{TGV_{jt+1}}{TGV_{jt}} \times \frac{MSE_{jt+1}}{MSE_{jt}} \tag{2.32}$$

$$MI_C^{VRS} = PEC_C \times TGC^{VRS} \times MSC, \tag{2.33}$$

where $TGV_{jt} = \theta_{jt+1}^{m(VRS)} \ \theta_{jt}^{T(VRS)}$, $MSE_{jt} = \theta_{jt}^{m(CRS)} \ \theta_{jt}^{m(VRS)}$.

PEC_C indicates pure efficiency change, TGC^{VRS} denotes the technological gap change and MSC represents meta–scale efficiency change.

2.11 Post-DEA analysis

The post-DEA analysis is conducted utilizing non-parametric Kruskal-Wallis H - a non-parametric method for testing whether samples originate from the same distribution. The study applies the test to analyze the significant influence of factors mentioned in the questions above on MFIs performance differences.

As a non-parametric method, the Kruskal–Wallis test does not assume a normal distribution of the residuals, unlike the analogous one-way analysis of variance. If the researcher can make the assumptions of an identically shaped and scaled distribution for all groups, except for any difference in medians, then the null hypothesis is that the medians of all groups are equal, and the alternative hypothesis is that at least one population median of one group is different from the population median of at least one other group.

Assume there are N observations divided into i groups. The test statistic is given by:

$$H = (N-1)\frac{\sum_{i=1}^{g} n_i(\bar{r}_i - \bar{r})^2}{\sum_{i=1}^{g}\sum_{j=1}^{n_i}(r_{ij} - \bar{r})^2}, \tag{2.34}$$

Here, n_i is the number of observation in group i, r_{ij} is the rank of the observation j (among all observations), which is in group i. $\bar{r}_i = 1/n_i \sum_{j=1}^{n_i} r_{ij}$ is the average rank of observations in a group i and $\bar{r} = 1/2(N+1)$ is the average of all r_{ij}.

The decision whether to reject the null hypothesis is made by comparing H to a critical value H_c obtained from a table for a given significance level. The significant value of the Kruskal–Wallis test indicates that at least one sample stochastically dominates at least one other sample.

Chapter 3

Practical framework - model Construction

3.1 DEA versus other approaches

The methodology used in the literature differs depending on the research objectives and available information. The common methodology that has hitherto been used in measuring MFI performance is traditional financial ratios or indicators similar to those used in studies of mainstream financial institutions. Several sets of financial indicators had been prescribed by groups of multilateral banks, microfinance rating agencies, donors, and voluntary organizations to measure MFI performance (Abrams and Ivatury, 2003; Jansson et al., 2003) and have been used in studies e.g. in Bhatt and Tang (2001), Churchill (1999), Khalily (2004), Koveos and Randhawa (2004), and Nanayakkara and Iselin (2012). The exhaustive list of all indicators prescribed by Abrams and Ivatury (2003) can be observed in Gutirrez–Nieto et al. (2007). This methodology measures the performance of institutions from a financial perspective and does not provide a framework for measuring social efficiency, which is critical for this study and therefore the methodology was not considered further as a suitable approach for the study.

There are classes of models for efficiency evaluation available in the literature, their application depends on available data, their types and quality. The main two families are parametric and non-parametric models. Parametric approaches assume an a priori specification on the production function. These approaches are well-established in the literature, however, a priori assumption on production function brings disadvantage as it is often difficult to argue that the production process follows the particular specification, e.g., a Cobb-Douglas, Translog or Fourier (Emrouznejad and De Witte, 2010). Non-parametric approaches, on the other hand, do not require any a priori assumptions on the production function. They, therefore, have more flexibility and, as such, let the data speak for themselves (Stolp, 1990). A disadvantage of this family lies in the restrictive curse of dimensionality and they often deliver a large variance and wide confidence interval. Within each of these families, both deterministic and stochastic approaches exist.

The following approaches from both parametric and non-parametric families of models were considered:

Parametric Regression – an appropriate technique subject to the usual econometric problems (e.g. simultaneity resulting from observed inputs being correlated with the unobserved inefficiency term). The technique associated with potential model misspecification and biases if the true functional form is not correctly chosen. The model usually allows only one dependent variable and therefore studies aggregate output. This contradicts with the initial assumption of multiple input – multiple output framework of this study and due to this reason parametric regression was not selected for the efficiency assessment.

Nonparametric Regression – technique has the advantage of removed requirement of specification of the functional form, which comes at a price due to slower convergence. Multiple input – multiple output framework assumption is still violated by this approach and therefore approach was not taken forward for consideration.

Data Envelopment Analysis (DEA) is a non-parametric approach and therefore no assumption about the underlying technology is required. DEA constructs a piece-wise linear-segmented efficiency frontier based on best practice and develops a function whose form is determined by the most efficient producers. The approach has no scope for random error, making it more vulnerable to data errors. Furthermore, results are sensitive to the selection of inputs and outputs. Therefore when DEA models are built, data quality and input-output composition should be carefully considered. The approach simultaneously allows multiple inputs and outputs, which is an important benefit for the study.

Stochastic Frontier Analysis (SFA) is also approach with the objective of efficiency frontier constructions. SFA is a parametric approach and allows for statistical noise. The sources of inefficiency can be analysed and quantified for every evaluated unit. On the other hand, it is associated with typical for parametric approaches disadvantages discussed above.

Free Disposal Hull proposed by Deprins et al. (1984) is a non–parametric approach, which similarly to DEA constructs efficiency frontier, however it relaxes the convexity assumption of basic DEA models. This relaxation makes the approach less sensitive to outliers then DEA, but the problem still remains. It is also argued in the literature whether relaxation is appropriate.

Stochastic semi-Nonparametric Envelopment of Data (StoNED) proposed by Kuosmanen and Kortelainen (2011). Like DEA, StoNED is able to estimate an axiomatic production function relaxing the functional form specification required in most implementations of SFA. StoNED is also consistent with the econometric models of noise, providing a distinct advantage over standard DEA models. The approach, however, has been criticised for its potential for mixing statistical noise and inefficiency (Skinner, 1994). The approach associated with many benefits, however, it assumes output to be scalar therefore does not allow for the multiple input and multiple output production.

As a result of the review, DEA was selected to measure the efficiency of Microfinance institutions in the empirical part of the study. DEA was preferred over other approaches because two advantages important for this study: a) multiple input - multiple output framework and b) ability to measure relative efficiency rather than absolute efficiency.

Provision of multiple input - multiple output framework is important due to the dual objective environment in which the microfinance industry operates. The microfinance movement began with a very specific social objective, which differentiates microfinance from all other categories of financial services. Because of this fundamental objective, studies assessing individual institution performance always include one or another measurement of social impact. Financial sustainability is another important performance measurement, as it assesses the ability of an institution to continue providing services over time. Thus, in modern literature, researchers measure the performance of microfinance institutions focusing on these two main objectives and therefore enabling multiple outputs in the modelling approach is important for empirical studies.

Interestingly, measurement of productive efficiency based on input-output ratio was proposed by Farell in the 1950s, although only a single input-output scenario was considered. Later in the 1970s, authors Charles, Cooper and Rhodes expanded the method proposed by Farell, allowing multiple input-outputs to be considered in the production scenario. The framework has since been used for efficiency measurements of organizations such as business firms, financial institutions, manufacturing companies, governmental agencies, educational units, hospitals and other decision-making units and many modifications of DEA models initially proposed in the 1970s have been developed since.

Ability to measure relative efficiency is another important argument in favour of utilizing DEA. Absolute efficiency is unknown and in fact cannot be estimated realistically, meaning that targets for individual institutions cannot be objectively defined. Thus assessing efficiency by comparing an institution against the industry leaders gives a realistic estimation of the current efficiency as well as the ability to define achievable targets.

3.2 Model Orientation

In DEA methodology, there are two main approaches to efficiency measurement differing in objective direction: input oriented and output-oriented models. Input oriented models study the utilization of input resources by DMUs under the assumption of fixed values of output resources across the set of units. On the contrary, output oriented models measure efficiency based on the production of outputs under the premise of fixed values of inputs for all units in the set. There is also a range of non-oriented models which allow the simultaneous optimization of inputs and outputs. If constant returns to scale are assumed, both input and output oriented models would construct the same efficiency frontier, and the same DMUs will be recognized as efficient/inefficient for both types of approaches. On the other hand, if variable returns to scale are assumed, the frontier and estimates would be different for input and output oriented models.

The choice of one or the other model might be based on the specific characteristics of the data set analyzed (Murillo-Zamorano, 2004). For instance, for regulated sectors, such as the electronics sector, where output is usually assumed to be exogenous, and inputs operate in competitive markets, the use of input-oriented rather than output oriented models seems to be the best choice. On the other hand, when the analyzed DMUs focus on the output maximization, for instance, hospitals operating with a fixed number of staff, the output-oriented model is used. Output-oriented models are " ...very much in the spirit of neo-classical production functions defined as the maximum achievable output given input quantities " (Färe et al., 1994).

There are studies in the subject literature, where authors build multiple models with both input and output orientation to achieve a better understanding of the DMUs operation and potential. Such an example could be a study of the banking industry in the Czech Republic conducted by Toloo (2014).

Interestingly, Coelli and Perelman (1996) show that the choice of a particular orientation rarely has more than a minor influence upon the reported efficiency scores. We drew a similar conclusion from the empirical exercise conducted on the MFI dataset used in this research. The exercise is presented in the section 4.3.1. The section also expands on the model orientation utilized in the current research.

3.3 Assumption on returns to scale

As described in section 2.4, returns to scale relate the rate of increase in production to the associated increase in the factors of production in the long run. There are constant returns to scale and variable returns to scale, which are further divided into increasing returns to scale and decreasing returns to scale. Most of the DEA models need to have a type of returns to scale specified beforehand, and therefore the decision on whether to assume CRS or VRS needs to be made. As in the case of model orientation, the optimal type of returns to scale is based on the specific characteristics of the data set analyzed.

There are a number of studies in the literature focusing on the efficiency and productivity of the banking sector in various regions; however, few studies focus on the microfinance sector's efficiency and productivity. Therefore, there is a large gap in the literature. Although banking and microfinance industries are conceptually different due to a double bottom objective line specific to microfinance institutions, some operational components of the two industries have similarities, and certain assumptions made for banking industry can be applicable to the microfinance industry as well, including the type of returns to scale.

While the selection of model orientation might not impact on the resulting efficiency values significantly, the choice of the type of returns to scale usually have a strong impact on the result of the DEA model. The VRS boundary is less demanding of performance than the CRS boundary and usually, application of the VRS model results in a higher number of efficient DMUs in a sample. Efficiencies estimated under VRS are at least as high as those estimated under CRS (Thanassoulis, 2001). The assumption of constant returns to scale is not appropriate in many real-life contexts. Constant returns to scale are impossible to sustain when input-output variables include averages, indices or arbitrary measurement scales (Thanassoulis, 2001).

Section 4.3.2 expands on the returns to scale type used in this research.

3.4 Input - Output selection

The selection of the model inputs and outputs is always challenging, as it profoundly affects the further efficiency evaluation, target estimations and conclusions of the model in general. The input-output combination should be structured to comply with two main requirements: exclusiveness and exhaustiveness.

As Thanassoulis (2001) indicates, the relationship of exclusiveness and exhaustiveness between inputs and outputs in a DEA assessment means that, subject to the exogeneity of factors involved, the inputs, and inputs alone, must influence the output levels, and only the outputs being used in the assessment. The exclusiveness and exhaustiveness can, however, be relaxed in cases when the researcher assumes that omitted variables will not alter the proportionality across DMUs of the values of the input-output variables being used. The author suggests the starting identification of an input-output composition from establishing the type of efficiency to be assessed. Once the efficiency type is defined, industry knowledge and scholarly references can be used to form the initial set of inputs and outputs, which are further reduced to include only necessary components. Sensitivity analysis can be further conducted to refine the input-output composition utilizing correlations, analysis of variance or OLS regression, for instance. The correlation analysis for this research is presented in section 4.4.3. The author states the ultimate aim is that the input-output set used should conform to the exclusivity, exclusiveness and exhaustiveness requirements and should involve as few variables as possible.

Another significant concern when selecting input-output composition is whether there are a sufficient number of DMUs in the sample for the LP model to account for all input-output combinations. Avkiran (2006) explains that typically the choice and the number of inputs, outputs and the DMUs determine how good the discrimination is between efficient and inefficient units. There are two conflicting considerations when evaluating the size of the data set. One factor is to include as many DMUs as possible, because with a larger population there is a higher probability of capturing high-performance units that would determine the efficient frontier and improve discriminatory power. The other conflicting consideration with a large data set is that the homogeneity of the data set may decrease, meaning that some exogenous impacts of no interest to the analysis, or beyond the control of the manager, may affect the results (Golany and Roll, 1989).

Boussofiane et al. (1991) indicate that to get good discriminatory power out of the CCR and BCC models, the lower bound on the number of DMUs should be the multiple of the number of inputs and the number of outputs. Dyson et al. (2001) recommend a total of two times the product of the number of input and output variables. The reason for having such a high ratio of DMU number to model variable number derived from the issue that there is flexibility in the selection of weight to assign to input and output values in determining the efficiency of each DMU.

The general rules for input-output selection are the following:

- The input-output composition should be selected in accordance with the type of efficiency assessed;
- The inputs and outputs should satisfy requirements of exclusivity, exclusiveness and exhaustiveness;
- The number of input and output variables should be as low as possible;

- There must be a sufficient number of DMUs in the analyzed dataset (the number of DMUs should be higher than the multiple of the number of inputs and the number of outputs).

3.5 Missing values

As stated in the article of Charnes et al. (1978), for DEA modelling it is mandatory that all inputs and outputs are populated for all DMUs in the dataset with strictly positive values, If the dataset contains missing values, it needs to be transformed into a fully populated dataset.

Two possible solutions are available to treat missing values within the dataset: a) removal of observations with missing values from the dataset and b) substitution of missing values with proxy values or with default values.

- a) removal of observations with missing values from the dataset

This approach is frequently used by researchers when building DEA models. However, if the blank entries do not cause any other harm to the analysis, besides the missing information of the specific data entry itself, then discarding existing, available information certainly cannot improve matters (Kuosmanen, 2009). Elimination of some DMUs from the sample impacts not only eliminate DMUs, but also efficiency estimations of DMUs remaining in the dataset, thus making the estimations less precise. It is likely that the efficiencies of remaining DMUs will be overestimated.

Senel et al. (2016) conducted an empirical study proving that elimination of DMUs with missing values results in a significantly higher average margin of error in the efficiency estimate than in the case of using substitutes for missing values. For the fully populated dataset, authors deleted a randomly selected set of values and ran a substitution algorithm for the missing values. Three DEA models then were produced using a) a full dataset, b) a reduced dataset with eliminated DMUs containing missing values and c) a dataset with substituted missing values. The results have shown across different levels of missing values, the model with substituted values consistently provides a smaller margin of error in the estimation than the model with eliminated DMUs. For a 1% missing value level, the average error is 0.03% when applying substitutions versus 2.27% when eliminating DMUs from the model. For a 5% level, however, the difference decreases to 2.07% versus 2.81%. A similar study was conducted in this research, the results presented in the section 4.4.1.

For the eliminated DMUs, the model would not be able to estimate any efficiency ranking in this case. If the efficiency of a certain DMU with missing values is particularly important, this approach is not practical. To answer the main questions of our study, and to build a cross-economy comparison, it is essential to have as many DMUs operating on the market as possible included in the model. Thus, the elimination of DMUs with missing values is not an attractive option for this study.

- b) substitution of missing values with proxy values or with default values

The approach of missing value substitution offers benefits in comparison to the DMU elimination approach. It allows utilization of all available data and reduces the chance of efficiency overestimation for a DMU with no missing values. It also allows us to achieve a significantly lower margin of error in the estimation of efficiency; however, the selection of an appropriate technique for substitution is of critical importance.

For instance, in the example above Senel et al. (2016) demonstrated a significantly lower average margin of error in the efficiency estimate when using missing value estimation as opposed to eliminating DMUs with missing values from the dataset. Nevertheless, the average error highly depends on the quality of the algorithm used for the substitute estimations. In the study, the average error gap between two approaches decreases as the proportion of missing values increases. It is thus possible that after reaching a certain level of missing values, use of substitution algorithm may cause a higher margin of error than DMU removal. It is thus important to select an appropriate technique for substitution.

It is generally safe to substitute missing values with default values. For inputs, the missing values are replaced with exceedingly high values (adjusted to the scale of specific input). For outputs, missing values are replaced with exceedingly low values (also adjusted to the scale of the output). Thus, the impact of the unit is not eliminated overall, but the only impact of specific values within the unit is eliminated. The unit can, however, still obtain a 1.00 efficiency score if guaranteed by other non-missing inputs and outputs; thus. the default value substitution technique does not eliminate DMUs from the frontier development, but it eliminates the chance of efficiency overestimation for the DMU.

Although relatively few studies have been published so far, the topic is currently being discussed in the literature and is attracting increasingly more attention in academic circles (as well as data envelopment analysis overall). Several methods of treating the missing value issue in relation to the specification of DEA datasets have been proposed in the literature.

Kuosmanen and Post (2002) proposed the weight-restricted DEA models by making a modification to the usual weight restrictions. Later in 2009, Kuosmanen (2009) presented a systematic attempt to use data containing missing values in DEA. The proposed methodology replaces missing inputs with selected dummy entries (significantly large values) and for missing values in outputs, Kuosmanen (2002) proposed using zero values. The Charnes et al. (1978) requirement of having strictly positive values is then relaxed by applying modified weight restriction, which functions normally for the observed data, but relaxes the weight restriction in case of dummies for blank entries so that the missing data will not count in the analysis.

Smirlis et al. (2006) proposed a pair of interval DEA models for computation of the efficiency of DMUs in the presence of missing data. The approach makes it possible to evaluate DMUs with missing values, along with other DMUs, with crisp data. Within the approach, missing values are substituted with intervals which the missing values could belong to. Then, proposed DEA models identify an efficiency interval for the efficiency score of the DMUs with missing values. Later Azizi (2013) presented some drawbacks due to the use of the variable production frontier for computation of the efficiency intervals of DMUs. The indicated drawbacks were mainly related to the efficiency overestimations when the intervals are used. Azizi (2013) then proposed an alternative interval DEA model based on interval arithmetic. In 2015, Kazemi Matin and Azizi proposed further updates to the interval-based approach to apply to missing data (Kazemi Matin and Azizi, 2015).

Tamaddon et al. (2009) proposed using a linear function for the missing data, obtained by using a convex combination of the interval beginnings and endings. Such an approach could be used if the data are crisp and the intervals are regular. The approach works in the following way: firstly, authors determine the missing amounts via the sum of other DMUs inputs and outputs in the crisp case; then, in the event that the data intervals are regular, authors obtain the upper and lower bounds of the missing data via crisp processes. Then, by using a convex combination of the interval beginnings and endings, a linear function of an analogous variable with each one of the inputs and outputs components is obtained. In such a way, a function for the missing data is obtained through crisp processes.

Kao and Liu (2000) adopt the concept of a membership function used in fuzzy set theory for representing missing data. Kao and Liu (2000) used fuzzy sets for modelling integer intervals for missing data. They replaced intervals for missing values and used the observed data for estimating membership functions of fuzzy efficiency scores. Kao and Liu (2007) also proposed a fuzzy approach to deal with missing values. Authors claim that while the conventional DMU deletion method overestimates the efficiencies of the remaining DMUs, the fuzzy set approach produces results which are very close to those calculated from complete data.

Chen et al. (2014) introduced a multiple linear regression analysis to estimate missing values. The authors used a valid argument to apply regression analysis to the DEA data: the DEA technique assumes the homogeneity of DMUs for a production process, which meets the requirement of regression analysis.

The authors propose a three-step approach:

- Step 1. Denote the variable with missing values as the dependent variable and the remainder as independent ones, then go to Step 2.
- Step 2. For each DMU where there are other independent variables with existing missing values, exclude it from the analysis; otherwise, use the multiple linear regression model to obtain the regression equation and go to Step 3. If all values of remaining independent variables of the current DMU are missing, then replace the dependent variable of the current DMU with a mean of the variable excluding the DMUs with missing values and go to Step 3.
- Step 3. Calculate the predicted values using the regression equation in Step 2 and go back to Step 1 until all missing values are estimated.

The approach performs adequately in comparison to other techniques when empirically tested on the data from US commercial banks. Similarly to other studies, the average margin of error increases with an increase in the missing value level (0.06% for 1% missing values, 0.16% for 2% missing values and 0.4% for 5% missing value level).

This approach might be the best approach for the studies where data from one period are considered. However, for our study, there are data from multiple periods available and for the missing DMU values, where historical data on the missing input/output are available, utilization of these data brings additional benefit over value estimation using regression as described by Chen et al. (2014).

Senel et al. (2016) proposed the use of an expectation maximization (EM) algorithm to handle missing values during DEA modelling. The EM algorithm is an iterative method of finding maximum likelihood estimates of parameters in statistical models, where the model depends on unobserved latent variables. The EM iteration alternates between performing an expectation (E) step, which creates a function for the expectation of the log-likelihood evaluated using the current estimate for the parameters, and a maximization (M) step, which computes parameters maximizing the expected log-likelihood found on the E step. These parameter estimates are then used to determine the distribution of the latent variables in the next E step. This application was mentioned above. Although providing good results with the low level of missing values, with an increase in the level of missing values the average error increases faster than, for instance, when multiple linear regression analysis is applied.

Thus, for this research, it was decided to use default values for the substitution of missing values. However, the other option was empirically tested as well and results are presented in the section 4.4.1

3.6 Unbalanced dataset

The presence of an unbalanced dataset generally doesn't cause an issue for the DEA modelling if data from multiple time periods are modelled separately. If a body of research requires an assessment of productivity change over time and therefore the use of approaches such as the Malmquist index, strictly balanced panel data are then required (Li, 2009). This means that all DMUs must be observed in all time periods. One way of enabling unbalanced panel data to meet the balanced requirement for the Malmquist index calculation is the elimination of DMUs which have missing records in some time periods. The drawback of this approach is the same as when applying data elimination to treat missing data within the single dataset, namely the fact that the research sample size is significantly reduced. This method, however, is frequently used in the literature on this subject.

The alternative approach proposes reassembling data into several balanced sub-panels based on time groups. The most preferable method, however, is to substitute missing records with the records containing default values and thus populate the entire dataset. Productivity change estimations will not be valid for the specific DMUs and the particular time intervals where substitutions were made, but the presence of full dataset for each time period increases the precision of efficiency estimations.

3.7 Correlation

There is no strict rule for the correlation limitations in DEA models, and significant correlation between inputs and outputs is generally allowed if it is expected due to variable structure and nature (Efendic and Hadziahmetovic, 2017). Correlated variables, therefore, are kept in a model if they are important components for the efficiency analysis (Widiarto and Emrouznejad, 2015; Efendic and Hadziahmetovic, 2017; Saen et al., 2005).

Efendic and Hadziahmetovic (2017) argue that researchers may be tempted to add as many inputs and outputs as they believe are important or relevant for the purpose of their analysis, but problems arise if some of them are highly correlated (Jenkins and Anderson, 2003). Another issue is that as we increase the number of inputs and outputs in the DEA model, the number of DMUs with 100% efficiency also increases, and by adding an irrelevant variable in the model the result obtained could also change (Pedraja-Chaparro et al., 1999).

Some studies, however, provide empirical evidence that if the correlation between model vectors (input or output vectors) is higher than a certain threshold, one of the input (output) vectors could be omitted with no significant impact on the resulting efficiency estimates (Sean et al., 2005). Authors provide different estimations for the threshold. Sean et al., 2005, present their study results showing that if in BCC and CCR the model's correlation coefficient between the two input vectors is 0.96 or above, one of the input vectors could be omitted. In Banker et al. (1984), Charnes et al. (1978) the threshold is set at 0.94. There are other studies proposing lower threshold values, for instance, study by Sean et al. (2005), which mentions a value of 0.9.

Mecit and Alp (2012) proposed a different application of the correlation indicators in data envelopment analysis. The authors suggest a modification to the CCR model with additional model constraints driven by variable correlations. The variable relationship is then taken into account in assigning the weights of the variables when calculating the efficiency score, with the suggested approach deriving the balanced weight of the variables.

The correlation analysis for this research is presented in section 4.4.3.

3.8 Outliers

Due to its inherent determinism, DEA models react sensitively to outliers in datasets. In DEA framework, an outlier is a unit with an input-output mix that significantly differs from the rest of the units (Emrouznejad, 2010). This can be due to a measurement error, or as a result of the outlier having different operating practices. Outliers that are efficient can introduce bias into the analysis and therefore analysis of outliers should be conducted before the DEA modelling.

To explain the potential impact of having outliers in the dataset, we will use example of one input – one output production similar to the example provided by Boyd et al (2016). Below figure 3.1 displays input–output combinations of a simulated dataset of DMUs on the left side and corresponding DEA efficiency frontier on the right side. Variable returns to scale assumed here.

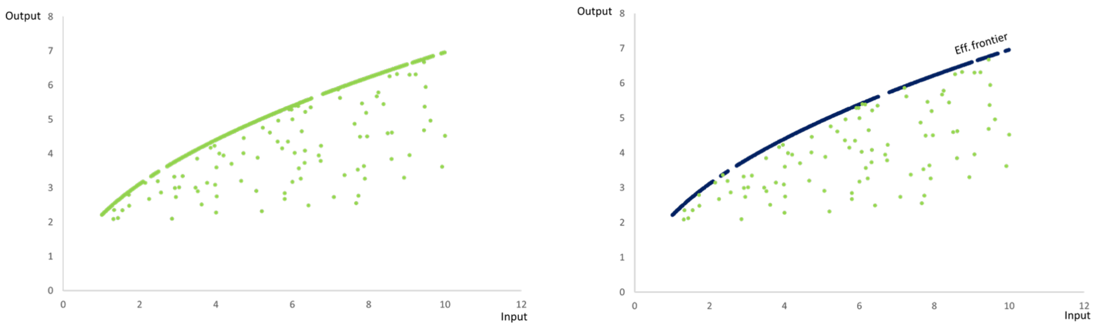

Figure 3.1: Input–output combinations and corresponding DEA efficiency frontier - example of dataset without outliers

The resulting frontier is a piecewise linear approximation of the true function that generated the data. The true frontier and DEA estimated frontier are superimposed on the figure.

Using the same data, we now generate several outliers above the frontier. These data and corresponding frontier are displayed in the figure 3.2.

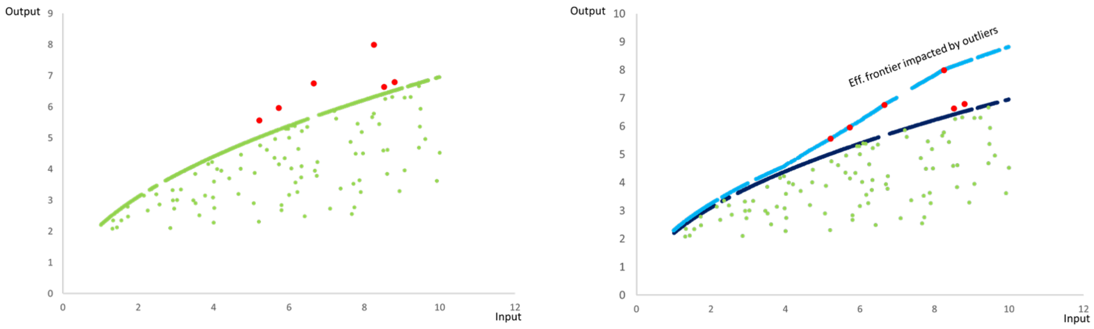

Figure 3.2: Input–output combinations and corresponding DEA efficiency frontier - example of dataset with presence of outliers

In this example, outliers drive the new DEA efficiency frontier (displayed by the light blue line) to be higher than the true frontier. As a result, the efficiency scores are biased and distance to the efficiency frontier is overestimated.

There no uniquely defined guidelines on how to detect and treat outliers in the DEA modelling methodology. As stated in Ahamed et al. (2015), Timmer (1971) was the first to recognize the high sensitivity of DEA scores when outliers are present, in linear programming problems. By suitable finding, the threshold value, a specified per cent of firms were removed from the reference set to arrive at output elasticities with respect to inputs. The percentage of firms removed from the data is subjective.

Andersen and Petersen (1993) suitably tailored the DEA constrains to assess super efficiency scores of efficient units. Their approach allows to rank order efficient units and instead of usual limitation of scores to 100%, super efficient units obtain scores above 100%. In their approach input and output vector of a unit under evaluation is removed from the reference set. Consequently, the input vector falls below the input efficient frontier and the deletion pushes frontier toward inefficient units. Deletion of an efficient unit from the reference set leads to the contraction of the input set. Such efficient unit whose deletion from the reference set resulted in the maximum contraction of the input set is the most influential observation, possibly an outlier. The threshold value of super-efficiency score to identify outliers is due to subjective choice. Formulation of the super efficiency DEA models presented in the section 2.9. The empirical study of the current research uses super-efficiency DEA models to identify potential outliers (discussion is provided in the section 4.4.5).

Chapter 4

Empirical study: social and financial efficiency assessment of microfinance institutions

4.1 Background and study questions

This chapter presents the two-stage empirical study. At the first stage, DEA is applied to measure the social and financial efficiency of microfinance institutions operating in the economies of Sub–Saharan Africa. The analyzed time period is 2004 - 2017. Cross-efficiency charts are constructed for the detailed analysis of the DMU's position on both social and financial efficiency scales. The results then aggregated on the economy level, and a similar comparison is conducted. At the second stage of the study, the set of external environmental factors and internal factors of an institution's operating structure are examined in order to indicate whether there is a relation between factor values and efficiency levels.

The aim of the study is to determine what characteristics efficient microfinance institutions possess, and what characterizes the macro environment associated with the higher performing institutions. The overtime efficiency dynamic and DMU prioritization between social and financial objectives are also among the main interests of the study.

The study focuses on the Sub–Saharan Africa region for two reasons:

- Although the microfinance industry helps to fight poverty in almost all poor regions across the world, the Sub–Saharan Africa region is witnessing a slower development of the industry compared to Asia, Latin America or the Middle East and North

African regions. The poverty level in the region meanwhile remains the highest in the world. Thus, the issue seems to be more urgent to the Sub–Saharan Africa region than to other regions.

- Due to a professional engagement, the author has experience in operations of microfinance institutions, regulatory authorities and international organizations in the Sub–Saharan Africa region and was involved in various projects focused on process optimization, customer onboarding, risk management and collection strategies across 7 countries of the region. Utilization of industry knowledge during the DEA analysis is useful, as mentioned in section 3.4 (Thanassoulis, 2001).

The study addresses nine main questions formulated as follows:

- What is the financial and social efficiency of microfinance institutions across developing countries of the Sub–Saharan African region? Do most institutions operate close to the efficiency frontier or away from it?
- What is the productivity change over time periods? What is the change in the time of external shocks such as the 2008 global financial crisis?
- Social and financial objectives - are they mutually exclusive?
- Is there a mission drift in the microfinance industry observed over time?
- Does the composition of products offered by microfinance institutions impact on efficiency? Where do the institutions focusing on support of small and medium business stand on the efficiency scale?
- Are microfinance institutions providing deposit products in addition to lending products more efficient than the ones providing only lending products?
- Does gender matter? Are women-focused microfinance institutions more efficient compared to the overall sample?
- What could be the increase in the number of consumers if all microfinance institutions in the study were operating relatively efficiently.
- Do the regulations impact on the efficiency of the microfinance industry? Are institutions more efficient in the more regulated markets?
- Do the infrastructural components such as credit registries and credit bureaus matter? Are institutions operating in the markets with credit bureaus more efficient compared to the institutions operating in markets with no credit bureau?

- Does the presence of international funding projects focused on the improvement of the microfinance environment bring about higher efficiency?

The rest of this chapter is arranged as follows: section 4.2 provides the overview of previously conducted academic studies on the topic. Section 4.3 with its subsections describes arguments and decisions leading to the application of the specific DEA model. This includes the discussion about DEA versus other approaches, the robustness test of the potential impact of model orientation change, arguments leading the selection of variable returns to scale and input-output composition. Chapter 4.4 then provides details of the data used for the study. Besides the data description, subsections on the missing data issue and its empirical solution, dataset normalization, correlation analysis and the issue of an unbalanced data panel are included. Chapter 4.5discuses results of the first stage analysis, on both DMU and economy levels. Subsection 4.5.2 attempts to set up the achievable social targets for microfinance institutions. Subsection 4.5.3 investigates productivity change over time with the application of the Malmquist index, and subsection 4.5.4 describes the second stage analysis. Finally, subsection 4.6 concludes the study findings.

4.2 Related literature overview

The topic of empirical measurement of social and financial microfinance performance is increasingly attracting the attention of researchers. However, no standard methodology for the assessment of the double objective performance of microfinances has been developed yet. Various researchers have attempted to employ different methodologies to answer efficiency-related questions. A large number of studies measure the financial performance of microfinance institutions using financial indicators (Churchill, 1999; Bhatt and Tang, 2001; Khalily, 2004; Koveos and Randhawa, 2004; Nanayakkara and Iselin, 2012). Such studies, however, do not accommodate for the social component.

Studies which combine social and financial microfinance efficiency have adopted two principal estimation methodologies: Data Envelopment Analysis, a nonparametric approach to data envelopment, and Stochastic Frontier Analysis, a parametric approach to estimation by stochastic boundaries (Fall et al., 2018). Although the DEA isn't still widely used in microfinance, it has been used in several studies, among others in Gutirrez–Nieto et al. (2009), Gutirrez–Nieto et al. (2007), Islam et al. (2011), Hassan and Sanchez (2009), Nghiem et al. (2006) and Bassem (2008). The studies cover different geographical regions from single economy studies (Efendic and Hadziahmetovic, 2017; Lebovics, 2016; Azad, 2015a) to cross-economy and cross-continental studies (Widiarto and Emrouznejad, 2015; Widiarto et al., 2017; Hudon et al., 2018; Bassem, 2008). There is, however, no in-depth study covering economies of the Sub–Saharan African region in full.

Significant attention in the literature is dedicated to the relation between social and financial performance and the question of whether two efficiencies are mutually exclusive. Reichert (2018) indicates that there were 3299 articles on the topic written as of 2016, of which 61 of them were empirical studies. Lebovics et al. (2016) studied the trade-off between social and financial efficiencies of microfinance institutions in Vietnam. Based on an analysis of 28 Vietnamese MFIs for the year 2011, authors found no correlation between those two types of efficiencies, meaning that there is no trade-off between them. Hudon et al. (2018) analyzed institutions in South Asia showing that out of 496 institutions, 24 fulfil both objectives simultaneously, while the remaining institutions find it difficult. Gutirrez–Nieto et al. (2009) studied the relationship between financial and social efficiency. They concluded that when faced with a choice between social and financial efficiency, MFIs choose financial performance in order to be able to continue with their social aims. 89 international MFIs were analyzed in the study, and only 13 show a higher level of social efficiency in comparison to financial efficiency. Other authors also indicated evidence of the "mission drift" (Armendariz and Szafarz, 2011; Beisland and Mersland, 2013). In this research, we investigate the relationship between social and financial efficiency in an attempt to answer whether the two objectives are mutually exclusive.

To provide a structured review of empirical studies focused on measurement of social and financial microfinance performance using DEA, I composed the table 4.1 containing the overview of the main study characteristics. 20 frequently cited studies are presented in the table.

Author	DEA Type	Inputs	Outputs	RTS	MFIs	Geo	Period	Key findings
Qayyum and Ahmad (2006)	Output and Input oriented DEA	- Number of credit officers - Cost per borrower	Number of loans	CRS and VRS	15 Pakistani, 25 Indian and 45 Bangladeshi MFIs	Selected South-Asian countries	Not specified	- Full three countries combine analysis revealed that there are two efficient MFIs under CRS and five efficient MFIs under VRS assumption in these countries. - The analysis revealed that the inefficiencies of MFIs in Pakistan, India and Bangladesh are mainly due to technical nature.
Nghiem et al. (2006)	Input oriented DEA	- Labour costs - Non-labour costs	Number of depositors	VRS	46	Vietnam	2006	MFI Age & distance to township affects MFI efficiency
Fluckiger and Vassiliev (2007)	Output oriented DEA	- Number of employees - Assets - Operating expenses	- Number of loans - Net operating revenue	VRS	39	Peru	2003	Average efficiency of 39 Peruvian MFIs in 2003 is 85.5%
Gutiérrez-Nieto et al. (2007)	Output oriented DEA	- Credit officers - Operating expenses	- Gross loan portfolio - Loan Outstanding - Interest & fee revenue	CRS	30	Latin America	2001-2002	Country effect & NGO status affect efficiency scores (multivariate analysis)
Bassem (2008)	Input oriented DEA	- Personnel - Total Assets	- Women borrowers - Return on Assets	CRS and VRS	35	Mediterranian	2004-2005	Medium-sized MFIs are found to be more efficient
Gutiérrez-Nieto et al. (2009)	Output oriented DEA	- Assets - Operating expenses - Number of employees	- Gross loan portfolio - Women borrowers - Index of benefit to poor - Financial revenue	CRS	89	Global	2003	- To be socially efficient MFIs need to be financially efficient - When faced choices, MFIs tend to prioritize financial objective over social
Hassan & Sanchez (2009)	Output and Input oriented DEA	- Total financial expenses - Operating expenses - Number of employees	- Gross loan portfolio - Total funds - Financial revenue - Number of borrowers	CRS and VRS	214 (in 2005) 45 (2001-2005)	Latin America MENA SA	2001-2005	· Higher TE for formal MFIs - SA MFIs have higher TE than Latin America and MENA - Inefficiency source is pure TE - TE stagnant in 2001-5 period
Sedzro and Keita (2009)	Output oriented DEA	- Number of employees - Physical capital - Financial capital - Total deposits	- Loans per year - Investments - Interest revenue - Number of borrowers - Number of depositors	CRS and VRS	161 (in 2000) 210 (in 2001) 168 (in 2002)	WAEMU (West African Economic and Monetary Union)	2001-2002	· Countries environment affect perfomance differences
Nawaz (2010)	Data envelopment analysis (three-stage)	Total factor productivity approach			204 MFIs	54 countries	2005-2006	Reinforce the importance of government support
Haq et al. (2010)	Output and Input oriented DEA	- Number of employees - Operating expenses - Cost per borrower - Cost per saver	- Gross loan portfolio - Borrowers per staff - Savers per staff - Total savings	CRS VRS	39	Africa Asia America	2004	- High level of cost efficiency fall due to NPL for Bank-MFI - NGO-MFIs are more efficient in P - Bank-MFIs are more efficient under I

Pal (2010)	Output and Input oriented DEA	- Number of credit officers - Cost per borrower as a proxy for expenditure	Three year average portfolio outstanding	CRS and VRS	39	India	2007-2009	- Debt equity ratio and financial expenses per asset are negatively related with TE and PTE. - The technical efficiency figures for East, South and, North and West are 0.66, 0.544, and 0.697, respectively, while the average pure technical efficiencies for these locations respectively range between 0.819-0.894, 0.712-0.719 and 0.778-0.9. there are two technically efficient MFIs under CRS assumption and six technically efficient MFIs under VRS assumption among the 39 MFIs
Gebremichael and Rani (2012)	Malmquist index	- Number of employees - operating expense/ administrative expense	- Interest & fee revenue - Gross loan portfolio - Loan outstanding	VRS	Balanced panel dataset of 114 observations from 19 MFIs	Ethiopia	2004-2009	Improvement of technical efficiency (e.g. management practices) is the main source of productivity growth
Kipesha (2012)	Input oriented DEA	- Total assets - Revenues - Number of employees	- Gross loan portfolio - Financial revenue	CRS and VRS	35	East Africa	2009-2011	- TE differences between East African countries - Bank & NBFI have higher TE vs NGO & Credit Union
Bassem (2014)	Malmquist index	- Number of employees - Operating expense	- Interest & fee revenue - Gross loan portfolio - Loans outstanding		A balanced panel with 198 observations from 33 MFIs.	Middle East and North Africa	2006-2011	- Overall productivity progress of 4.9 % per annum. - Technical efficiency change (management practices) matters to improve productivity performance while scale efficiency placed detrimental impact
Tahir and Tahrim (2015)	Dynamic Malmquist approach	- Operating expense - Total assets	- Gross loan portfolio - Number of active borrowers		A balanced panel datasets of 13 MFIs	Cambodia	2008-2011	Overall productivity progress of 4.9 % attributed mainly to technological change while scale efficiency placed a very trivial positive impact and negative impact of pure technical efficiency change
Bibi and Ahmad (2015)	Malmquist productivity index, output-oriented DEA	- Number of employees - Operating expenses	- Gross loan portfolio - Number of loans outstanding		Balanced panel dataset of 198 observations from 85 MFIs.	SAARC (South Asian Association for Regional Cooperation)	2003-2011	Microfinance business has reported general productivity regress in the study period despite the fact that all the SAARC MFIs have positive TFP development except for the years 2005-2006, 2007-2008, 2008-2009
Widiarto and Emrouznejad (2015)	Output and Input oriented DEA	- Assets - Operating expenses - PAR 30 - Number of employees	- Financial Revenue - Inverse of Average Loan Balance per GNI per capita - Number of Borrowers	CRS and VRS	63 (EAP) 29 (MENA) 113 (SA)	EAP MENA SA	2009-2010	- Trade-off between dual objectives can be managed & pursued concurrently - IMFIs & MFIs tie in overall efficiency yet MFIs excel in scale efficiency - MFIs mostly topped IMFIs in outreach & sustainability - Not-for-profit MFIs deliver higher outreach
Mia and Chandran (2016)	Malmquist productivity index	- Operating exp./Asset - Number of employees	- Financial productivity (Financial revenues/ assets) - Social outreach productivity balance per borrower - Number of depositors		162	Bangladesh	2007-2012	- After classifying the output into financial and social outreach, we also observed that social outreach productivity was higher (5 % per annum) than the financial productivity of 3.9 % per annum. - In terms of depth of outreach, there was productivity progress of 15.8 % per annum while it was only 1.2 % per annum for breadth of social outreach

Efendic and Hadziahmetovic (2017)	Meta-frontier DEA approach	- Number of employees - Total assets	- Financial Revenue - Gross Loan Portfolio - Number of Active Borrowers	VRS	15 MFIs, 88 observations	Bosnia and Herzegovina	2008-2013	- The correlation between financial and social efficiency is positive and statistically significant, suggesting that more financially efficient MFIs are more socially efficient - Large and medium sized MFIs have a lower level of both financial and social efficiency than smaller ones. - Crisis had a negative effect on both financial and social efficiency, while the difference between the two efficiencies slightly decreased within the period 2008 to 2011.
Widiarto et al. (2017)	Non-oriented hyperbolic DEA	- Assets - Operating expenses - Number of employees	- Financial Revenue - Inverse of Average Loan Balance per GNI per capita - Number of borrowers	CRS and VRS	1461 DMUs from 628 not-for-profit MFIs in 87 countries	Africa, EAP, EECA, LAC, MENA and SA.	2003-2012	- Group lending is the best method in achieving highest overall and social efficiency in Africa and MENA, yet it is village banking that prevails in these efficiency measures in LAC. - Not-for-profit DMUs in all regions in this study show generally satisfactory financial efficiency scores. - Findings on other factors related to efficiencies, i.e. borrowings, total donation, portfolio at risk 30 days, portfolio at risk 90 days, interest rates, MFI age, regulation status, and legal format, support the argument that appropriate performance analysis should best be done on regional level.

Table 4.1: Microfinance efficiency studies with DEA application

Many of researches attempt to identify the relationship between efficiency level and external environmental factors or internal factors of the institution operating structure by applying techniques such as regression analysis or nonparametric tests as a second stage after the efficiency analysis. (Widiarto and Emrouznejad, 2015) applied nonparametric tests to analyze factors such as size, age, profit-orientation, target portfolio and regulation status, finding significant dependencies between some of the factors and the efficiency level. Widiarto et al. (2017) used TOBIT regression to analyze the loan methodology and found that a particular type of lending (group loans) was associated with higher social efficiency than individual lending. Among the other structural factors analyzed by researchers are gender focus, presence of foreign investments and foreign ownership, product composition, deposit schemes, loan terms, loan types, and loan channels. The research of Hartarska and Nadolnyak (2007) tested this hypothesis, stating that microfinance institutions providing deposit services to their clients have higher social efficiency due to the lending capital increase enabled by the deposit scheme. The research did not indicate strong evidence either in favour of accepting or rejecting the hypothesis. The study of Reichert (2018) tested the hypothesis that institutions focusing on female borrowers have lower financial efficiency and in fact, the study results confirm this hypothesis.

This research also investigates the relationship between efficiency levels and institution structural factors, focusing on four of them: the presence of a deposit scheme, borrowers gender prevalence, SME target group and the prevailing term of the loan. Among the environmental factors investigated in the various bodies of research, regulation is frequently analyzed. Research conducted by Hartarska and Nadolnyak (2007) concluded that the presence of regulation does not impact on microfinance efficiency. The results are generally consistent across studies and generally contradict the common opinion that regulation highly impacts on microfinance operations and their efficiency. In the opinion of this study, the regulation factor requires deeper analysis, because it consists of multiple components. Instead of representing regulation by a single binary variable, we propose to separate regulation components and investigate their relationship with microfinance efficiency individually. This research covers an analysis of two regulation components: legislation and limitations of the interest ceiling. Another factor we have separated is the presence of a credit registry or credit bureau. This factor is only partially related to regulations because while credit registries are public organizations, credit bureaus can be and frequently are operated by private companies (although they need governmental support to operate to a full market scale). Other studies include credit bureau presence into the regulatory factor. However, we prefer to analyze its relation to efficiency individually. Finally, the current research analyzes the relationship between efficiency and presence of microfinance-focused projects run by international organizations providing support to developing countries in their fight against poverty.

4.3 Methodological framework

In order to define an appropriate methodological approach for the research, an extensive literature study was conducted in a search for the answer to the fundamental question: what approaches can be used to measure efficiency and what benefits do they offer? It was very important for the research to use key study questions as a starting point and driver for approach selection rather than assume any specific methodology without careful considering the study objectives. Data envelopment analysis was selected due to the ability to provide a framework, which enables answering the study questions without significant limitations of initial study assumptions. Discussion on all considered approaches is held in the subsection 3.1. Later when the choice of methodology was narrowed down to data envelopment analysis, further literature investigations have taken place to specify the type of model and its parameters to be used for the empirical part of the research. The section below expands on the reasoning leading to the methodology definition. The section dedicates separate paragraphs to answer each of the questions:

- Why the study was not limited to specific model orientation, but several output-oriented and non-oriented models were built
- Why variable returns to scale were assumed for the microfinance industry
- How unbalanced panel was handled during the multiple year modelling

4.3.1 Study model orientation

DEA theory states that different model specifications (input-oriented, output-oriented and non-oriented) could yield different outcomes. It is interesting to understand how the resulting efficiency estimations can change depending on the selection of model orientation. To answer this question, we tested the sensitivity of DEA resulting efficiency level by building three models: input-oriented, output-oriented and non- oriented. All three models were built using the same dataset (the dataset described in the upcoming section 4.4.1 "Handling missing data") and using the same input-output combination (the overall efficiency specification used as in table

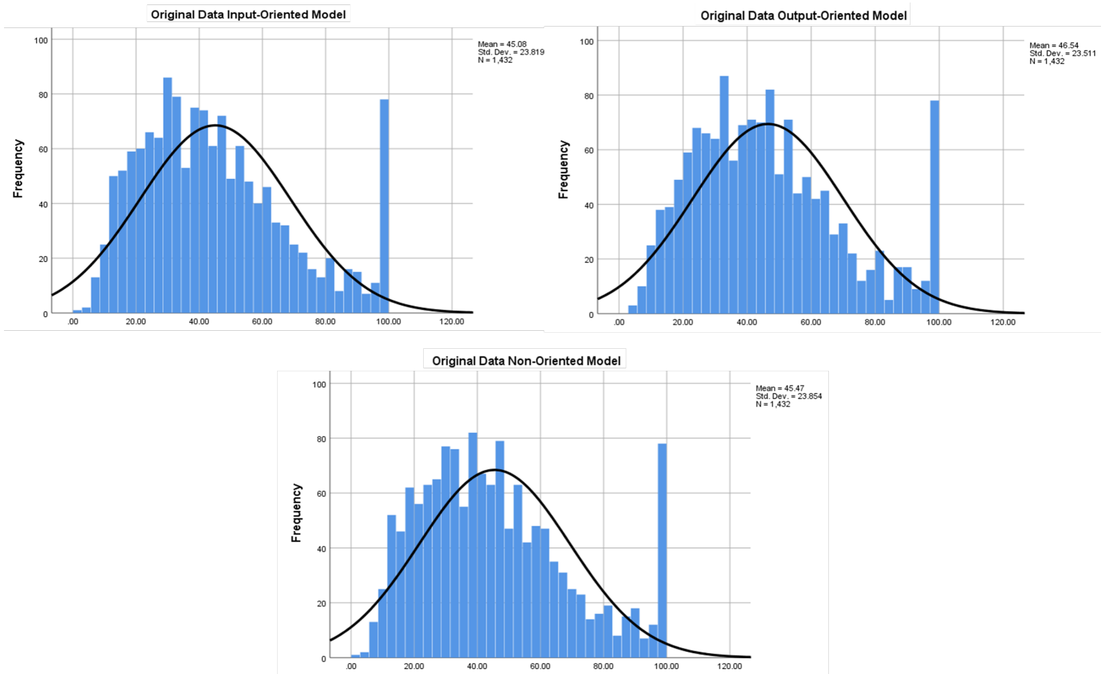

Figure 4.1: Model orientation sensitivity test

Although the distributions have a similar shape and contain a similar proportion of efficient DMUs, it doesn't indicate whether the same DMUs are efficient across all three models. To answer this question we have divided efficiency scale into 5 bands ($[0;0.25)$, $[0.25;0.5)$, $[0.5;0.75)$, $[0.75;1.00)$ and 1.00) and constructed cross-tabular pair-wise comparison of three models, the results presented in the tables 4.2, 4.3 and 4.4. Across all three models, an average of 96% of DMUs fall within the same efficiency band, which demonstrates low sensitivity of the resulting efficiency levels to the selection of input-oriented, output-oriented or non-oriented DEA models, at least in case of the dataset used for this research.

		Output-Oriented DEA					
		[0; 0.25)	[0.25; 0.5)	[0.5; 0.75)	[0.75; 1.00)	1.00	Total number of DMUs
Non-Oriented DEA	[0; 0.25)	275	26				301
	[0.25; 0.5)		582	22			604
	[0.5; 0.75)		1	337	2		340
	[0.75; 1.00)			1	118		119
	1.00					68	68
	Total number of DMUs	275	609	360	120	68	1432

Table 4.2: Pairwise comparison of model orientation: Non-Oriented versus Output-Oriented

		Input-Oriented DEA					
		[0; 0.25)	[0.25; 0.5)	[0.5; 0.75)	[0.75; 1.00)	1.00	Total number of DMUs
Non-Oriented DEA	[0; 0.25)	298	3				301
	[0.25; 0.5)	12	592				604
	[0.5; 0.75)		10	330			340
	[0.75; 1.00)			4	115		119
	1.00					68	68
	Total number of DMUs	310	605	334	115	68	1432

Table 4.3: Pairwise comparison of model orientation: Non-Oriented versus Input-Oriented

		Input-Oriented DEA					
		[0; 0.25)	[0.25; 0.5)	[0.5; 0.75)	[0.75; 1.00)	1.00	Total number of DMUs
Output-Oriented DEA	[0; 0.25)	298	3				301
	[0.25; 0.5)	38	570	1			609
	[0.5; 0.75)		32	327	1		360
	[0.75; 1.00)			6	114		120
	1.00					68	68
	Total number of DMUs	310	605	334	115	68	1432

Table 4.4: Pairwise comparison of model orientation: Output-Oriented versus Input-Oriented

This research aims to answer the question of how far from the frontier of efficiency microfinance institutions operate, and what factors impact on the efficiency level. This question does not limit us to input or output orientation, either of them could be used. Thus, the nature of the study question does not lead to the selection of unambiguous model orientation.

Now it is important to consider the nature of the data the model is applied to. The dataset consists of a wide range of microfinance institutions operating in different market environments. Thus, there are units operating in remote areas, rendering potential for outreach limited by the volumes of the local population. As Widiarto et al. (2017) pointed out in their research of not-for-profit microfinance organizations, evaluating their efficiency using an output-oriented model would not be fair and would lead to discrimination of such companies against the rest of the units in the dataset. The recent innovative developments in the microfinance industry bring more arguments to this discussion. The growth of online and mobile lending now allows customers from remote areas to apply for and receive a loan without visiting the institution's branch, which significantly expands outreach opportunities for microfinance institutions and reduces the impact of territorial limitations. When this innovation becomes widespread across all the microfinance markets, we will be able to dismiss the territory limitations during the model construction However for now we must consider it valid.

In the same research of not-for-profit microfinance, Widiarto et al. (2017) argue that assuming input orientation for all units uniformly would discriminate MFIs already in input shortage. Thus, they propose the usage of a non-oriented DEA model allowing both orientations to be taken into account. This gives units an opportunity to increase their efficiency by optimizing input and output weights simultaneously as long as inputs are not increased, and outputs are not decreased. The model is described in section2.8 Following the example of previous authors, this study utilizes a non-oriented DEA model for the first stage of DEA modelling. For the further stages of the research, such as productivity change over time using the Malmquist index and post-DEA analysis (which relies on the construction of meta-frontier), the research uses output-oriented DEA models. Usage of different orientations within the research is reasonable due to the fact that model selection orientation has a relative impact on the resulting efficiency levels, as has been demonstrated above.

4.3.2 Variable returns to scale

There is a number of studies in the literature focusing on the efficiency and productivity of the banking sector in various regions. However, few studies focus on the microfinance sector's efficiency and productivity. Although banking and microfinance industries are conceptually different due to a double-objective line specific to microfinance institutions, some operational components of the two industries have similarities, and certain assumptions made for banking industry can be applicable to the microfinance industry as well, including types of returns to scale. When deciding between the use of constant or variable returns to scale, we largely relied on the literature overview and the arguments used in the related studies (in both the banking and microfinance industries).

Azad et al. (2016b) applied the assumption of variable returns to scale when investigating the efficiency of major microfinance institutions in Bangladesh. Efendic and Hadziahmetovic (2017) employed a VRS input-oriented DEA model when assessing the social and financial efficiency of microfinance institutions in Bosnia and Herzegovina. The authors' further research indicated that when financial efficiency is considered, 64.7% of DMUs have decreasing returns to scale, and 19.3% have increasing returns to scale. The input model orientation was selected due to the objective of evaluating the efficiency of management of MFIs in managing inputs to produce desired social and financial outputs. Qayyum and Ahmad (2006) used a sample of 85 South Asian MFIs (45 MFIs in Bangladesh, 25 MFIs in India and 15 MFIs in Pakistan) and found that six Bangladeshi MFIs, five Indian MFIs and eight Pakistani MFIs were efficient under the assumption of variable returns to scale, while under the assumption of constant returns to scale the number of efficient DMUs is extremely low.

The argument supporting the selection of VRS is that institutions of both microfinance and banking industries operate on different ends of the scale, from very small to very large. The imbalance in data magnitudes could cause an issue in cases whereby the CRS are assumed, as for the constant returns to scale it is fair that output/input proportions remain consistent at any level of the operation scale. The model built under VRS does not depend on data magnitude, and therefore VRS is a more appropriate assumption for the study.

Additionally, the assumption of CRS would not be valid for the current research also because of use of the "portfolio at risk" variable (section 4.3.3), which is ratio variable and requires VRS.

4.3.3 Input-output selection

When selecting the input and output combinations, we relied on the literature references and previous applications of efficiency models in the microfinance industry.

Based on the conducted literature review, with respect to the availability of data in our sample, four inputs and three outputs reflecting the research goals were selected for the model: Input variables:

- Assets (A) This represents a total of all net asset accounts. The input is frequently used by other authors, among which are studies of Fluckiger and Vassiliev (2007), Widiarto et al. (2017), Widiarto and Emouznejad (2015), Tahir and Tahrim (2013), Kipesha (2012), Gutiérrez-Nieto et al. (2009), Hassan and Sanchez (2009) and Bassem (2008). According to the Mix database description, financial assets are presented according to standard IFRS categories based on the treatment of those assets, whether financial assets at fair value through profit or loss, financial assets available for sale, or held-to-maturity. Financial assets not presented in MFI statements. treated as short-term investments according to one of these accounting treatments, are classified as cash and cash equivalents. As a result, cash and cash equivalents balances may be higher than reported previously.

- Operating Expense (O) Included herein are all expenses related to operations, e.g. all personnel expenses, depreciation and amortization, and administrative expenses. The variables frequently used by researchers Fluckiger and Vassiliev (2007), Gutiérrez-Nieto et al. (2007), Gutiérrez–Nieto et al. (2009), Hassan and Sanchez (2009), Haq et al. (2010), Bassem (2014), Tahir and Tahrim (2015), Bibi and Ahmad (2015), Widiarto and Emrouznejad (2015), Widiarto et al. (2017).

Some studies utilize the component of the variable instead of its original value (Nghiem et al., 2006), for instance, included labour costs or modified variable (Mia and Chandran, 2016) included operating expenses divided by asset.

- Portfolio at Risk 30 Days (R) Portfolio at Risk 30 days

Portfolio at Risk 30 days (R) indicates the proportion of total portfolio with 30 days or higher delinquency. This includes the entire unpaid principal balance, including both the past due and future installments, but not accrued interest. It also includes loans that have been restructured or rescheduled. The variable was used in the study Widiarto and Emrouznejad (2015). The study debates as to whether the variable should be used as an input or output. The variable indicates the quality of the portfolio and the values of the variables (or, as it is more correct to say, its relative values in comparison with other market players). These depend on the risk management strategy adopted by the institution's management. The better their risk strategy for the loan origination process, the lower the level of the portfolio at risk, resulting in lower credit losses and higher revenues. Therefore, the variable is included in the input specification.

There are two alternative variables in the MIX database: portfolio at risk 30 days and portfolio at risk 90 days. If we were conducting a study of the banking industry, 90 days delinquency would be more appropriate to use, as 90 days past due is a common definition of default where banking products are concerned. The microfinance industry, however, provides a significantly shorter loan term then banking, as thus 30 days past due is a commonly used definition of default for microfinance loans.

- Number of employees (E)

The variables indicate the number of individuals who are actively employed by an MFI. This number includes contract employees or advisors who dedicate the majority of their time to the MFI.

The variable is widely used in other studies, the number of employees is utilized as inputs in studies of Bassem (2008), Hassan and Sanchez (2009), Sedzro and Keita (2009), Kipesha (2012), Haq et al. (2010), Fluckiger and Vassiliev (2007), Gutirrez– Nieto et al. (2009), Gebremichael and Rani (2012), Bassem (2014), Bibi and Ahmad (2015), Widiarto and Emrouznejad (2015), Mia and Chandran (2016), Efendic and Hadziahmetovic (2017), Widiarto et al. (2017). There are also studies (Qayyum and Ahmad, 2006; Gutirrez–Nieto et al., 2007; Pal, 2010) whereby authors use the number of credit officers instead of the number of employees. This study argues that the number of credit officers is only partially representative of the labour force. Credit officers are facing borrowers during the application process, and it is quite common especially in the Sub–Saharan African region that credit officers are only responsible for the recipient of the loan application, whereas application decisioning is conducted by the underwriting team. Customer life cycle, however, is not limited to the application process, as customer management, collection and other stages might be influential in a customer's relationship with a lender. Therefore, this study believes that the use of the number of employees as a DEA input variable is more appropriate than the number of credit officers.

Output variables:

- Financial Revenue (F) this variable represents revenues from the loan portfolio and other financial assets representing output in the production approach to measuring sustainability. The variable is utilized in studies of Fluckiger and Vassiliev (2007), Hassan and Sanchez (2009), Gutirrez–Nieto et al. (2007), Gebremichael and Rani (2012), Kipesha (2012), Bassem (2014), Widiarto and Emrouznejad (2015), Efendic and Hadziahmetovic (2017), Widiarto et al. (2017). This study did not limit the variable definition to the interest fee revenues as Sedzro and Keita (2009) did, because some of the DMUs receive fee-based income from other activities or other financial assets outside of the loan portfolio.

- Inverse of average loan balance (I)

This is the first of two output variables representing microfinance outreach. Two dimensions of outreach are considered in this research: depth and breadth and the inverse of the average loan balance here represent the depth of outreach. The general intention for microfinances is to have smaller average loan balances, as it means that the institution has penetrated deeper toward the poorest of the poor community - the poorest segment usually demand a small-sized loan. Due to the fact that value and purchasing power differs between countries, the variable has been standardized over GNI per capita. In its use as output in DEA models herein, this variable is used in its inverse format so as to have the output characteristic where the larger value is the better. The variable has used in previous studies of Gutirrez–Nieto et al. (2009), Widiarto and Emrouznejad (2015) and Widiarto et al. (2017).

- Number of Active Borrowers (B)

This refers to the number of individuals who currently have an outstanding loan balance with the MFI or are primarily responsible for repaying any portion of the gross loan portfolio. Herein, it is used as an output to resemble the breadth of outreach (the MIX database definition). The variables represent the breadth dimension of outreach. The variables are used in studies of Widiarto and Emrouznejad (2015), Tahir and Tahrim (2015), Hassan Sanchez (2009), Sedzro and Keita (2009), Widiarto and Emrouznejad (2015), Efendic and Hadziahmetovic (2017) and Widiarto et al. (2017). Researchers Qayyum and Ahmad (2006), Fluckiger and Vassiliev (2007), Bibi and Ahmad (2015) use number of loans, although this is a biased indicator as it fails to account for repeated customers taking multiple loans over time. Thus, the number of borrowers benefitting from microfinance services will be lower than the number of loans. Bassem (2008) and Gutirrez–Nieto et al. (2009) use the number of female borrowers, which is also analysed in this study, but in the second phase of the study. Haq et al. (2010) use the number of borrowers per staff member.

Variable	Role	Definition	Link with Literature	Units
Assets (A)	Input	Total of all net asset accounts.	Fluckiger and Vassiliev (2007), Widiarto et al. (2017), Widiarto and Emouznejad (2015), Tahir (2013), Kipesha (2012), Gutirrez–Nieto et al. (2009), Hassan and Sanchez (2009), Bassem (2008).	USD (000)
Operating Expense (O)	Input	All expenses related to operations, e.g. all personnel expenses, depreciation and amortization, and administrative expenses	Fluckiger and Vassiliev (2007), Gutirrez–Nieto et al. (2007), Gutirrez–Nieto et al. (2009), Hassan Sanchez (2009), Haq et al. (2010), Bassem (2014), Tahir and Tahrim (2015), Bibi and Ahmad (2015), Widiarto and Emrouznejad (2015), Widiarto et al. (2017)	USD (000)
Portfolio at Risk 30 Days (R)	Input	The proportion of total portfolio with 30 days or higher delinquency	Widiarto and Emrouznejad (2015)	%
Number of employees (E)	Input	the number of individuals who are actively employed by an MFI. This number includes contract employees or advisors who dedicate the majority of their time to the MFI.	Bassem (2008), Hassan and Sanchez (2009), Sedzro and Keita (2009), Kipesha (2012), Haq et al. (2010), Fluckiger and Vassiliev (2007), Gutirrez–Nieto et al. (2009), Gebremichael and Rani (2012), Bassem (2014), Bibi and Ahmad (2015), Widiarto and Emrouznejad (2015), Mia and Chandran (2016), Efendic and Hadziahmetovic (2017), Widiarto et al. (2017)	Numeric
Financial Revenue (F)	Output	revenues from loan portfolio and other financial asset	Fluckiger and Vassiliev (2007), Hassan Sanchez (2009), Gutirrez–Nieto et al. (2007), Gebremichael and Rani (2012), Kipesha (2012), Bassem (2014), Widiarto and Emrouznejad (2015), Efendic and Hadziahmetovic (2017), Widiarto et al. (2017)	USD (000)
Inverse of average loan balance (I)	Output	The inverse of the average loan balance standardized over GNI per capita. (I)	Gutirrez–Nieto et al. (2009), Widiarto and Emrouznejad (2015) and Widiarto et al. (2017)	USD Inversion
Number of Active Borrowers (B)	Output	Number of individuals who currently have an outstanding loan balance with the MFI or are primarily responsible for repaying any portion of the gross loan portfolio	Widiarto and Emrouznejad (2015), Tahir and Tahrim (2015), Hassan & Sanchez (2009), Sedzro and Keita (2009), Widiarto and Emrouznejad (2015), Efendic and Hadziahmetovic (2017) and Widiarto et al. (2017)	Numeric

Table 4.6: DEA input-output usage and references

Efficiency Specification	Input Variables	Output variables
Overall efficiency	Assets (A), Operating expenses (O), Portfolio at risk 30 days (R), Employees (E)	Financial revenue (F), Average loan balance per Borrower (in inverse form) – (I), Number of borrowers (B)
Financial efficiency	Assets (A), Operating expenses (O), Portfolio at risk 30 days (R), Employees (E)	Financial revenue (F)
Social efficiency	Assets (A), Operating expenses (O), Portfolio at risk 30 days (R), Employees (E)	Average loan balance per Borrower (in inverse form) – (I), Number of borrowers (B)

Table 4.7: Input -– output configuration in DEA model specifications

4.4 Dataset

The data for the study were obtained from several data sources:

- Performance data on individual financial institutions were obtained from the Microfinance Information Exchange Market database;
- Macro level indicators used to study second phase efficiency as well as for normalization of DEA input and output values were obtained from the World Bank database of World Development Indicators.

Microfinance Information Exchange is a non-profit organization focusing on data collection from financial service providers serving the low-income population around the world. The database provides transparency to financial sectors serving low-income populations in emerging markets, covering all six regions of developing markets (Sub–Saharan Africa, Latin America and The Caribbean, East Asia and the Pacific, Middle East and North Africa, Eastern Europe and Central Asia, and South Asia). Collected data is used by policymakers, financial services providers, socially responsible investors and researchers to build or contribute to an inclusive financial services ecosystem.

Our study utilizes MIX data on the Sub–Saharan Africa region. Data on 583 microfinance institutions from 38 countries were extracted from the database. The content of the dataset includes financial, operational, and social performance data on an annual basis. Thus, annual data covering the period of 2004-2017 were utilized in the study. The MIX data are used for the composition of inputs and outputs in the DEA models. It is important to mention that as microfinance institutions were entering and exiting markets at different points in time, not all 583 institutions were operating simultaneously during the 2004-2017 period, which brings the research to an issue of an unbalanced dataset, discussed further in section 4.4.4.

The tables 4.8, 4.9 and 4.10 contain descriptive statistics on the data used for the DEA modelling. The statistics produced on the final dataset after normalization and missing data substitutions exercises are described in the upcoming section 4.4.2. The standard deviation values indicate significant deviations from the mean value for all inputs and outputs across all time periods. This corresponds to the initial expectation, as the microfinance dataset is constructed from a wide range of organizations operating on different ends of the scale, from small to large financial institutions.

As the MIX database is reaching its maturity, some of the records contain missing values on either financial, operational or social data. This fact has its impact on several steps

Input/Output	2004		2005		2006		2007		2008	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Assets('000) (A)	7.8	18.5	54.1	686.5	51.6	665.0	11.0	35.5	65.3	706.4
Operating expenses('000) (O)	12.8	32.2	26.7	43.4	15.1	34.6	12.6	31.3	11.2	29.1
Portfolio at risk 30 days (R)	32.2	65.9	28.5	37.5	31.4	38.6	27.1	38.0	22.2	32.8
Employees (E)	390.1	1605.7	267.0	1197.6	217.7	966.1	410.3	1533.3	383.2	1286.5
Financial revenue (F)	1421.9	3213.2	1235.6	3153.8	1406.2	3793.8	2041.5	6049.1	2903.5	9491.2
Average loan balance per Borrower (in Inverse form) – (I)	15.5	53.9	13.0	24.4	12.3	20.0	11.2	18.5	11.8	21.2
Number of borrowers('000) (B)	16.5	40.9	15.5	46.6	17.6	52.2	22.1	64.3	25.6	79.8

Table 4.8: Descriptive Statistics of inputs and outputs for 231 MFIs 2004-2008

Input/Output	2009		2010		2011		2012		2013	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Assets ('000) (A)	198.9	1315.9	842.2	2761.0	999.9	2977.7	1182.1	3214.4	347.4	1788.0
Operating expenses ('000) (O)	14.2	31.9	17.7	36.4	25.9	42.2	31.8	45.1	22.3	39.8
Portfolio at risk 30 days (R)	27.9	36.6	40.0	43.4	42.7	43.7	40.6	42.8	31.8	40.3
Employees (E)	1320.0	9171.5	750.7	2251.5	607.0	1947.4	432.4	1492.6	743.7	2141.6
Financial revenue (F)	3989.8	11866.3	2784.5	11596.3	3216.2	13725.4	3428.7	16600.1	3323.4	14711.0
Avg. loan balance per Borrower (in Inverse form) – (I)	7.9	9.8	23.2	170.3	9.5	25.4	10.7	26.9	6.3	9.6
Number of borrowers('000) (B)	33.1	98.1	22.8	74.3	21.1	71.8	21.4	66.0	25.6	78.6

Table 4.9: Descriptive Statistics of inputs and outputs for 231 MFIs 2009-2013

Input/Output	2014		2015		2016		2017	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Assets('000) (A)	93.6	806.8	99.9	847.9	425.6	1930.2	33.0	137.5
Operating expenses('000) (O)	19.9	37.2	25.6	41.4	24.9	40.5	22.2	38.9
Portfolio at risk 30 days (R)	33.1	41.2	25.4	36.6	22.8	33.6	19.1	30.6
Employees (E)	706.4	2012.7	919.5	2341.8	995.5	2360.9	694.3	1720.5
Financial revenue (F)	4524.0	13650.8	3754.2	8691.0	6911.1	23219.4	5643.0	19578.2
Average loan balance per Borrower (in Inverse form) – (I)	6.7	10.2	8.3	12.3	9.4	13.3	9.5	11.7
Number of borrowers('000) (B)	30.0	91.8	32.9	84.0	47.8	120.0	49.2	124.5

Table 4.10: Descriptive Statistics of inputs and outputs for 231 MFIs 2014-2017

of our study (selection of DEA inputs and outputs, creation of DMU model exclusion criteria, interpretation of results and economy-level aggregation) and thus extra steps were taken to handle the issue (as described in section 4.4.1). All monetary values in the MIX database are converted into common currency and provided in USD. This saved us from the necessity to apply an exchange rate for data validity for each observation. Nevertheless, before entering the DEA model, data were normalized so that financial indicators of microfinance institutions operating in different economies are comparable across the economies of the Sub–Saharan African region (normalization steps are described in section 4.4.2).

For the second phase efficiency study macro-level data from the World Bank database was used. This was also for the normalisation of DEA input and output values. The World Development Indicators database contains 1,600 time series indicators for 217 economies, with data for many indicators going back more than 50 years. Annual economy data is based on GDP per capita, GNI per capita, consumer price index, public and private credit bureau coverage, use of IMF credit. The depth of the credit information index was extracted in correspondence to the specification of the MIX-based dataset (38 countries of Sub–Saharan Africa regions in the period of 2004-2017), (described in section 4.5.4).

4.4.1 Handling missing values

As mentioned in the dataset description, missing values were present in records across the dataset. As stated in the classic article of Charnes et al. (1978), for DEA modelling it is mandatory that all inputs and outputs are populated for all DMUs in the dataset with strictly positive values, otherwise, an unfeasible solution error will occur in the optimization procedure. Thus, it was necessary to transform the dataset into a fully populated one. For clarification, I would like to state that this section refers to the issue of missing data for individual DMU inputs or outputs within the single time period observation. Missing observations across time periods (due to the inactive operation of a DMU during a specific fiscal year, or due to the fact that data were not collected for a specific fiscal year) will be discussed further in section 4.4.4.

The optimal approach for the missing data among other factors depends on the nature of data, therefore the choice of approach might differ in various studies. To answer the question of the optimal approach for our dataset, we have conducted an exercise focused on testing several approaches. The expectation-maximization algorithm, regression estimation, strategic substitution using dummy values and removal of observations with missing values were selected for the test.

In the original dataset of 2409 observations, each input and output variable contains a certain level of missing values (table 4.12). To obtain a benchmark dataset against which the performance of the aforementioned approaches can be compared, the following subset was created: all observations containing at least one missing value were removed from the original dataset. The resulting dataset is formed of 1432 fully populated observations (benchmark dataset, hitherto referred to as the "original data" dataset). Randomly selected values were then removed in the same proportions as the proportions of missing values in the initial dataset of 2409. This is done to replicate the composition of the initial dataset. Thus, the "missing data" dataset was generated. Each of the four approaches was then applied to the "missing data" dataset, and the DEA model was built on each of the 5 datasets: "original data" dataset and 4 alternative datasets with substituted missing values. All DEA models were built with VRS and non-oriented model direction.

Descriptive statistics of the resulting DEA efficiency levels are presented in the table 4.14. Some descriptive statistics, such as mean values are not comparable across the

	Number of observed values	Number of missing values	% of missing values
Assets	2 333	76	3%
Expenses	1 979	430	18%
Risk	1 953	456	19%
Personnel	2 341	68	3%
Revenues	1 990	419	17%
Average Loan	2 276	133	6%
Borrowers	1 946	463	19%

Table 4.12: Missing values in the original dataset of 2409 DMUs

models, and it is not the intention of the exercise to achieve the closest to original dataset mean efficiency. However, such a statistic as a number of efficient DMUs is important, as it shows which approaches cause overestimated efficiency levels (regression approach in this case). The achievement of a similar distribution of the DMUs on the efficiency scale is desirable. Figure 4.2 displays distributions of the efficiency values for corresponding approaches. EM and strategic substitutions approaches provide the closest to the original dataset distributional shapes. Strategic substitutions are further used in the research. It is important to mention that the EM approach produces estimates on an unbounded set of real values and the dataset obtained using this approach often contains negative values, which further need to be substituted to obtain a dataset suitable for DEA modelling. Table 4.14 and figure 4.2 present EM results with already modified negative values as per Bowlin (1998), where the author mentions the substitution of a very small positive value for the negative value if the variable is an output. As expected, when using the deletion approach, the efficiency for the remaining DMUs are overestimated.

	Original Data Non-Oriented Model	Regression Data Non-Oriented Model	EM Data Non-Oriented Model	Strategic Substitution Data Non-Oriented Model	Non-Oriented Model with Removed Missing's
N	1 432	1 432	1 432	1 432	580
Mean	45.47	34.16	51.66	46.85	59.85
Std. Deviation	23.85	32.83	21.99	25.88	22.48
Number of efficient DMUs	68	193	82	88	67
Range	97.23	99.34	98.26	100	87.53
Minimum	2.77	0.66	1.74	0	12.47
Maximum	100	100	100	100	100
Percentiles - 25	27.58	8.23	36.76	29.1	42.36
Percentiles - 50	41.76	20.09	48.14	45.06	56.45
Percentiles - 75	59.31	50.63	63.99	62.92	74.37

Table 4.14: Descriptive statistics of alternative approaches to handle missing data

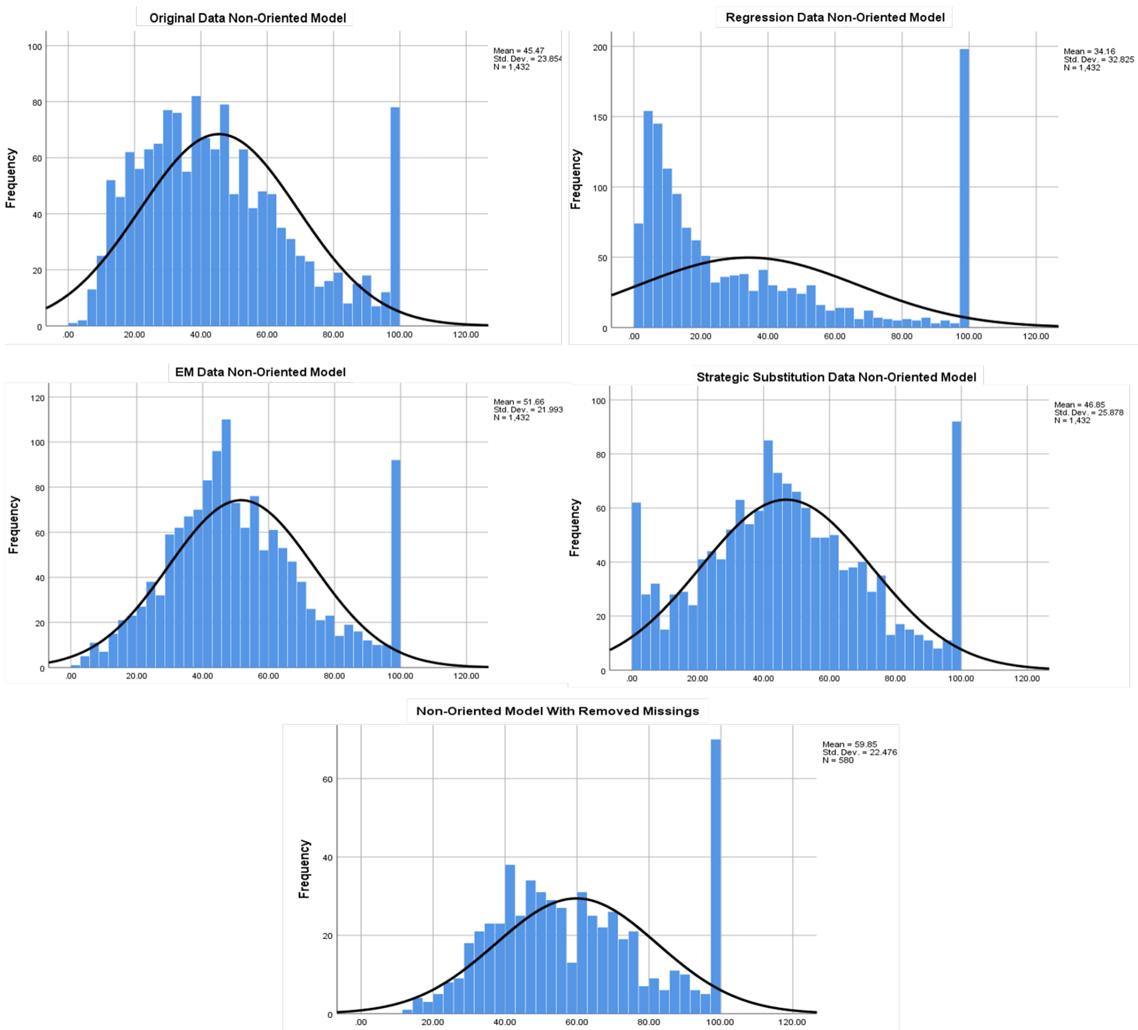

Figure 4.2: Distributions of the efficiency values of the resulting DEA model after application various approaches for missing data treatment

4.4.2 Dataset normalization

As in the current research, we compare microfinance institutions operating on 38 markets of the Sub–Saharan African region; it is logical to ask whether data is comparable across the economies. There are several details we need to take into account to answer this question:

- what assumption is made on returns to scale
- whether data types are included in input - output composition
- whether the homogeneity requirement of DMUs is met

Returns to scale

The overall microfinance market consists of institutions operating on different ends of the scale from very small, employing dozens of personnel and servicing hundreds of consumers, to large institutions having thousands of staff and providing services to millions of consumers. This fact causes an imbalance in data magnitudes as such that they would be considered as a problem under the assumption of constant returns to scale. For constant returns to scale, it is fair that output/input proportions remain consistent at any level of the operation scale. Mean normalization would be applied to all inputs and outputs of the model to solve the imbalance in data magnitudes, making sure that the data is of the same or similar magnitude across and within data sets.

In our research, however, variable returns to scale were assumed as discussed in section 4.3.2. The model built under variable returns to scale does not depend on data magnitude and allows the efficiency frontier to fit returns to scale as observed in the data, either increasing or decreasing returns to scale. Thus, imbalance in data magnitudes does not represent an issue for our research and there is no need for an extra step with mean normalization to be taken.

Input and output composition

There are four inputs and three outputs overall utilized in the DEA model. Inputs represented by assets, operating expenses, portfolio at risk and number of employees. Outputs are represented by revenues, inverse average loan per borrower and number of borrowers. Four variables (assets, expenses, revenues and inverse average loan per borrower) are expressed in monetary values; two variables (employees and number of borrowers) are expressed in integer values, and portfolio at risk is represented by a proportion value 0.1 to 100.

The question to be discussed in this section relates to the fact that the same value of the monetary variable (expenses or revenue, for instance) would have a different benchmark in the economies across Sab-Saharan Africa. If all inputs and outputs in the model were monetary values, the issue would be eliminated, because even though absolute values are not comparable, output/input ratios would maintain this property.

Due to the fact that our DEA model combines different data types, we needed to ensure the comparability of output/input ratios within the dataset. For example, if the value of revenues divided by personnel equals 1000 USD, this value should have the same practical meaning across all the countries used in the dataset. For this reason, all monetary values were standardized over GNI per Capita. All monetary values were extracted from the MIX database in the same currency (USD). Thus, no currency conversion is needed. Indicators of GNI per capita were obtained from the World Bank database (also in USD) for the period 2004-2017, and dataset variables assets, expenses, revenues and inverse average loan per borrower were weighted by GNI per Capita of the corresponding country in the relevant year of observation.

Such an approach is commonly used in empirical studies when cross-economy data is aggregated in the model. However, we noticed that it is rare for DEA studies to use such standardization. Abdulai and Tewari (2016) in their study of the efficiency of microfinance Institutions in Sub–Saharan Africa built a stochastic efficiency frontier. In their study, the dataset utilizes a combination of monetary and non-monetary values across 10 Sub–Saharan African economies, with no standardization applied prior to the model build. Widiarto and Emrouznejad (2015), on the other hand, applied GNI per Capita standardization when conducting a cross-economy study of social and financial efficiency of Islamic microfinance institutions. The standardization, however, was applied only to one variable (average loan per borrower), but not to other monetary variables (assets, operational expenses and revenues are utilized in the study as well).

Homogeneity requirement of DMUs

When conducting DEA analysis, it is vital for all DMUs to have the same operation process consuming the same inputs and producing the same outputs. When analyzing microfinance institutions across the Sub–Saharan African region, we have indicated specific differences in conditions under which DMUs operate as well as specifics of individual DMUs (target population, for instance). However, the general operation process and input consumption and output production are preserved across all DMUs in the sample, and thus the homogeneity requirement is met.

To provide a satisfactory answer to the question of this section whether data utilized in the research is comparable across the economies, we can summarize the above-discussed arguments:

- Variable returns to scale assumed in the research allows for consistent comparison of institutions operating on different ends of the scale;

- The combination of different data types in the Input / Output composition raises the question of cross-economy consistency, and thus GNI per Capita standardization is applied to monetary variables;
- Homogeneity requirement of DMUs is met.

4.4.3 Correlation analysis

The Spearmen correlation coefficients of inputs presented in the table 4.15, and the correlation coefficients of outputs are presented in the table 4.16.

The correlation matrix indicates a significant correlation between some of the inputs (assets and personnel) and a lower correlation between assets and expenses within the inputs. Within the outputs, there is 0.64 correlation between revenues and the number of borrowers. Such correlations are expected and are not alarming. All inputs and outputs should comply with the requirement of exclusiveness, although a certain level of correlation between inputs and between outputs is generally expected in the DEA models. Correlation generally does not play a crucial role in building the DEA model. However, some authors have made attempts to incorporate correlation coefficients between inputs and between outputs into the DEA methodology.

Saen et al. (2005) in the study of the effect of correlation between inputs and between outputs in data envelopment analysis proposed to use correlation coefficients to omit highly correlated pairs of inputs or outputs. The suggested correlation thresholds vary from 0.9 to 0.96.

For this research, the correlation matrix indicated a balanced correlation with a higher correlation between inputs of 0.76 and the highest correlation between outputs of 0.64. Thus, there are no concerns about correlation in the model, and no further actions need to be taken in this direction.

Other studies on a similar topic experienced higher correlations between inputs and outputs (for instance, Widiarto and Emrouznejad, 2015). All selected inputs and outputs thus remain in the DEA model specification as they are important inputs and outputs in assessing MFI efficiency. By definition, these strong relationships do not necessarily imply a causal relationship; in addition to this, the DEA algorithm will assign weights to these variables and maximize them according to their weights. On the contrary, the presence of high correlation herein confirms that the use of the parametric efficiency measurement method may not be appropriate due to the multicollinearity problem, which makes beta coefficients for correlated independent variables unreliable. The presence of multiple outputs also makes the application of DEA more appropriate in this study.

	Assets (A)	Operating expenses (O)	Portfolio at risk 30 days (R)	Employees (E)
Assets (A)	1.00			
Operating expenses (O)	0.58	1.00		
Portfolio at risk 30 days (R)	-0.17	-0.11	1.00	
Employees (E)	0.76	0.45	-0.16	1.00

Table 4.15: Correlation coefficients between model inputs

	Financial revenue (F)	Average loan balance (I)	Number of borrowers (B)
Financial revenue (F)	1.00		
Average loan balance (I)	-0.28	1.00	
Number of borrowers (B)	0.64	0.12	1.00

Table 4.16: Correlation coefficients between model outputs

4.4.4 Working with an unbalanced dataset

Due to the nature of the data in this study, there is an unbalanced dataset for the period 2004-2017. The balanced dataset requires the same set of DMUs to be presented and populated with data at each time period. The last two decades have been crucial for the development of the microfinance industry around the world. Many financial institutions start their operations every year, many existing institutions expand their operations on the new markets and others terminate their operations every year. Thus, unbalanced data across a period of 14 years is the most natural characteristic of the microfinance industry. The study questions require the provision of an extensive analysis of the microfinance market in the region, and thus the dataset should be formed as a complete set of observations as possible. Therefore, the DMUs with missing observations across time periods were not eliminated from the sample but kept with their original values. Besides, to answer the first study question "What is the financial and social efficiency of microfinance institutions across developing countries of the Sub–Saharan African region? Do most institutions operate close to the efficiency frontier or away from it?" an unbalanced dataset can be used, as independent models are run for each year.

In order to enable the Malmquist index calculation and thus a comparison of relative change in the efficiency of individual institutions across the time periods, we need to obtain a balanced dataset across analyzed time periods. There are two possible options of dataset modification: a) elimination of DMUs with missing records for some time periods, and b) addition of records with dummy or estimated substitution values. As discussed in section 3.5, DMU elimination associated with significant disadvantage of overestimating the efficiency for the rest of DMUs in the sample.

Thus, an alternative option was applied for this research, which is record addition with dummy or estimated value substitutions for the missing records.

4.4.5 Elimination of outliers

As discussed in the section 3.8, outputs of DEA models are sensitive to outliers. Presence of outliers in the reference set can bias the efficiency frontier and overestimate the distance to the frontier for inefficient units. Therefore, extra analysis is needed to identify and potentially remove outliers from the reference set. There is no standard guidance for identification of outliers in the DEA methodology. In the current research, we have employed super efficiency models proposed by Andersen and Petersen (1993) to identify potential outliers. The approach if frequently used by authors, however, as Ahamed et al (2015) pointed out, the threshold value of super efficiency score to remove outliers is due to subjective choice and it varies significantly in the literature.

As authors also pointed out, it is important to consider the origin of super efficiency for individual units. It can be due to a measurement error, or as a result of the outlier having different operating practices. Some level of super efficiency also can indicate the truly strong performance of the unit and in such case, the unit is not necessarily indicated as an outlier. Therefore in the current research after building super efficiency models (both input and output oriented models as formulated in the section 2.9 were build) for each observation year separately, we manually reviewed data on every units with efficiency level > 100% to understand the origin of super efficiency and treat the unit correspondingly. The nature of the data set used for the research allows to track changes in the input and output values year by year and therefore to obtain a comprehensive overview of the unit dynamics prior and after the year it was flagged as super efficient by the DEA model. Such manual review was undertaken for units flagged as super efficient at least by one of the two (input and output oriented) models. DMUs with extreme values of super efficiency (over 300%) were eliminated from the reference set with no regards to the origin of the super efficiency. DMUs with lower values of super efficiency, where we have indicated potential measurement error or unreliable data entries, were eliminated from the reference dataset as well. DMUs, for which we had a suspicion of different operating practices, were also eliminated from the reference dataset. There is a number of DMUs with lower values of super efficiency, which remained in the reference set as their data showed no signs of measurement error or different operating practices. For example, MFI Capitec operating in South Africa obtained efficiency scores slightly over 100% for several years of the observation period, however, the institution had indeed very strong position on the market, which is supported by good quality data. On the contrary, Sun Shade Foundation operating in Ghana is a small MFI showing high performance over the years 2015-2017. The data indicate that institution has constantly increasing assets, operating expenses, a number of borrowers and revenues, however, a number of employees remains constant (11 people) over the 3 years, which is generally unusual for MFIs and raises suspicion of incorrectly reported data. Therefore, the unit was removed from the reference set for all three observation years. A number of removed outliers for each year of observation period provided in the table 4.17.

4.5 Results and discussion

4.5.1 First Stage DEA Analysis

The first stage of the study attempts to answer the following study questions:

- What is the financial and social efficiency of microfinance institutions across developing countries of the Sub–Saharan African region? Do most institutions operate close to the efficiency frontier or away from it?
- What is the productivity change over time periods? What is the change in the time of external shocks such as the 2008 global financial crisis?
- Social and financial objectives - are they mutually exclusive?
- Has the microfinance industry witnessed a mission shift over time?

At the first stage, DEA models are applied to data on all available DMUs. Individual models are built for each year of the 2004-2017 period. Social, financial and overall efficiency are assessed as per model specification in section 4.3.3. The analysis herein focuses on VRS non-orientated frontier results. Thereafter, efficiency scores are plotted into the social–financial efficiency matrix (SFE) charts originally proposed by Widiarto and Emrouznejad (2015). The matrix is drawn with social efficiency at X-axis and financial efficiency at Y-axis to observe MFI positioning regarding these objectives. The matrix area is divided into four quadrants counterclockwise: quadrant I in the top right for high social high financial efficiency (the ideal quadrant where both objectives are relatively pursued concurrently), quadrant II for high financial and low social efficiency, quadrant III for low levels of both financial and social efficiencies and quadrant IV in the bottom right for high social efficiency low financial efficiency areas. The matrix is later produced for economy-level aggregated results.

The current construction of the matrix was proposed by Widiarto and Emrouznejad (2015), and in the recent studies other authors frequently use this or slightly modified form of visualization of the dual performance measures. The matrix is a convenient tool used to map MFI performance against its dual bottom objectives.

Table 4.17 displays aggregated results of the efficiency coefficient estimated by DEA models. The results are split into observation periods and by efficiency types (overall, social and efficient).

		Observation period													
Efficiency type	Indicator	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Overall efficiency	Number of DMUs	147	205	220	206	197	162	190	218	172	149	150	136	98	84
	of excluded outliers	4	7	6	7	4	9	3	6	8	3	6	5	6	1
	Median efficiency	58.49	67.43	68.87	70.80	51.09	73.69	60.96	65.54	60.57	77.27	77.91	75.92	78.28	85.72
	Std. Dev.	27.26	30.31	28.06	26.54	29.96	25.77	26.45	29.68	30.33	28.67	24.31	27.50	28.68	22.21
	Minimum	1.65	1.92	4.36	4.58	0.94	6.77	6.28	2.27	5.64	1.75	9.01	5.03	2.97	17.61
	Maximum	100	100	100	100	100	100	100	100	100	100	100	100	100	100
	25th percentile	40.60	40.77	45.94	52.38	30.07	56.30	43.33	41.79	37.26	55.11	57.70	53.60	53.41	63.88
	75th percentile	89.52	94.67	97.70	98.78	81.27	100.00	85.17	96.36	94.31	100.00	100.00	100.00	100.00	100.00
	Number of fully efficient DMUs	27	49	52	51	35	43	34	48	39	47	47	37	34	30
	% of fully efficient DMUs	18%	24%	24%	25%	18%	27%	18%	22%	23%	32%	31%	27%	35%	36%
Social efficiency	Number of DMUs	147	205	220	206	197	162	190	218	172	149	150	136	98	84
	of excluded outliers	4	7	6	7	4	9	3	6	8	3	6	5	6	1
	Median efficiency	25.83	30.42	33.29	41.99	25.57	35.57	31.66	27.21	29.34	33.95	34.33	33.45	41.02	38.75
	Std. Dev.	30.57	31.25	31.35	31.59	31.43	31.59	31.00	32.17	31.44	31.92	34.69	35.40	35.14	32.24
	Minimum	0.16	0.35	0.42	0.62	0.48	0.81	1.03	0.32	0.57	1.66	3.33	1.17	1.44	4.83
	Maximum	100	100	100	100	100	100	100	100	100	100	100	100	100	100
	25th percentile	14.05	14.21	16.82	21.30	12.92	18.38	15.00	14.42	16.10	18.59	15.18	15.58	18.48	21.92
	75th percentile	51.23	61.29	59.52	68.01	51.90	64.96	55.79	56.41	56.01	68.54	83.69	82.16	90.33	70.13
	Number of fully efficient DMUs	17	26	33	34	26	23	25	32	25	22	28	27	23	17
	% of fully efficient DMUs	12%	13%	15%	17%	13%	14%	13%	15%	15%	15%	19%	20%	23%	20%
Financial efficiency	Number of DMUs	147	205	220	206	197	162	190	218	172	149	150	136	98	84
	of excluded outliers	4	7	6	7	4	9	3	6	8	3	6	5	6	1
	Median efficiency	53	55.22	56.02	58.26	37.68	69.74	56.7	60.89	52.50	72.20	70.30	65.39	69.82	78.27
	Std. Dev.	27.07	31.88	27.89	26.04	29.13	25.86	26.40	30.75	32.22	31.03	26.07	29.38	28.31	27.96
	Minimum	1.65	1.92	3.44	4.58	0.94	4.92	1.14	0.51	1.36	1.6	0.42	2.86	2.97	6.57
	Maximum	100	100	100	100	100	100	100	100	100	100	100	100	100	100
	25th percentile	37.05	30.09	41.79	42.77	21.51	51.27	37.99	36.85	25.96	52.94	51.68	47.85	49.88	53.46
	75th percentile	78.71	83.67	88.09	79.73	67.19	93.06	75.30	82.47	80.46	100.00	98.46	87.84	91.69	100.00
	Number of fully efficient DMUs	21	39	37	29	20	34	22	36	31	43	37	27	22	24
	% of fully efficient DMUs	14%	19%	17%	14%	10%	21%	12%	17%	18%	29%	25%	20%	22%	29%

Table 4.17: Hyperbolic non – orientated technical efficiency

The first row of the table presents the dynamic of DMU counts observed in the MIX database. Initially increasing, the number decreased in 2008-2009, which might be related to the general recession of the financial industry during the economic crisis. An increase in the number of MFIs is observed shortly after the crisis reached its peak in 2011. A decrease in the number of observations in the latest time periods can be partially explained by a delay in the data submission to the MIX database for the latest fiscal years. It is worth mentioning that the MIX database, despite being the biggest database containing microfinance industry data, still has missing data on some MFIs.

As discussed in the sections 3.8 and 4.4.5, before producing the final results, we have conducted an analysis to eliminate outliers from the reference set. For this purpose, super efficiency models (both input and output oriented models) were constructed. Units with efficiency level $>$ 100% in at least one of either input or output oriented models were flagged as potential outliers and further manually analyzed. DMUs with extreme values of super efficiency (over 300%) were eliminated from the reference set with no regards to the origin of the super efficiency. DMUs with lower values of super efficiency, where we have indicated potential measurement error or unreliable data entries, were eliminated from the reference dataset as well. DMUs, for which we had a suspicion of different operating practices, were also eliminated from the reference dataset. The Second row of the table 4.17 presents the number of DMUs, which were flagged as outliers and therefore were excluded from the reference set.

Further rows 3-10 summarize the resulting DEA efficiency scores for each year of the observation period. Even though the table displays time period results side-by-side, we do not recommend comparing results between separate columns (side-by-side presentation was done in order to avoid displaying 14 separate tables). As independent models on individual time periods were constructed and each year DMU efficiencies were benchmarked against different frontiers, efficiency estimations are not comparable across time periods. Comparing efficiencies derived from different models is an error easily made by many researchers when starting their work with data envelopment analysis.

The number of observations in the sample impacts some indicators in the table. For instance, under the ceteris paribus assumption, the median efficiency would have a lower value for a dataset with a higher number of observations than for dataset with the lower number of observations according to the basic principles of DEA methodology. In the same way, the proportion of efficient DMUs would be higher in the time period with the smaller dataset, and our results presented in the table above are in line with these expectations. On the other hand, there is a peculiar characteristic observed in the results: when comparing a number of overall efficient DMUs and a number of socially efficient and financially efficient DMUs, it is logical that there will be more overall efficient DMUs than social efficient DMUs or financial efficient DMUs. This is easily explained by the model specification: the overall efficiency model has three outputs (the social efficiency model utilizes two outputs and a financial one), and thus provides DMUs with more flexibility on the weight assignment. Using the same logic, we would assume that there are more social efficient DMUs then financially efficient DMUs, as the social efficiency model utilizes more variables, although it is only in 2007, 2008, 2010 and 2016 that there are more socially efficient DMUs, than financially efficient ones. For the rest of the observation periods, the numbers of financially efficient DMUs prevail over the numbers of socially efficient DMUs. This might be an early indicator in our study showing that microfinance institutions have a larger focus on the financial objective than on social objective.

To understand the DMUs performance better on both scales of social and financial efficiency, below there is a set of figures presenting SFE matrices developed as described at the beginning of this section and produced for each observation period. This analysis is an addition to the analysis of overall efficiency and can be used to pursue improvement in both objectives.

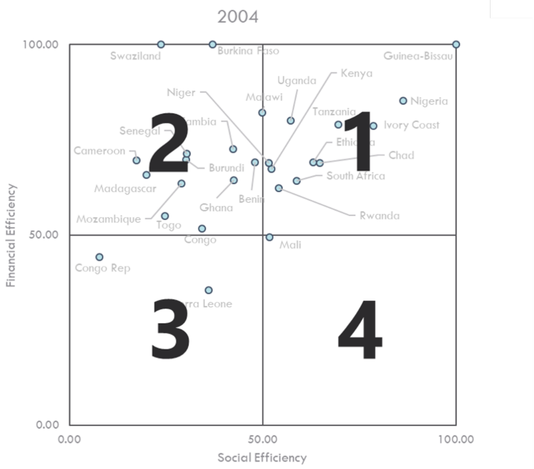

Figure 4.3: SFE matrix

Figure 4.3 visualizes the concept. The scale of the social efficiency is plotted on the vertical axis; the scale of financial efficiency is plotted on the horizontal axis. Although plots are not comparable across the time periods, we can draw some conclusions based on the unit distribution among the matrix quadrants. For convenience, let's consider point (50, 50) for a center of a chart and use a standard definition of four quadrants around the chart center. Quadrant 1 is then associated with high social high financial efficiency, quadrant 2 – with high financial and low social efficiency, quadrant 3 – with low levels of both financial and social efficiencies and quadrant 4 – with high social efficiency low financial efficiency.

The figures 4.4, 4.5 and 4.6 are used to map units against their dual objectives. The 2004 chart shows units mostly aggregated in the second and the third quadrants with the large aggregation of units having social efficiencies below 50%. In 2005, 2006 and 2007 units are spread across the first, second and third quadrants with more units operating closer to the frontiers for both social and financial efficiencies. In 2008, however, most of the units operate far from the efficiency frontiers (both social and financial) with a fair amount of units on the social efficiency frontier and very few units on the financial efficiency frontier. Majority of units fall into the third quadrant, where both social and financial efficiencies below 50%. This is consistent with research findings of Efendic and Hadziahmetovic (2017), where authors indicated that the crisis had a negative effect on both financial and social efficiency of microfinance institutions in Bosnia and Herzegovina. As reported in Di Bella (2011), the global financial crisis affected microfinance institutions as lending growth was constrained by scarcer borrowing opportunities, while the economic slowdown negatively impacted asset quality and profitability.

Balkenhol (2008) provides a discussion on the topic, arguing that those who see microfinance as a subset of the commercial financial sector and consider commercial microfinance as the only real microfinance, have always advocated the alignment of microfinance with commercial business models. The crisis has exposed the risks of this approach: refinancing costs go up, foreign exchange risks rise since "85% of debt financing to microfinance institutions is in foreign currency" (Reille, 2008). Foreign investment in MFIs turns out to be much volatile than expected, and short-term yield expectations increasingly drive the pricing policies of MFIs that want to be integrated into the commercial market. The shake-up of the financial sector as a whole, therefore, also undermines the wisdom of strategies to reduce microfinance to a subset of the financial market.

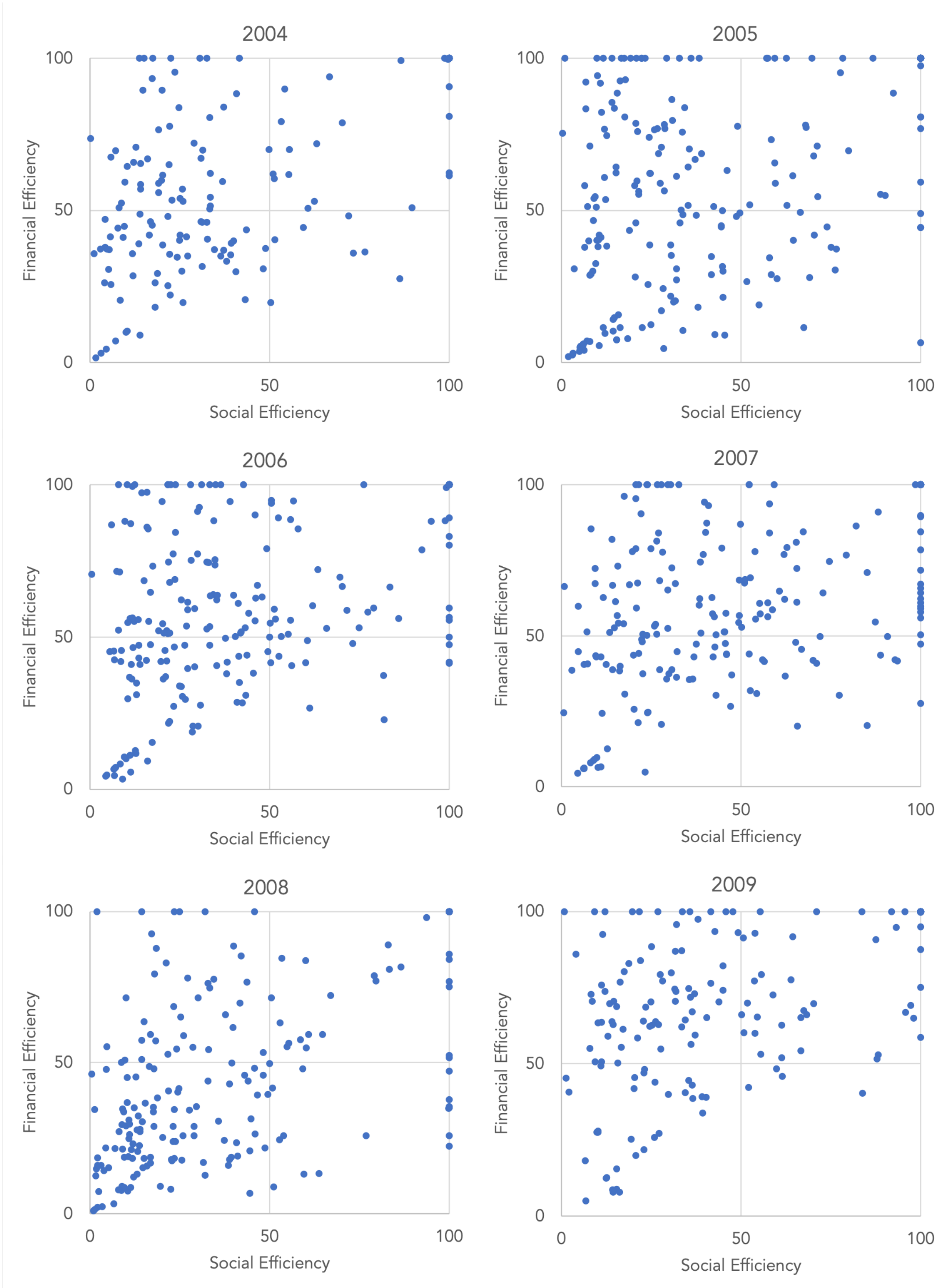

Figure 4.4: Social-Financial efficiency matrix of DMUs for 2004 - 2009 time periods

The author brings into attention, there is, however, another perception of microfinance which emphasizes the need for a balance of social impact and financial performance. In this view, commercialization is a necessary but not sufficient criterion of good performance in microfinance. Hence microfinance can remain separate from the mainstream financial sector, and develop its own business models. The key words in this school of thought are: proximity, client services, reliability, autonomy and impact on poverty. We, therefore, see that although the distribution of units in 2008 in figure 4.4, is shifted towards the first quadrant, there is still a large amount of units in first and second quadrant showing their resilience in the times of financial crisis.

From the asset and current portfolio profitability point of view, it is generally assumed that the financial crisis would have a negative impact. However, from the market and short-term loan demand perspective, it is observed that opportunities for microfinance business increase during the financial crisis due to the move of customers from prime banking portfolio towards subprime portfolio. Under these conditions consumers who were able to repay traditional banking loans before the financial crisis, experience financial difficulties. As their credit risk increases, they no longer eligible for traditional loans and therefore express demand in microfinance loans. This was observed in multiple economies when a late-crisis and post-crisis periods associated with expanded portfolios for MFIs with available lending capital and establishment of new MFIs. This could be one of the arguments explaining the change in the SFE matrix distribution in 2009.

In 2009 the distribution changes and units are distributed mainly between the first and the second quadrants with a significant focus on the second quadrant (high financial efficiency and low social efficiency).

In the 2010 chart, a set of units occur in the second quadrant, some of them even have very high social efficiency and very low financial efficiency. A relatively low number of units operate on the financial efficiency frontier or very close to it. On the 2011 chart, units are distributed across second and third quadrants with the majority of units operating very far from the social efficiency frontier. A similar distribution is observed on the 2012 chart, although here a large group of units can be observed concentrated in the far corner of the third quadrant (low social efficiency and low financial efficiency). Besides this group, the majority of units operate far from the efficiency frontiers. This raises a suspicion that a significant disbalance might have occurred in the dataset for the year 2012, and thus closer look into this is needed. Charts for the years 2013, 2014, 2015 and 2016 display similar trends with the majority of units being placed in the first and the second quadrants, thus indicating prioritization of the financial objective over the social objective. The dataset for the year 2017 has the lowest number of observations, and strong conclusions can be drawn from the chart. However, a certain focus on the financial objective is observed in the chart consistent with previous time periods.

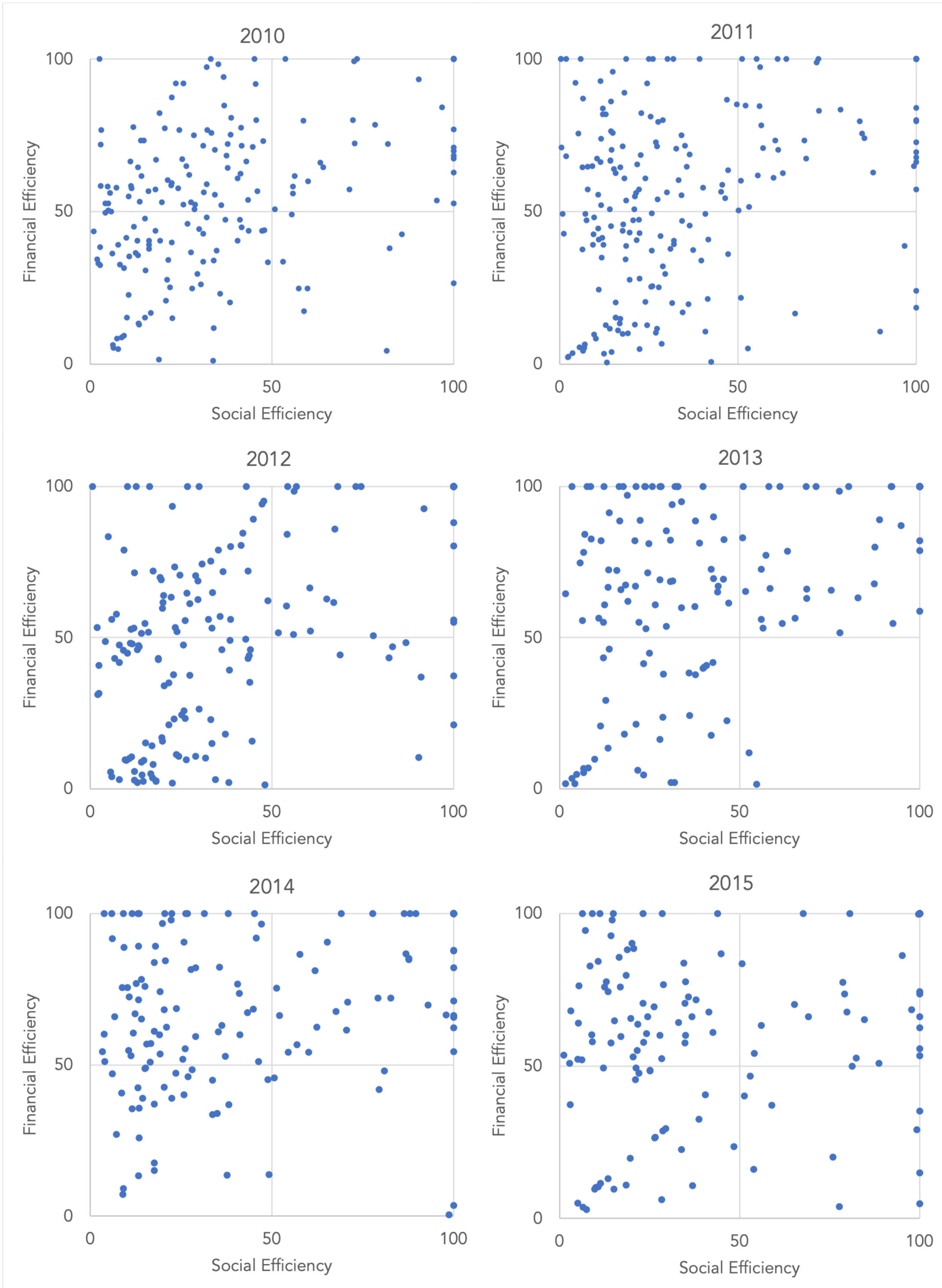

Figure 4.5: Social-Financial efficiency matrix of DMUs for 2010 - 2015 time periods

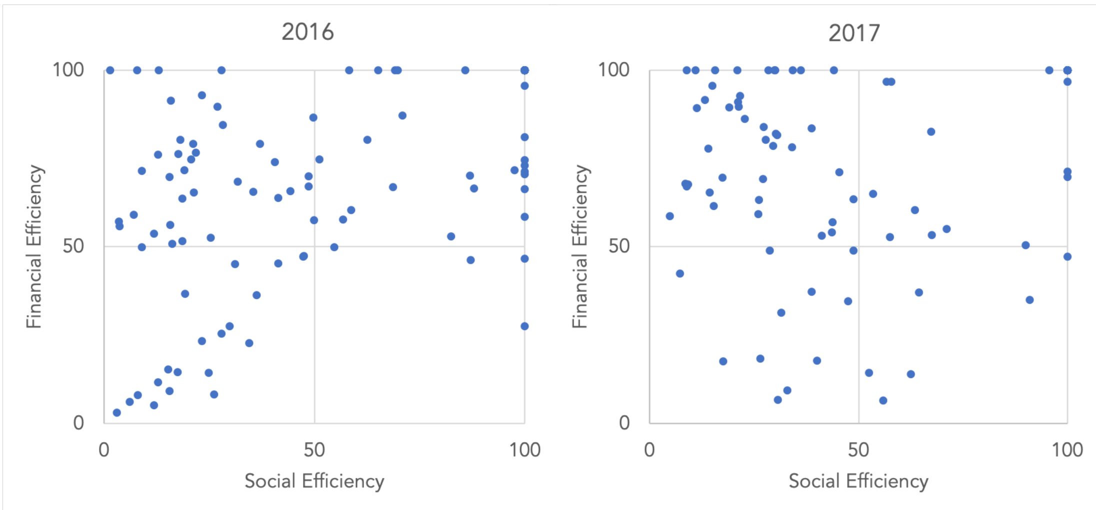

Figure 4.6: Social-Financial efficiency matrix of DMUs for 2016 and 2017 time periods

Figure 4.7 aggregates the quadrant allocation of institutions in the SFE matrices between 2004-2017. From the figure, it is clear that quadrant IV, which corresponds to high social efficiency and low financial efficiency, is the least populated. Quadrants I and II (both quadrants are focused on high financial efficiency) became more populated over time indicating an increasing focus of institutions on the financial objective. In 2008, 61% of all DMUs fall into quadrant III, indicating a difficult year for the majority of DMUs in both social and financial contexts.

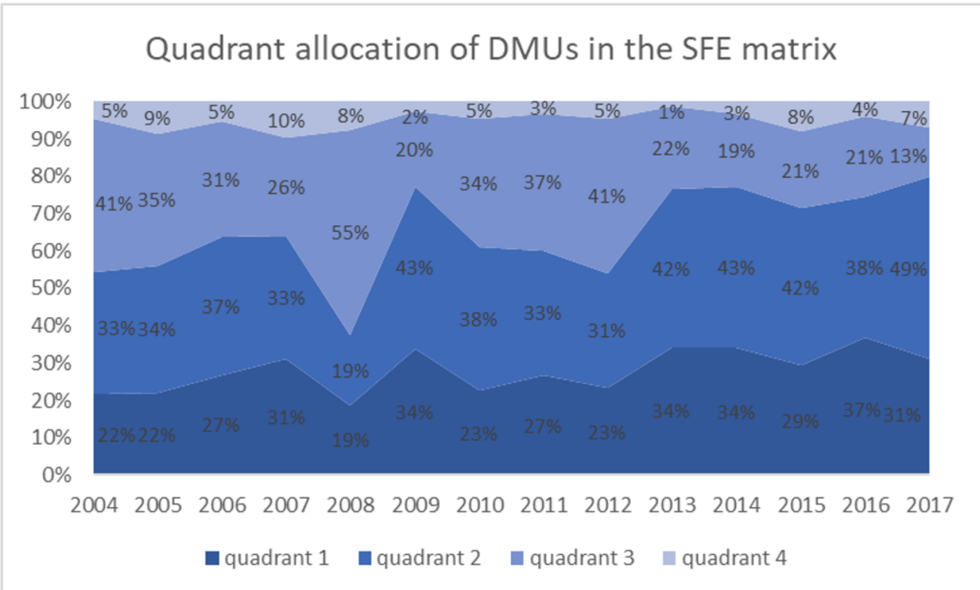

Figure 4.7: Quadrant allocation of institutions in the SFE matrix

After analysing DEA results at the DMU level, the results were aggregated on the economy level by taking the mean efficiency score across the units operating in an economy during the time period under analysis. SFE matrices then were created, similarly with the scale of social efficiency plotted on the vertical axis, and the scale of financial efficiency on the horizontal axis. Figures 4.8, 4.9 and 4.10 illustrate the SFE matrices for the 38 analysed economies during the period 2004 - 2017.

According to the figure 4.8, in 2004 and 2005, the majority of economies are concentrated near borders of the second quadrant, which is associated with high financial efficiency and low social efficiency. Interestingly, there are no economies in the fourth quadrant, where social efficiency dominates over financial efficiency. In 2006 and 2007, economies are more spread across the four quadrants with most economies aiming for high financial efficiency and low social efficiency. There is a visible shift toward the third quadrant in 2008, where both financial and social efficiencies are low. The time period is associated with the financial crisis and such a shift is generally expected. In the next year, however, the distribution of economies across four quadrants significantly changes, most of the economies achieve high financial efficiency. The trend is very interesting, although it is not unexpected. In the literature, it is discussed that the post-crisis and late-crisis periods are often associated with an advantageous environment for the microfinance operations, as demand for small-value loans increases. Efendic and Hadziahmetovic (2017) in their study of social and financial efficiency of MFIs in Bosnia and Herzegovina also noticed that the difference between the two efficiencies slightly decreased within the period 2008 to 2011, which led authors to the conclusion that MFIs retained their social role. The following 3 years show a shift of economies closer to medium financial efficiency levels indicated by the 50% line on the charts. In 2013, 2014 and 2015 economic means were distributed across the first and second quadrant, with almost no economies in the fourth quadrant. In 2016 and 2017, however, some economies (Senegal and South Africa) entered the fourth quadrant, indicating a bigger focus on achieving high social efficiency than on achieving high financial efficiency.

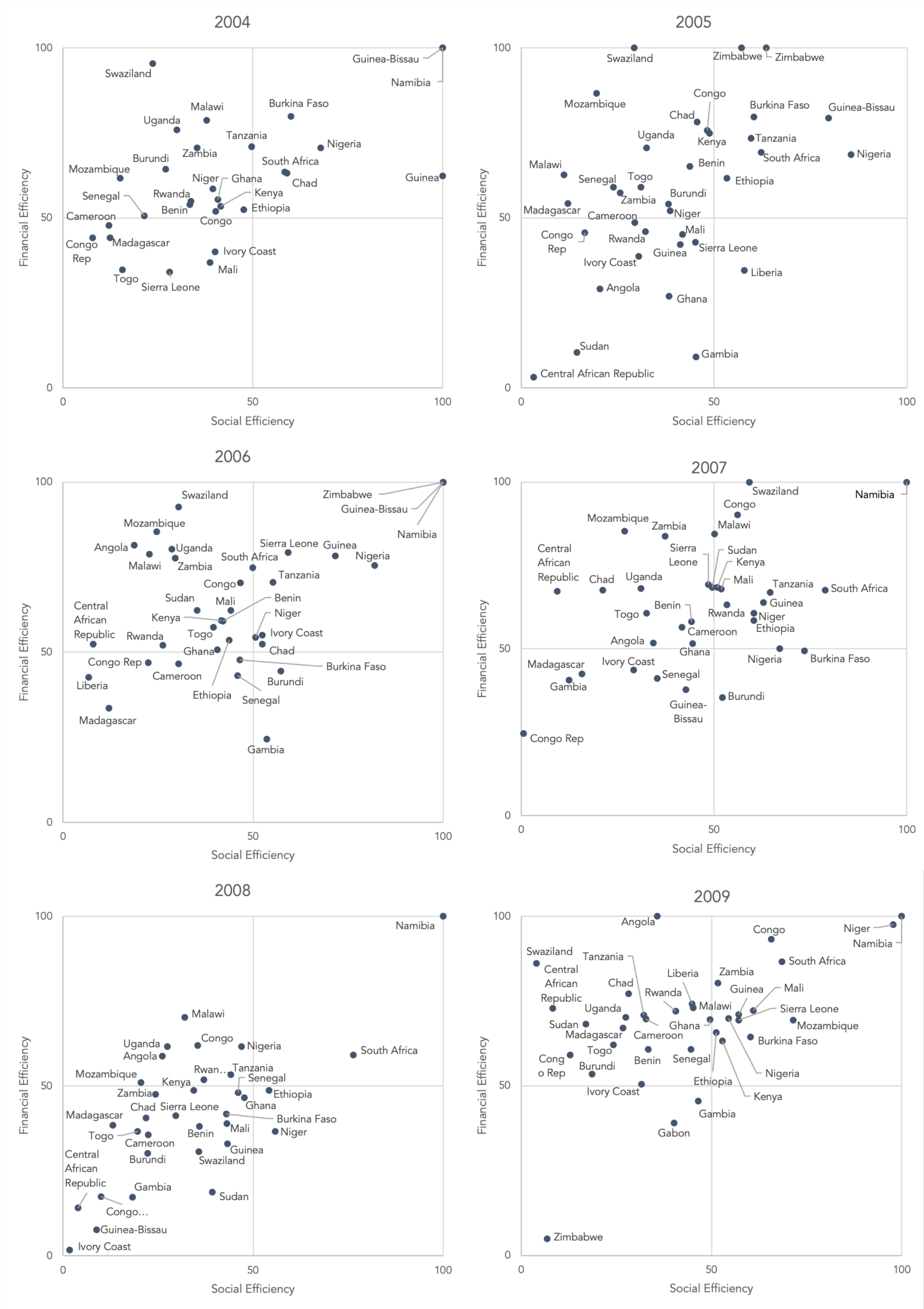

Figure 4.8: Social-Financial efficiency matrix by countries for 2004 - 2009 time periods

Figure 4.11 aggregates quadrant aggregates the quadrant allocation of countries in the SFE matrices from 2004-2017. As in the case of institution allocation, for

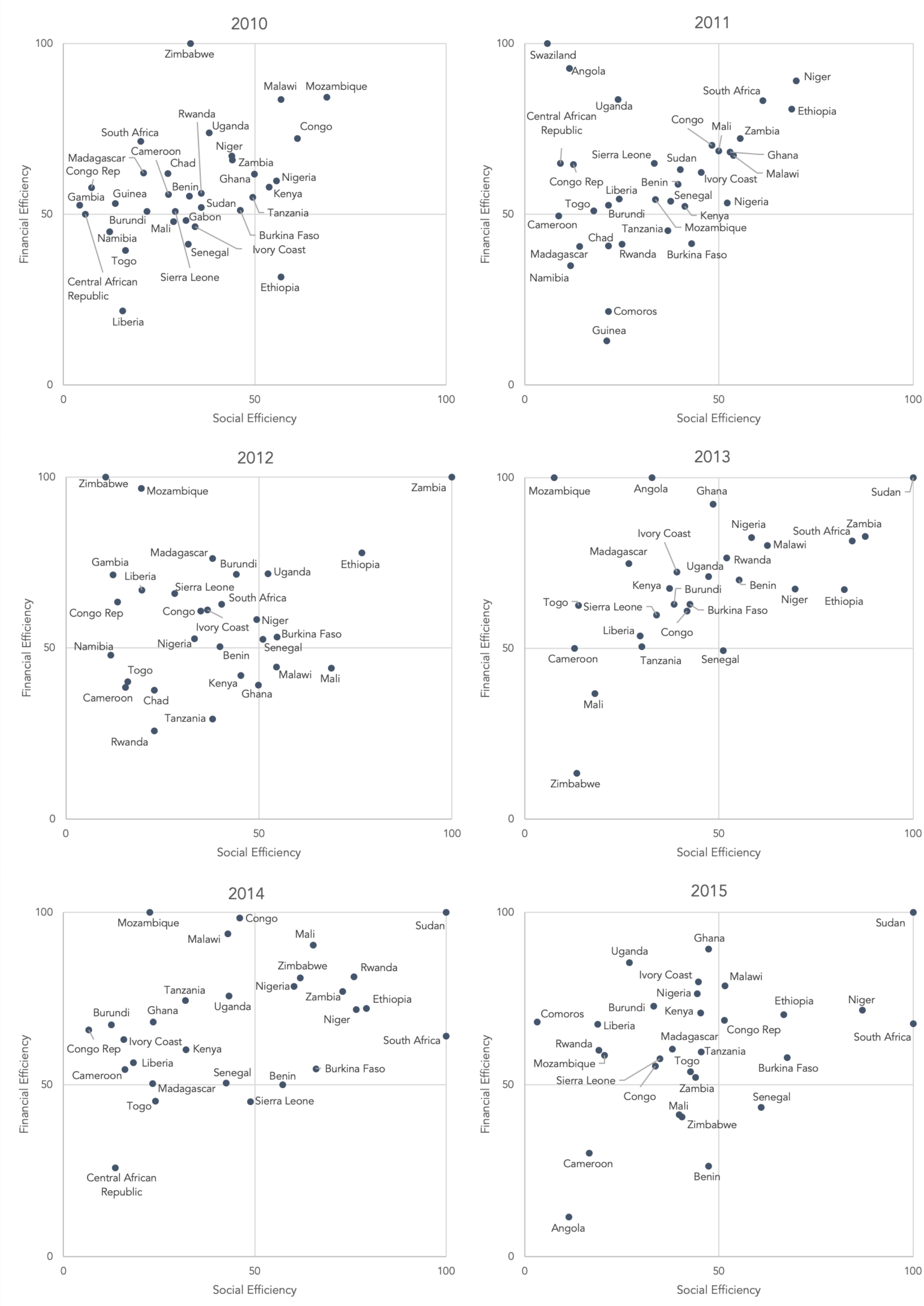

Figure 4.9: Social-Financial efficiency matrix by countries for 2010 - 2015 time periods

the country allocation quadrant IV has the lowest population. Quadrants I and II are the most populated quadrants for most of the years except 2008 when 79% of

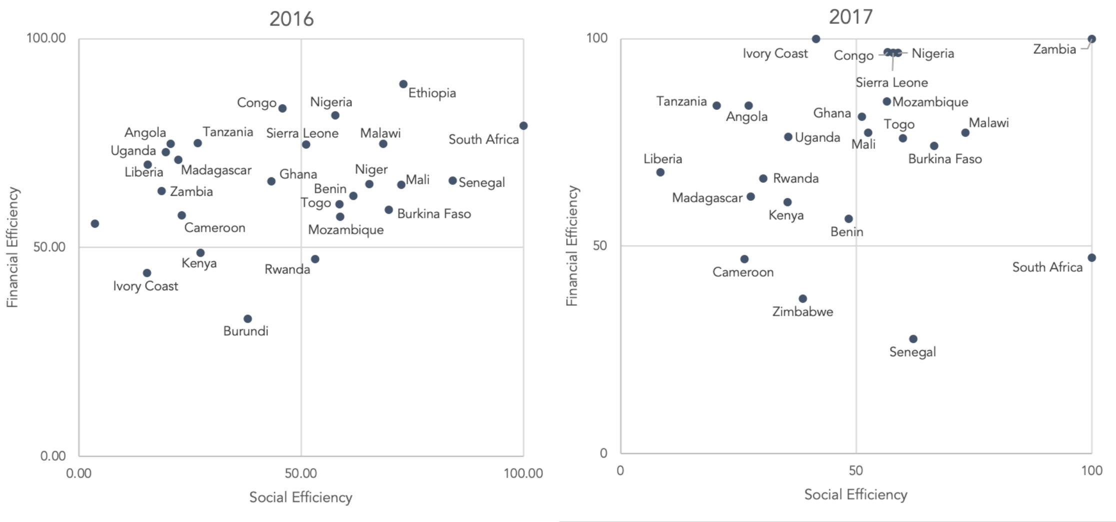

Figure 4.10: Social-Financial efficiency matrix by countries for 2016 and 2017 time periods

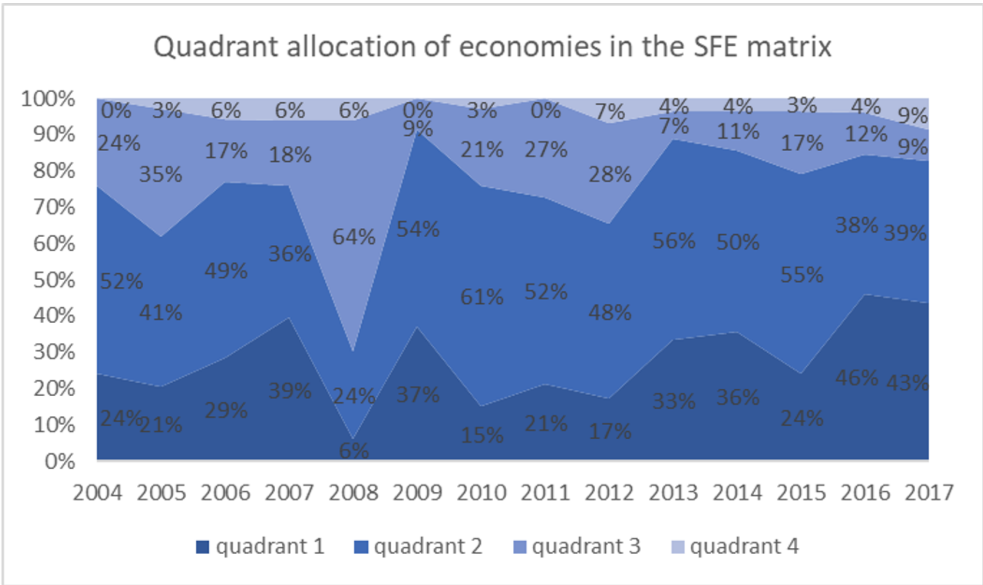

Figure 4.11: Quadrant allocation of countries in the SFE matrix

countries fall into the quadrant III with low efficiency in both social and financial contexts.

Some trends can be better observed when units are analyzed on individual DMU or economy level. Therefore we've selected several economies to look at their year-by-year performance in separation. In general, strong prioritization of the financial objective over the social objective was observed during the entire observation period and Uganda seems to be one of the economies supporting such prioritization. For DMUs operating in Uganda, the mean efficiency level positioned economy in the second quadrant of the SFE matrix indicating a stronger focus on financial objective over social. As highlighted in figures 4.12 and 4.13, efficiency mean levels for Uganda remained in the second quadrant during the entire observation period with exception of 2012, when it moved into the edge of the first quadrant. However during the latest years of the observation period focuses of DMUs in the sample became more diverse, for DMUs operating in Uganda focus does not shift over the time and the economy average remains in the second quadrant.

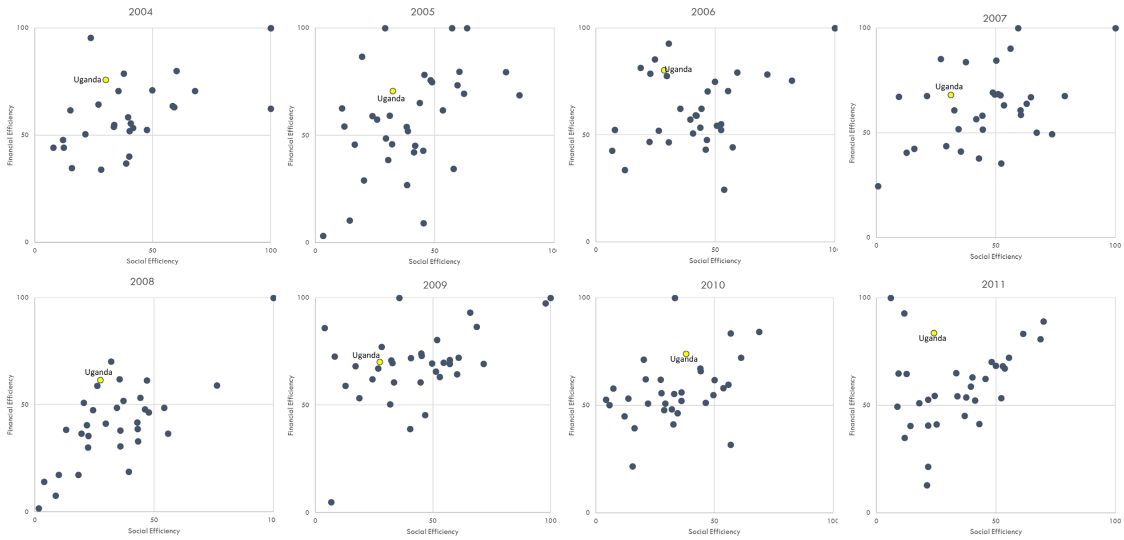

Figure 4.12: Social-Financial efficiency matrix for 2004 - 2011 - Uganda

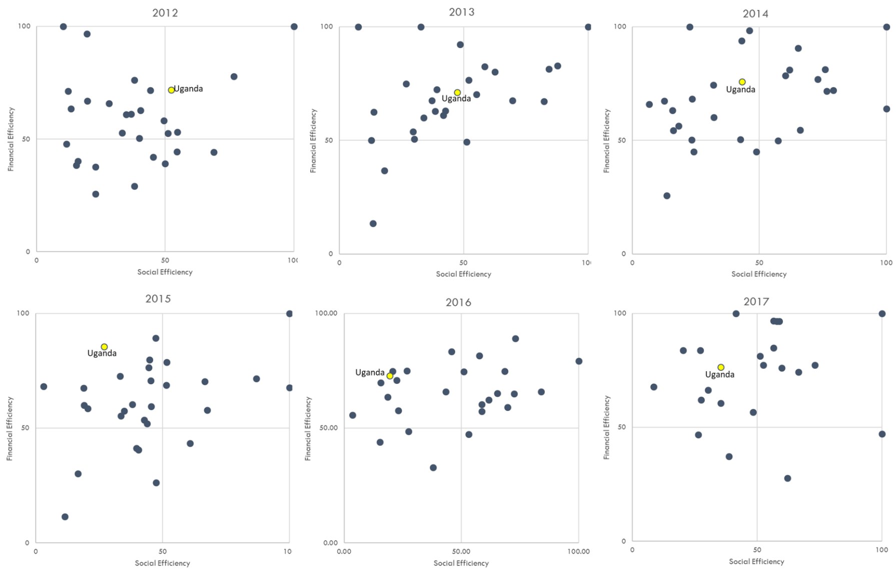

Figure 4.13: Social-Financial efficiency matrix for 2012 - 2017 - Uganda

On the other hand, the analysis does not show any strong indicators of mutual exclusivity of financial and social efficiency. On the contrary, it shows that some economies (Burkina-Faso, for example) are positioned on the diagonal of the chart for most of the time intervals, which indicates approximately equal levels of social and financial deficiencies when compared against the sample. This is highlighted in figures 4.14 and 4.15. The findings are consistent with the microfinance sustainability and mission drift research conducted by Kar and Rahman (2018), where authors found that poverty alleviation and financial sustainability objectives can be achieved simultaneously.

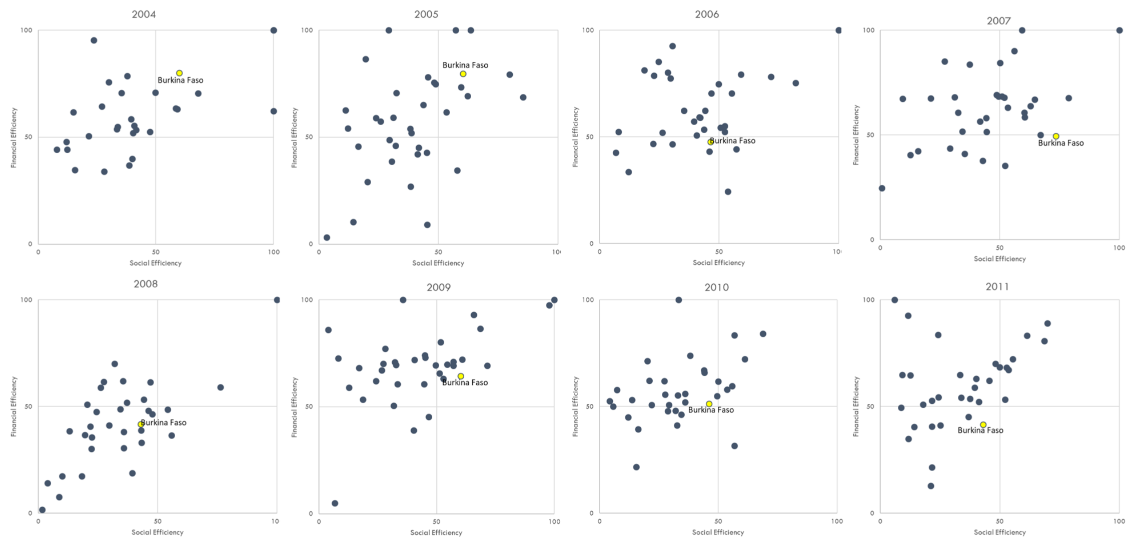

Figure 4.14: Social-Financial efficiency matrix for 2004 - 2011 - Burkina-Faso

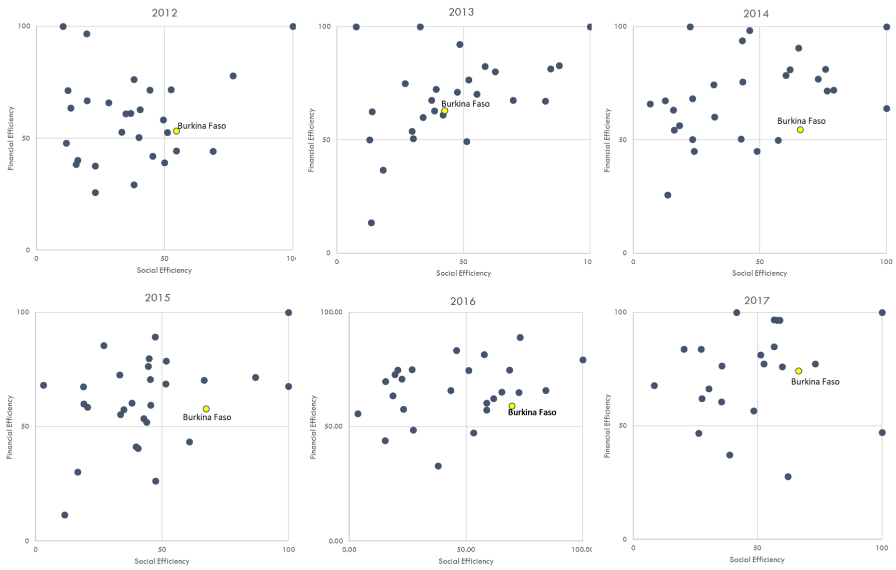

Figure 4.15: Social-Financial efficiency matrix for 2012 - 2017 - Burkina-Faso

Finally, some economies indicate a shift of the focus over time. DMUs operating in South Africa experienced a significant shift towards the highest social efficiency level in 2014 - 2017 (fig. 4.16 and 4.17). At the same time the microfinance environment in the country was undergoing structural changes. The governmental program called Project Evolution started in 2011 and fully implemented in 2014 provided a unified credit market into a single data sharing platform to be utilized by both MFI and banking institutions.

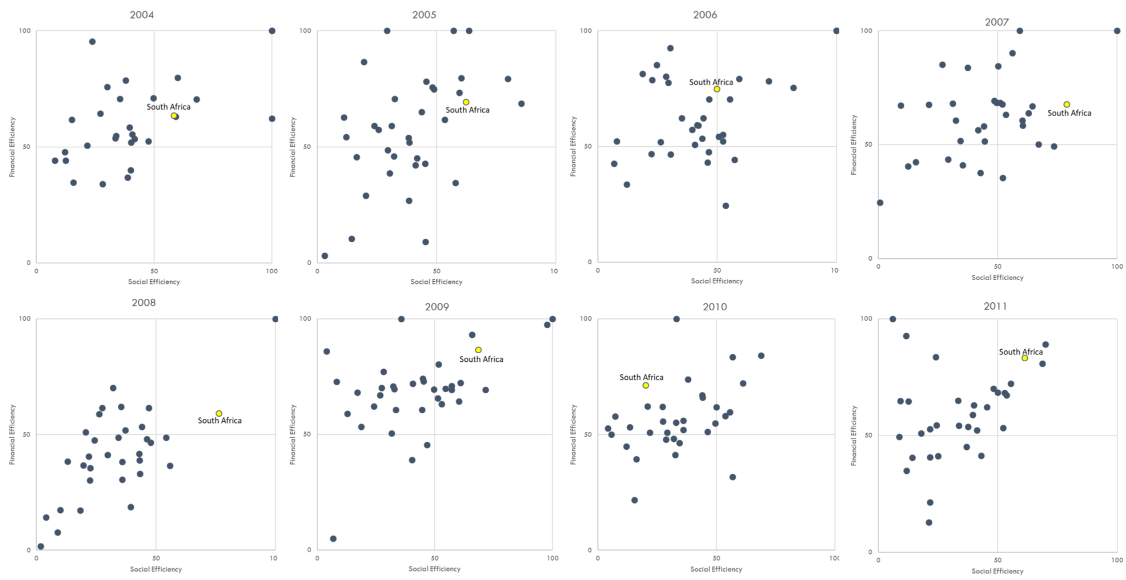

Figure 4.16: Social-Financial efficiency matrix for 2004 - 2011 - South Africa

This analysis allows for at least a partial answer to the question of whether double objectives specific for the microfinance industry are mutually exclusive. The

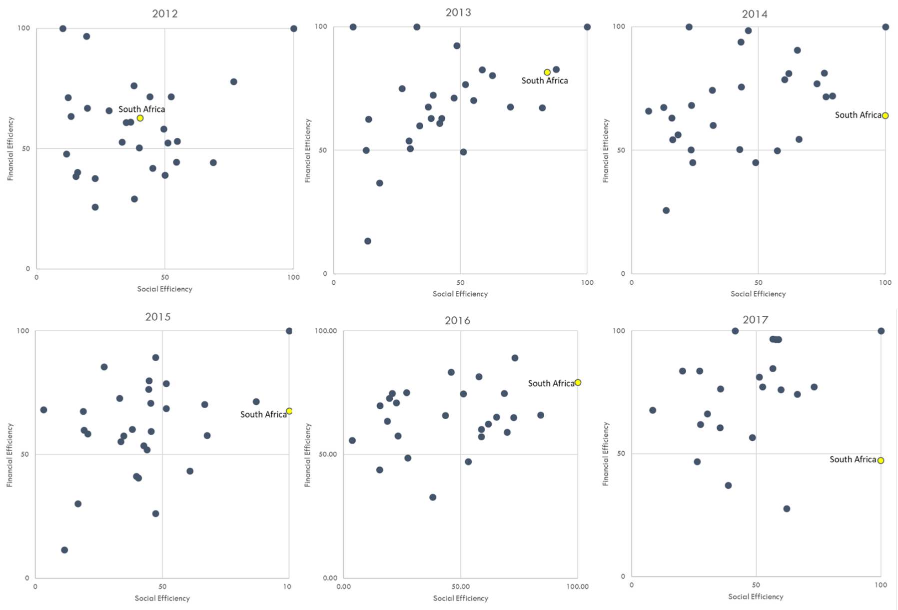

Figure 4.17: Social-Financial efficiency matrix for 2012 - 2017 - South Africa

analysis doesn't show any strong indicators of mutual exclusivity of financial and social efficiency. On the contrary, it shows that some economies (Burkina-Faso, for example) are positioned on the diagonal of the chart for most of the time intervals, which indicates approximately equal levels of social and financial deficiencies when compared against the sample. The findings are consistent with the microfinance sustainability and mission drift research conducted by Kar and Rahman (2018), where authors found that poverty alleviation and financial sustainability objectives can be achieved simultaneously. Based on the research results, authors suggest improving productivity and efficiency of service delivery methods through strategies including increasing the numbers of borrowers per loan officials.

This analysis, however, shows that the majority of economies focus more on the achievement of high financial efficiency than on the achievement of high social efficiency. Such results are generally expected and they do indicate a lack of focus on the social objective.

4.5.2 Achievable social targets

The study question analysed in this section is the following:

- What could the increase in the number of served consumers be if all microfinance institutions under investigation were operating relatively efficiently?

The question of achievable social targets derived from the DEA models was especially interesting for this research. In other words, having currently observed values of output variables, assigned by the DEA model weights, we want to calculate what values of output variable could have been if all financial institutions in the sample operated efficiently. The high number of people served by microfinance institutions is often used as the main argument promoting the social benefit of the microfinance industry, and without a doubt this argument is valid. In microfinance Barometer 2017, for instance, it is stated that the worldwide microfinance industry serves 123 million customers, which is a very impressive number. In our research, however, the question we answer is the following: are the current volumes served by MFIs representative of the feasible limit, or there is a potential to increase the consumer portfolio without increasing the use of input resources. Thus, assuming the current level of input variables for DMUs are fixed, we estimate the overall target value of the output variable number of borrowers.

Such an estimation in the context of data envelopment analysis is perfectly valid and does not provide an overestimated unrealistic target. On the contrary, the target might be underestimated. Data envelopment analysis works on the basis of relative comparison, and when estimating efficiency and targets the values are driven by the market leader. Thus, the targets reveal what the level of inputs and outputs could have been if all units were operating with the same efficiency as the market leader. On the absolute efficiency scale, a market leader might operate far from absolute efficiency. However, we do not take into account this concern and only consider a relative comparison of DMUs.

The table below provides the current and target overall volumes of consumers served by the financial institutions in our sample. The estimates provided using two DEA models, namely the model for overall efficiency and the model for social efficiency. Therefore, the first four columns of the table relate to the estimates derived from the overall efficiency model, and the last four columns are the estimates derived from the social efficiency model. The target estimates are provided for the variable number of borrowers, although it is assumed that the unit has other targets as specified by the modelling results. No prioritization of the number of borrowers over other variables was made to derive the estimates in the table. When considering the overall efficiency model, it is assumed that the DMU might have additional targets for other inputs/outputs and can pursue both social and financial efficiency simultaneously. When social efficiency is considered, it is assumed that the performance of the DMU is judged by social outputs only (number of borrowers and average loan amount) and the DMU then prioritizes its social objective from the dual bottom-line objectives.

Year	Actual overall eff	Target overall eff	Actual/Target, %	Potential Gain, %	Actual social eff	Target social eff	Actual/Target,%	Potential Gain, %
2004	2 506 165	3 640 848	69%	31%	2 506 165	3 270 403	77%	23%
2005	3 297 066	3 939 638	84%	16%	3 297 066	4 229 839	78%	22%
2006	3 995 952	4 685 304	85%	15%	3 995 952	5 244 671	76%	24%
2007	4 714 860	5 565 145	85%	15%	4 714 860	5 763 919	82%	18%
2008	5 151 580	6 308 727	82%	18%	5 151 580	6 339 798	81%	19%
2009	5 671 260	7 773 261	73%	27%	5 671 260	6 994 317	81%	19%
2010	4 405 388	4 940 596	89%	11%	4 405 388	5 438 120	81%	19%
2011	4 740 522	5 495 065	86%	14%	4 740 522	6 041 225	78%	22%
2012	3 861 725	4 441 327	87%	13%	3 861 725	4 899 834	79%	21%
2013	3 900 624	4 377 141	89%	11%	3 900 624	5 086 480	77%	23%
2014	4 685 761	5 548 520	84%	16%	4 685 761	5 943 340	79%	21%
2015	4 639 549	6 306 162	74%	26%	4 639 549	6 211 804	75%	25%
2016	4 980 591	6 000 687	83%	17%	4 980 591	6 405 046	78%	22%
2017	4 184 783	4 642 436	90%	10%	4 184 783	5 380 251	78%	22%

Table 4.19: Current and target overall volumes of consumers served by the financial institutions in the sample

The table indicates that there is a potential for an increasing number of consumers benefiting significantly from microfinance products. The trend of Potential Gain columns suggests that the gap between actual and target values decreases over time. However, there seems to be a significant jump in 2015, where the portfolio served by microfinance institutions could have been increased by 25-26% (depending on what efficiency model is chosen). When applying the ratio to the indicators provided in the Microfinance Barometer (123 million consumers overall), it is fair to conclude, by the most modest calculations, the number of consumers served by the microfinance industry can be increased by 30 million without the addition of extra input resources. Even though our estimations are derived from an analysis of the Sub–Saharan African region and overall estimation should have been deduced from the entire microfinance industry analysis including other regions, the conclusion is still valid. This could be explained by the earlier discussed specifics of data envelopment analysis: in the smaller DMU set efficiencies tend to be overestimated and targets underestimated. If adding DMUs from other regions to the model, there is a high chance that the mean efficiency would become lower and targets thus higher leading to a higher estimation of the overall target.

4.5.3 Productivity change over time

The aim of this section is to contribute additional evidence to the study question partially discussed in previous sections:

- What is the productivity change over time periods? What is the change in the time of external shocks such as the 2008 global financial crisis?

We use the Malmquist index to assess productivity change over time and answer the question of productivity variation in the time of external shocks such as the 2008 global financial crisis.

As discussed in the section 2.10, there are various modifications of Malmquist Index methodology each providing estimation of productivity change under certain assumptions. Ray-Desli Index, for instance, provides a consistent measurement for DMUs under VRS. It, however, lacks circularity and its adjacent period components can provide different measures of productivity change. Therefore, Ray-Desli Index is suitable for comparison of two subsequent time periods and less suitable for comparison of non-subsequent time periods. For direct comparisons of unit performance across different time periods, Circular Malmquist Index can be employed. Under the assumption that feasible technology in the base period stays feasible in the future period, meta–frontier envelops observations from different time periods into one production set. In our research, we conducted the analysis using both Ray-Desli Index and Circular Malmquist Index. This was done to provide an overview of productivity change from two different perspectives: first from subsequent periods comparison provided by Ray-Desli Index and second from global meta-frontier provided by Circular Malmquist Index.

Application of both indexes requires balanced input dataset. Due to the nature of the data in this study, the dataset is unbalanced. To enable the Malmquist index calculation, the dataset was transformed into balanced by the addition of records with dummy substitution values for the periods where observations were missing. Productivity change estimations will not be valid for the specific DMUs and the particular time intervals where substitutions were made, but the presence of full dataset for each time period increases the precision of efficiency estimations. Detailed discussion is provided in section 4.4.4.

Ray-Desli Malmquist Index proposed by Ray and Desli (1997) and calculated as described in section 2.10.2. The index is divided into three components:

$$MI_{RD} = PEC \times TC^{VRS} \times SEC_{RD}$$

, where PEC (Pure Efficiency Change) represents the change in a distance to frontier, SEC (Scale Efficiency Change) explains how a change in the scale on which DMU operates impacts the overall productivity change and TC (Technology Change) explains the frontier shift in two subsequent time periods. As all DMUs in the sample are included in the calculation of the frontier position, the frontier is then considered to represent the production environment. Therefore, frontier shift over time is interpreted as a general development or recession of the production environment. Such interpretation is generally valid, as changes in the environment would often be earliest reflected in the operation shift of market leaders. $MI_{RD} > 1$ implies improvement, $MI_{RD} < 1$ implies deterioration and $MI_{RD} = 1$ implies stability.

Circular Malmquist Index was introduced by Pastor and Lovell (2005) and developed further in its decomposition by Portela and Thanassoulis (2008). We present it in division into tow components:

$$MI_C = EC_C \times BS_C$$

, where where the first component is the Efficiency Change and the second component is the technological gap change (Boundary Shift).

Table 4.20 displays the geometric mean values of the Ray-Desli Malmquist Index components for the period 2004 - 2017, and the corresponding percentage change is in brackets. The overall efficiency model with output orientation was applied. The percent change was calculated by taking ln from the original values: $\Delta TC^{VRS} = ln(TC^{VRS})$, $\Delta SEC_{RD} = ln(SEC_{RD})$, $\Delta PEC = ln(PEC)$ and $\Delta MI_{RD} = ln(MI_{RD})$.

Table 4.20 shows the deterioration of Technology Change during the period 2004-2007 with insignificant improvement between 2005 and 2006. During 2008, the industry frontier experienced strong growth of 33% in comparison to 2007, followed by a drop of 35% in a subsequent year. The frontier had a further 13% growth, after which followed year of deterioration of 12%. Further, an improvement was observed during 2012, 2014 and 2016 and deterioration in 2013, 2015 and 2017.

The Scale Efficiency Change shows a stable trend over the entire period with a slight increase of 5%, 3%, 4% and 3% over the period 2005-2009, which ties in with the beginning of operations for many institutions and therefore it is expected for institutions to change the operational scale during the initial period of operations. The peak improvement, however, observed during 2013 - 2014 period (8%). Pure Efficiency Change also indicated general improvement except for periods of 2007 -

Period	TC^{VRS}(ΔTC^{VRS})	SEC$_{RD}$(ΔSEC_{RD})	PEC (ΔPEC)	MI$_{RD}$(ΔMI_{RD})
2004 - 2005	0.79 (-23%)	1.01 (1%)	1.56 (45%)	1.25 (23%)
2005 - 2006	1.01 (1%)	1.05 (5%)	1.39 (33%)	1.47 (39%)
2006 - 2007	0.94 (-6%)	1.03 (3%)	1.4 (34%)	1.36 (31%)
2007 - 2008	1.39 (33%)	1.04 (4%)	0.8 (-22%)	1.16 (14%)
2008 - 2009	0.7 (-35%)	1.03 (3%)	1.5 (41%)	1.09 (8%)
2009 - 2010	1.14 (13%)	1.01 (1%)	1.01 (1%)	1.17 (15%)
2010 - 2011	0.89 (-12%)	1.01 (1%)	1.28 (25%)	1.15 (14%)
2011 - 2012	1.03 (3%)	1.02 (2%)	1.2 (18%)	1.25 (22%)
2012 - 2013	0.87 (-14%)	1 (0%)	1.3 (26%)	1.14 (13%)
2013 - 2014	1.11 (10%)	1.09 (8%)	1.35 (30%)	1.63 (49%)
2014 - 2015	0.97 (-3%)	1.02 (2%)	1.05 (5%)	1.04 (4%)
2015 - 2016	1.03 (2%)	0.98 (-2%)	0.91 (-10%)	0.97 (-3%)
2016 - 2017	0.9 (-11%)	1.02 (2%)	1.26 (23%)	1.15 (14%)

Table 4.20: Ray-Desli Malmquist Index components for 2004 - 2017 years for Overall efficiency

2008 (22% deterioration) and 2015 - 2016 (10% deterioration). The overall MI_{RD} shows positive change values during the entire period of 2004-2017, showing a year-by-year productivity increase with exclusion of the 2015-2016 year, when 3% deterioration was observed.

Period	EC$_C$(ΔEC_C)	BS$_C$(ΔBS_C)	MI$_C$(ΔMI_C)
2004 - 2005	1.29 (25%)	0.97 (-3%)	1.13 (12%)
2005 - 2006	1.36 (31%)	0.75 (-29%)	0.84 (-18%)
2006 - 2007	1.46 (38%)	0.7 (-36%)	0.76 (-27%)
2007 - 2008	0.94 (-6%)	1.01 (1%)	0.81 (-21%)
2008 - 2009	1.59 (46%)	0.54 (-62%)	0.69 (-37%)
2009 - 2010	1.03 (3%)	0.84 (-18%)	0.82 (-20%)
2010 - 2011	1.27 (24%)	0.59 (-54%)	0.61 (-49%)
2011 - 2012	1.27 (24%)	0.51 (-67%)	0.54 (-61%)
2012 - 2013	1.5 (41%)	0.51 (-68%)	0.6 (-51%)
2013 - 2014	1.32 (28%)	0.81 (-21%)	0.89 (-12%)
2014 - 2015	1.09 (9%)	0.72 (-33%)	0.74 (-30%)
2015 - 2016	1.21 (19%)	0.85 (-16%)	0.9 (-11%)
2016 - 2017	1.27 (24%)	0.77 (-26%)	0.89 (-12%)

Table 4.21: Circular Malmquist Index Components for 2004 - 2017 years for Overall efficiency

Similarly, table 4.21 displays values of the Circular Malmquist Index components for the period 2004 - 2017, and the corresponding percentage change is in brackets. Consistently, the overall efficiency model with output orientation was applied. The percent change was calculated by taking ln from the original values: $\Delta EC_C = ln(EC_C)$, $\Delta BS_C = ln(BS_C)$, and $\Delta MI_C = ln(MI_C)$.

Efficiency change indicated improvement during the entire 2004 - 2017 period with an exclusion of 2007 - 2008 period when there was observed 6% deterioration. Boundary shift meanwhile indicated negative change for all years except 2007-2008, when the boundary remained stable.

Figures 4.18 and 4.19 below provides a visualization of the Malmquist Components in the tables 4.20 and 4.21.

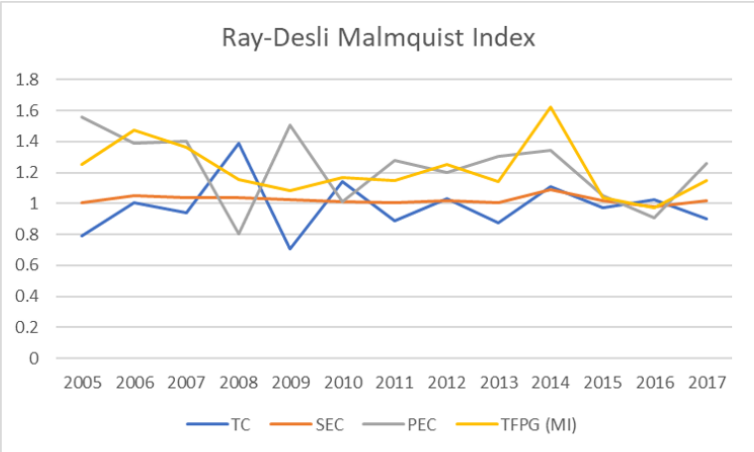

Figure 4.18: Ray-Desli Malmquist Index Components for 2004 - 2017 years for Overall efficiency

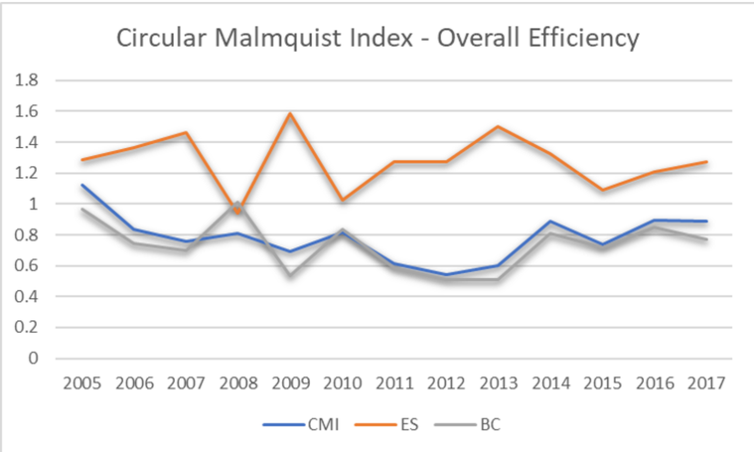

Figure 4.19: Circular Malmquist Index Components for 2004 - 2017 years for Overall efficiency

Tables 4.22 and 4.23 displays Ray-Desli Malmquist Index and Circular Malmquist Index Components respectively for social efficiency levels for period 2004 - 2017.

Table 4.22 indicates significant Technology Changes over the observation period with 2005, 2007, 2009, 2011, 2013 and 2015 years associated with deterioration

Period	TC (ΔTC)	SEC (ΔSEC)	PEC (ΔPEC)	TFRG(MI) (ΔMI)
2004 - 2005	0.83 (-19%)	1.02 (2%)	1.04 (4%)	1.05 (5%)
2005 - 2006	1.06 (6%)	1.05 (5%)	1.05 (5%)	1.12 (12%)
2006 - 2007	0.72 (-33%)	1.01 (1%)	1.37 (31%)	1.02 (2%)
2007 - 2008	1.09 (8%)	1.03 (3%)	0.93 (-7%)	1.08 (7%)
2008 - 2009	0.89 (-12%)	1.04 (4%)	1.16 (15%)	1 (0%)
2009 - 2010	1.24 (22%)	0.99 (-1%)	0.86 (-15%)	1.02 (2%)
2010 - 2011	0.64 (-44%)	1.03 (3%)	1.02 (2%)	0.98 (-2%)
2011 - 2012	1.03 (3%)	1.07 (7%)	1.23 (21%)	1.13 (12%)
2012 - 2013	0.83 (-19%)	0.99 (-1%)	1.09 (8%)	1.06 (6%)
2013 - 2014	1.01 (1%)	1.05 (5%)	1.01 (1%)	0.94 (-6%)
2014 - 2015	0.92 (-9%)	1.03 (3%)	1.25 (22%)	1.11 (11%)
2015 - 2016	1.05 (5%)	0.98 (-2%)	0.9 (-10%)	0.91 (-10%)
2016 - 2017	1.02 (2%)	1.02 (2%)	1.03 (3%)	1.11 (11%)

Table 4.22: Ray-Desli Malmquist Index Components for 2004 - 2017 years for Social Efficiency

(19%, 33%, 12%, 44%, 19% and 9% respectively) and rest of period associated with minor improvement with exclusion of 2009 - 2010, when Technology Change has shown significant increase of 22%. The Scale Efficiency Change shows a stable trend across the entire observation period with minor deterioration and increases. Pure Efficiency Change indicated several periods with significant improvements (31% during 2006 - 2007, 15% during 2008 - 2009, which however followed by 15% decrease in the subsequent year, 21% during 2011 - 2012 and 22% during 2014 - 2015).

Period	$\text{EC}_C(\Delta EC_C)$	$\text{BS}_C(\Delta BS_C)$	$\text{MI}_C(\Delta MI_C)$
2004 - 2005	1.23 (20%)	1.04 (4%)	1.19 (17%)
2005 - 2006	1.35 (30%)	0.67 (-41%)	0.67 (-41%)
2006 - 2007	1.73 (55%)	0.45 (-80%)	0.59 (-52%)
2007 - 2008	1.12 (11%)	0.64 (-45%)	0.6 (-51%)
2008 - 2009	1.4 (33%)	0.46 (-77%)	0.51 (-68%)
2009 - 2010	1.13 (12%)	0.48 (-73%)	0.49 (-72%)
2010 - 2011	1.3 (26%)	0.4 (-91%)	0.39 (-95%)
2011 - 2012	1.58 (46%)	0.32 (-114%)	0.38 (-97%)
2012 - 2013	1.43 (36%)	0.42 (-86%)	0.41 (-89%)
2013 - 2014	1.43 (36%)	0.49 (-71%)	0.59 (-54%)
2014 - 2015	1.61 (47%)	0.39 (-94%)	0.44 (-81%)
2015 - 2016	1.18 (16%)	0.54 (-62%)	0.55 (-60%)
2016 - 2017	1.12 (12%)	0.6 (-50%)	0.59 (-52%)

Table 4.23: Circular Malmquist Index Components for 2004 - 2017 years for Social efficiency

Components of the Circular Malmquist Index estimated by global frontier (table 4.23) indicate significant positive Efficiency Change and negative Boundary Shift over the observation period. Overall Circular Malmquist Index remained below 1 during the observation period.

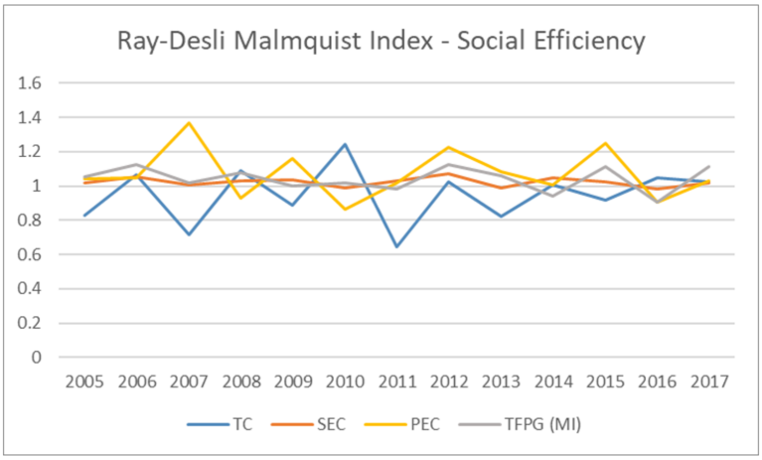

Figure 4.20: Ray-Desli Malmquist Index Components for 2004 - 2017 years for Social Efficiency

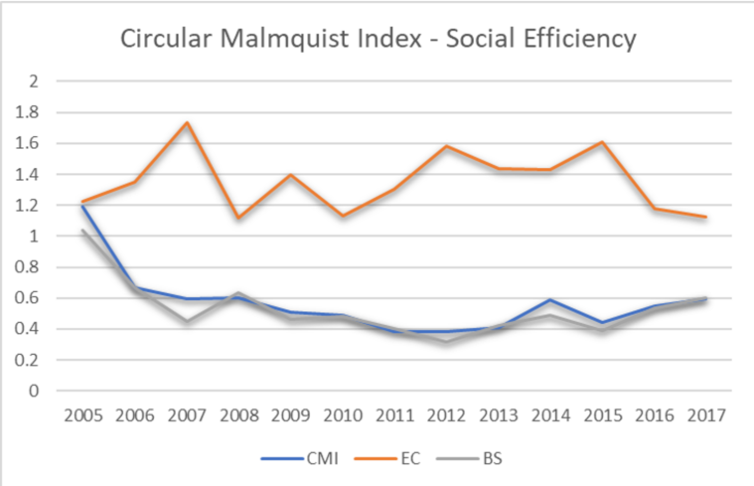

Figure 4.21: Circular Malmquist Index Components for 2004 - 2017 years for Social efficiency

Period	TC (ΔTC)	SEC (ΔSEC)	PEC (ΔPEC)	TFRG(MI) (ΔMI)
2004 - 2005	0.9 (-10%)	1 (0%)	1.13 (13%)	1.01 (1%)
2005 - 2006	1 (0%)	0.99 (-1%)	1.01 (1%)	1.03 (3%)
2006 - 2007	1.06 (6%)	1 (0%)	1.03 (3%)	1.09 (8%)
2007 - 2008	1.8 (59%)	1.01 (1%)	0.58 (-54%)	1.06 (6%)
2008 - 2009	0.55 (-61%)	0.99 (-1%)	1.81 (59%)	0.99 (-1%)
2009 - 2010	1.16 (15%)	1 (0%)	0.87 (-14%)	1.01 (1%)
2010 - 2011	0.91 (-9%)	0.99 (-1%)	1.16 (15%)	1.06 (6%)
2011 - 2012	1.04 (4%)	1 (0%)	0.96 (-5%)	1.06 (5%)
2012 - 2013	0.83 (-19%)	1 (0%)	1.18 (16%)	0.97 (-3%)
2013 - 2014	1.23 (21%)	0.99 (-1%)	0.76 (-27%)	0.95 (-6%)
2014 - 2015	0.95 (-5%)	0.99 (-1%)	0.93 (-7%)	0.93 (-7%)
2015 - 2016	1.11 (10%)	0.98 (-2%)	0.92 (-8%)	1 (0%)
2016 - 2017	0.83 (-19%)	1 (0%)	1.16 (14%)	0.96 (-4%)

Table 4.24: Ray-Desli Malmquist Index Components for 2004 - 2017 years for Financial Efficiency

Table 4.24 indicates volatile Technology Change and stable Scale Efficiency Change of Ray-Desli Index estimated for financial efficiency. Pure Efficiency Change is also very volatile. For instance, 54% deterioration observed during 2007 - 2008 followed by 59% improvement during 2008 - 2009. Another significant deterioration of 27% was observed during 2013-2014.

Period	EC$_C$(ΔEC_C)	BS$_C$(ΔBS_C)	MI$_C$(ΔMI_C)
2004 - 2005	1.25 (22%)	1.25 (22%)	1.42 (35%)
2005 - 2006	1.11 (10%)	1.01 (1%)	1.03 (3%)
2006 - 2007	1.14 (13%)	0.95 (-6%)	0.94 (-6%)
2007 - 2008	0.68 (-39%)	1.74 (56%)	1.17 (15%)
2008 - 2009	2.06 (72%)	0.83 (-19%)	1.17 (15%)
2009 - 2010	0.89 (-11%)	1.94 (66%)	1.82 (60%)
2010 - 2011	1.35 (30%)	1.08 (8%)	1.25 (22%)
2011 - 2012	1.08 (7%)	0.73 (-31%)	0.71 (-34%)
2012 - 2013	1.27 (24%)	1.04 (4%)	1.23 (21%)
2013 - 2014	0.86 (-16%)	1.47 (39%)	1.3 (26%)
2014 - 2015	1.06 (6%)	1.23 (21%)	1.35 (30%)
2015 - 2016	0.96 (-4%)	1.39 (33%)	1.36 (31%)
2016 - 2017	1.18 (17%)	1.3 (27%)	1.42 (35%)

Table 4.25: Circular Malmquist Index Components for 2004 - 2017 years for Financial efficiency

Circular Malmquist Index estimated for financial efficiency indicates significant changes in both Efficiency Change and Boundary Shift during the observation period. Overall Index remained higher than 1 for all periods except 2006 - 2007 when its value equal to 0.94 and 2011 - 2012 when its value equal to 0.71.

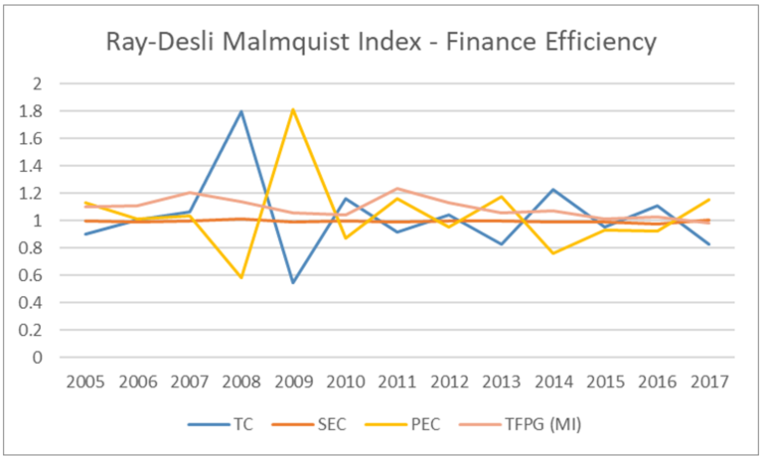

Figure 4.22: Ray-Desli Malmquist Index Components for 2004 - 2017 years for Financial Efficiency

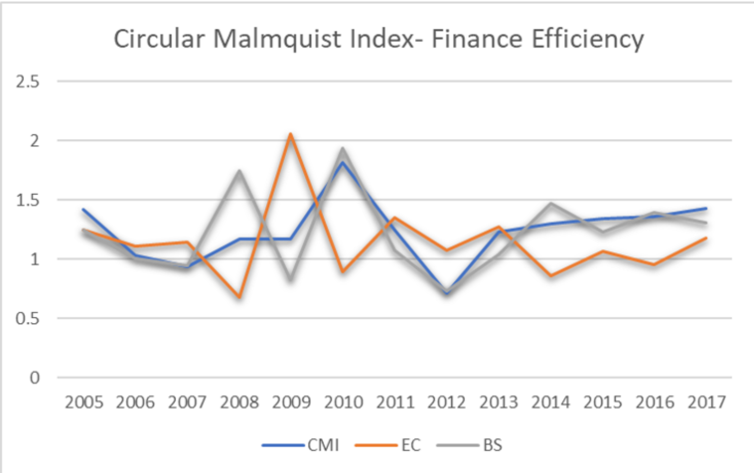

Figure 4.23: Circular Malmquist Index Components for 2004 - 2017 years for Financial efficiency

Interestingly, the Circular Malmquist Index indicates an overall positive production change for financial efficiency and negative for social efficiency. As expected, Malmquist Index indicates significant changes for both financial and social efficiencies during the period of economic crisis. Efficiency Change is positive for social efficiency and negative for financial efficiency for 2007 - 2008 period (as indicated in tables 4.25 and 4.23). The late crisis period, however, associated with significant positive Efficiency Change for financial efficiency (72%) and positive Efficiency Change of 33% for social efficiency.

4.5.4 Second stage post-DEA analysis

The post-DEA analysis was conducted in order to answer the study questions:

- Does the composition of products offered by microfinance institutions impact on efficiency? Where do the institutions focusing on support of small and medium business stand on the efficiency scale?
- Are microfinance institutions providing deposit products in addition to lending products more efficient than the ones providing only lending products?
- Does gender matter? Are women-focused microfinance institutions more efficient comparing to the overall sample?
- Do the regulations have a reflection on the efficiency of the microfinance industry? Are institutions more efficient in the more regulated markets?
- Do the infrastructural components such as credit registries and credit bureaus matter? Are institutions operating in the markets with credit bureaus more efficient compared to the institutions operating in the markets with no credit bureau?
- Does the presence of international funding projects focused on the improvement of microfinance environment associated with the higher efficiency?

The post-DEA analysis also brought additional evidence to the questions discussed in previous sections:

- What is the productivity change over time periods? What is the change in the time of external shocks such as the 2008 global financial crisis?
- Social and financial objectives - are they mutually exclusive?
- Is the microfinance industry witnessing a mission drift over time?

As mentioned in section 2.11, the post-DEA analysis was conducted utilizing non-parametric Kruskal–Wallis test - a non-parametric method for testing whether samples originate from the same distribution. This study applies the test to analyse the significant influence of factors mentioned in the questions above on MFIs' performance differences. For this purpose, the Circular Malmquist Index methodology was used to construct a meta-frontier across all time periods. There are other Malmquist Index methodologies which potentially could be applied here, such as Standard Malmquist Index or Ray-Desli Index. However, they lack circularity and therefore adjacent period components can provide different measures of productivity change. Circular Malmquist Index is suitable for direct comparisons of unit performance across different time periods and therefore it was employed for the second stage post-DEA analysis. Discussion on this topic provided in sections 2.10 and 4.5.3. Output - orientation was selected here to enable Malmquist application. As displayed in section 4.3.1, the resulting efficiency level has low sensitivity to the orientation selection, therefore usage of the output-orientated model is reasonable.

4.5.4.1 Economy-level factors

The following economy-level factors were analysed:

- Presence of a credit bureau
- Presence of the microfinance program led by the World Bank and International Finance Corporation (IFC)
- Presence of legislation for the microfinance industry
- Presence of interest rate limitation for the microfinance industry

Table 4.26 provides descriptive statistics of economy-level factor distribution. Interestingly, at the beginning of the observation period, only 45% of DMUs were operating in economies with MFI legislation, in 2014 this number reached 100% indicating increasing attention of regulatory organs to the industry operations. A similar trend observed for interest cap, 38% of DMUs were operating under the restriction of interest rate in 2004. The number increased to 73% by 2017. IFC projects were taking place at different times in different countries therefore there is no clear trend in the distribution. Significant increase of credit bureau establishment was observed during the years 2004 - 2017, 93% of DMUs were operating on markets with neither private or public register available in 2014, while in 2017, this number decreased to 8%.

Year	Presence of credit bureau			IFC Projects		MFI legislation		Interest Cap	
	No Bureau	Private Bureau	Public Registry	No	Yes	No	Yes	No	Yes
2004	93%	2%	5%	92%	8%	45%	55%	62%	38%
2005	89%	2%	9%	94%	6%	48%	52%	68%	32%
2006	76%	10%	14%	62%	38%	27%	73%	66%	34%
2007	45%	22%	33%	56%	44%	28%	72%	66%	34%
2008	46%	24%	30%	48%	52%	14%	86%	66%	34%
2009	24%	31%	45%	42%	58%	12%	88%	67%	33%
2010	20%	36%	44%	20%	80%	9%	91%	54%	46%
2011	22%	36%	42%	14%	86%	6%	94%	49%	51%
2012	21%	33%	46%	8%	92%	5%	95%	51%	49%
2013	13%	36%	51%	9%	91%	5%	95%	61%	39%
2014	6%	39%	54%	12%	88%	0%	100%	65%	35%
2015	13%	38%	48%	16%	84%	0%	100%	50%	50%
2016	10%	49%	41%	11%	89%	0%	100%	29%	71%
2017	8%	56%	35%	5%	95%	0%	100%	27%	73%
Total	38%	27%	35%	38%	62%	16%	84%	58%	42%

Table 4.26: Descriptive Statistics of economy-level factor distribution

- Presence of credit bureau

This factor indicates the existence of the data collection agency that gathers account information from operating on market creditors and allows usage of the information by other creditors. Generally, there are two types of such agencies: a public registry and a credit bureau (credit bureau also can be public, but more frequently it is a private company). The public registry has an initial objective to serve as an information pool to authorities to control the industry processes and drive regulation changes. Additionally, in some countries, public registries provide infrastructure for creditors to use collected data during the account origination and account management decisions. On the contrary, credit bureaus operate with an initial objective to provide a data sharing environment for creditors, and thus the main focus is on the increase of data exchange by creditors.

Both public registries and credit bureaus are present in the majority of developed economies. In some economies, multiple credit bureaus operate simultaneously bringing benefits to the economy from an antimonopoly perspective. On the developing markets, however, this infrastructure is only evolving, with various credit bureaus established during the last decade. It is thus interesting to compare the mean efficiency levels of microfinance institutions divided into groups by the presence of a credit bureau or public registry. In our classification, there are three groups: "No Bureau", "Public Registry" (indicating the existence of only public registry) and "Private Bureau" (Indicating the existence of a credit bureau, but not excluding the possibility of the existence of the public registry). As many bureaus were established during the observation period of 2004 - 2017, the groups were divided based on annual information. For instance, in Kenya both the public data collection agency and the private credit bureau were established in 2007. Therefore DMUs operating in Kenya prior to 2007 are in the group "No Bureau" and DMUs operating in Kenya in 2007 and later are in the group "Private Bureau".

- Presence of the microfinance program led by the World Bank and International Finance Corporation (IFC)

There are many international organizations providing support to developing countries in their fight against poverty. Specifically, for the microfinance industry and Sub–Saharan region, IFC is one of the leading global investors in terms of volume, a number of projects, longevity and extension of projects. Thus, the research separates programs led by IFC into a separate factor for analysis. Only microfinance-focused programs are included in the analysis; other poverty-reducing projects are ignored.

- Presence of legislation for the microfinance industry

The factor indicated the existence of specific microfinance legislation in an economy with two possible groups "Yes" and "No". If there is no separate legislation, but microfinance institutions fall into the general banking category, the DMUs operating in this economy would belong to the group "No". This is also the case if microfinance institutions are excluded from the general lending category and there is no separate legislation for the industry. This indicator does not reflect regulations, even though it is related to it in some sense. The reason for such a definition is the fact, that in this research we want to separate regulation-related components such as legislation and interest rate cap and investigate them separately. There are many other components of regulation not covered by the study for various reasons (lack of available data or irrelevance to the study questions).

- Presence of interest rate limitation for the microfinance industry

Interest rate limitation is generally expected to have a significant impact on the operation of creditors. It is frequently observed that after the introduction of the interest rate cap, the number of units operating on a market reduces, as some creditors decide to retrieve their operations from the market. As for all economy-level factors, the groups were divided based on annual information. DMUs operating in the economy before the introduction of the interest rate cap are separated into the group "No", and after the interest rate cap was introduced, all DMUs operating in this economy are moved to the group "Yes".

For each of the four categorisers, three null hypothesises were tested:

- The distribution of Overall Efficiency is the same across categories of categoriser;
- The distribution of Social Efficiency is the same across categories of categoriser;
- The distribution of Financial Efficiency is the same across categories of categoriser;

Table 4.28 presents the results of the Kruskal-Wallis test. Instead of providing a comparison of obtained H values against the critical values for a selected significance level, we provide p-values - the probability of obtaining a result is at least as extreme, given that the null hypothesis was true. The significance level of 5% is used. We therefore interpret results as the following: reject the null hypothesis if $p < 0.05$, and accept the null hypothesis if $p \geq 0.05$.

Categoriser	Asymptotic Significance - Overall Efficiency	Asymptotic Significance - Social Efficiency	Asymptotic Significance - Financial Efficiency
Credit Bureau Presence	0.000	0.000	0.000
IFC Project Presence	0.000	0.877	0.000
MFI Regulation	0.936	0.108	0.373
Interest Rate Cap	0.001	0.004	0.000

Table 4.28: Independent-Samples Kruskal-Wallis Test - economy level factors

- Presence of credit bureau

Results in the table 4.28 suggest rejection of the null hypothesis for all three efficiency sets. p-value of 0.000 for all three datasets indicates that there is a significant difference in the efficiency scores across different groups of credit bureau presence. As indicated in the table 4.26, 93% of DMUs were operating on markets with neither private or public register available in 2014, while in 2017, this number decreased to 8%.

The Kruskal-Wallis test answers the question of whether there is a significant difference between the groups or not, although it does not expand on the nature of the difference where it is present. Therefore for the deeper analysis, the following table was produced showing the category group mean efficiency level in relation to the dataset mean efficiency at the specified time period (the original results of the non-oriented DEA model as described in section 4.5.1 are used here). For instance, for the year 2004, the table shows that a group of DMUs operating on markets without any form of credit bureau have a 4% lower mean financial efficiency than the mean efficiency of the sample. Group of DMUs operating on markets with only public registry have a 12% higher mean financial efficiency and DMUs operating on markets with private credit bureau have a 30% higher mean financial efficiency than the mean efficiency of the 2004 sample.

From the table 4.29 it is concluded that the presence of the private credit bureau has a positive impact, although this trend decreases over time for all three overall, social and financial efficiency specifications. The conclusion is consistent with both literature references and practical experience. Indeed, when data sharing between microfinance institutions on the market is enabled by an operating credit bureau, customer onboarding, as well as further customer management, is associated with lower credit risks, which subsequently reduces credit losses and allows more efficient lending in both financial and social dimensions.

The existence of only a public registry on the market for most of the time periods is associated with lower than the sample mean efficiency level according to the table. The trend changes from negative to positive for the separate time periods. There is no unambiguous explanation for such a trend, the impact of the public registry depends on how it operates. In some economies, the public registry functions similarly to a private credit bureau providing an environment for data sharing and thus bringing data-sharing related benefits to the microfinance institutions. In other economies, public registries collect data only for internal use by authorities. Such an approach limits benefits for the market players significantly. It is interesting that for some of the time periods, the group "Public Registry" has a lower mean efficiency then group "No Bureau".

	Overall Efficiency			Social Efficiency			Financial Efficiency		
	No Bureau	Public Registry	Private Bureau	No Bureau	Public Registry	Private Bureau	No Bureau	Public Registry	Private Bureau
2004	-3%	5%	30%	-7%	1%	77%	-4%	12%	30%
2005	0%	-26%	47%	-6%	-19%	83%	-1%	-30%	60%
2006	-3%	-14%	32%	-5%	-32%	67%	-5%	-17%	44%
2007	3%	-15%	16%	-1%	-26%	46%	5%	-17%	14%
2008	-8%	-20%	58%	-12%	-32%	89%	-9%	-14%	49%
2009	-2%	-2%	5%	0%	-18%	29%	-5%	-1%	6%
2010	-8%	-10%	22%	-6%	-18%	32%	-15%	-6%	22%
2011	-6%	-6%	16%	5%	-28%	42%	-9%	-3%	14%
2012	-3%	-2%	4%	13%	-18%	19%	-14%	2%	4%
2013	-9%	1%	2%	7%	-24%	28%	-16%	5%	1%
2014	-1%	-12%	17%	41%	-42%	43%	-8%	-8%	15%
2015	-13%	-8%	17%	27%	-33%	38%	-23%	-4%	16%
2016	9%	-9%	9%	39%	-27%	25%	6%	-9%	9%
2017	1%	-3%	3%	34%	-13%	8%	1%	-3%	2%

Table 4.29: Country level results – Credit Bureau Performance

- Presence of the microfinance program led by the World Bank and International Finance Corporation

The Kruskal-Wallis test indicated a significant difference in the efficiency scores across groups differentiated by the presence of IFC projects However this was only the case for overall and financial efficiency specifications and not for social efficiency. p-value of 0.000 was observed for overall and financial efficiency specifications, for social efficiency p-value equals 0.877.

The table 4.31 indicated that the presence of IFC projects generally has a positive trend of the mean efficiency scores for both overall and financial efficiency specification. For the social efficiency, the trend is not clearly expressed, indicating a positive trend for some years and negative for others. This is an interesting finding, as IFC projects are usually focused on the creation of microfinance infrastructure with the final goal of improving the social impact of the industry. Study results show that financial efficiency benefits from the presence of IFC projects more than social efficiency. This finding is interesting, but not unexpected, as this question is thoroughly discussed in subject literature. Beisland and Mersland (2013) mention that subsidies and grants may constitute a portion of income for many MFIs (Yaron, 1992; Christen et al., 1995; Schreiner, 1997; Manos and Yaron, 2009), which positively reflects on the financial performance and sustainability. However, it doesn't necessarily have an impact on the outreach indicators.

	Overall Efficiency			Social Efficiency			Financial Efficiency		
	No	Yes	No Information	No	Yes	No Information	No	Yes	No Information
2004	-7%	21%	18%	-12%	-33%	40%	-6%	21%	16%
2005	2%	20%	-6%	0%	-18%	1%	-1%	24%	-1%
2006	-11%	13%	6%	-18%	-10%	33%	-10%	15%	4%
2007	-1%	-1%	3%	7%	-11%	-1%	-8%	2%	9%
2008	-4%	18%	-15%	0%	-1%	1%	-2%	28%	-29%
2009	-2%	6%	-5%	2%	7%	-11%	-2%	6%	-6%
2010	15%	-2%	-4%	10%	17%	-36%	1%	-2%	3%
2011	18%	6%	-18%	47%	10%	-32%	14%	5%	-16%
2012	5%	2%	-7%	83%	10%	-49%	-31%	1%	3%
2013		3%	-15%		-1%	7%		2%	-13%
2014		2%	-8%		-5%	25%		1%	-5%
2015		-2%	10%		-4%	20%		-3%	12%
2016		1%	-8%		0%	0%		0%	-3%
2017		2%	-24%		0%	-1%		2%	-22%

Table 4.31: Country level results – IFC Project Presence

- Presence of legislation for the microfinance industry

Only 45% of DMUs were operating in economies with MFI legislation in 2004 and by 2014 this number reached 100% indicating increasing attention of regulatory organs to the industry operations. The Kruskal-Wallis test indicated that no significant difference in the efficiency scores across groups was caused by the presence of legislation for the microfinance industry. The test suggests retaining the null hypothesis for all three efficiency specifications (p-value = 0.936 for overall efficiency, p-value = 0.108 for social efficiency and p-value = 0.373 for financial efficiency). This finding is interesting in itself, although it is not surprising. Hartarska and Nadolnyak (2013) found that legislation involvement does not directly affect performance either in terms of operational self-sustainability or outreach. The article also finds that less leveraged MFIs have better sustainability. The policy implication is that MFIs transformation into regulated financial institutions may not lead to improved financial results and outreach, according to authors.

From the year 2014, all countries in the dataset had already implemented microfinance legislation, thus the years 2014-2017 are missing in the table 4.32.

- Presence of interest rate limitation for the microfinance industry

At the beginning of the observation period, in 2004, 38% of DMUs were operating under the restriction of the interest rate. The number increased to 73% by 2017.

	Overall Efficiency		Social Efficiency		Financial Efficiency	
	No	Yes	No	Yes	No	Yes
2004	3%	-3%	-4%	4%	5%	-6%
2005	-11%	12%	-9%	10%	-12%	13%
2006	12%	-5%	16%	-6%	22%	-9%
2007	10%	-3%	23%	-8%	12%	-4%
2008	30%	-8%	34%	-9%	24%	-6%
2009	0%	0%	-1%	0%	1%	0%
2010	-6%	1%	-7%	2%	-5%	1%
2011	-16%	2%	-24%	2%	-22%	2%
2012	2%	0%	-52%	6%	1%	0%
2013	-22%	1%	-41%	2%	-27%	1%

Table 4.32: Country level results – MFI Legislation

The Kruskal-Wallis test indicated a significant difference in the efficiency scores across groups differentiated by the presence of interest rate limitation for the microfinance loans (p-value equals 0.001 observed for overall, p-value equals 0.000 for financial efficiency and p-value equals 0.004 for social efficiency). While the null hypothesis is rejected for all three efficiency specifications, it is interesting that the trend direction in the table 4.33 is different: for the overall and financial efficiency presence of interest rate cap is associated with reduced mean efficiency, and for social efficiency, the opposite trend is observed. For all time periods, DMUs operating on the market with an interest rate cap have a higher mean social efficiency than the mean efficiency of the sample.

The Widiarto and Emrouznejad (2015) study found the MFI regulatory status significantly affects overall, financial, and social efficiency, i.e. efficiency scores tend to be lower should MFIs be regulated, although the effect size of the trend is small. The initial presumption of the authors was that unregulated MFIs excel in social efficiency due to flexibility in operation whilst regulated MFIs lead in financial efficiency due to deposit taking authorization and due to stricter authority monitoring regarding profit and cost management. Our study results confirm this assumption in terms of social efficiency and challenge the presumption in terms of financial efficiency. As it is shown further in the section 4.5.4.2, the presence of a deposit-taking scheme has no relation to the MFI efficiency level.

	Overall Efficiency		Social Efficiency		Financial Efficiency	
	No	Yes	No	Yes	No	Yes
2004	4%	-8%	-3%	5%	4%	-8%
2005	-2%	5%	-8%	19%	-2%	4%
2006	3%	-9%	-3%	8%	7%	-16%
2007	3%	-6%	-6%	14%	5%	-13%
2008	5%	-12%	-6%	13%	9%	-20%
2009	0%	-1%	-9%	22%	0%	0%
2010	2%	-4%	-6%	14%	5%	-11%
2011	-5%	13%	-23%	52%	-4%	10%
2012	7%	-9%	-5%	7%	9%	-11%
2013	1%	-1%	-13%	16%	4%	-6%
2014	6%	-6%	-10%	10%	11%	-11%
2015	1%	-1%	-25%	30%	7%	-9%
2016	-7%	6%	-38%	32%	-3%	2%
2017	3%	-2%	-21%	16%	9%	-7%

Table 4.33: Country level results – Interest Rate Cap

The figure 4.24 visualizes the mean efficiency levels utilized in the Kruskal-Wallis test.

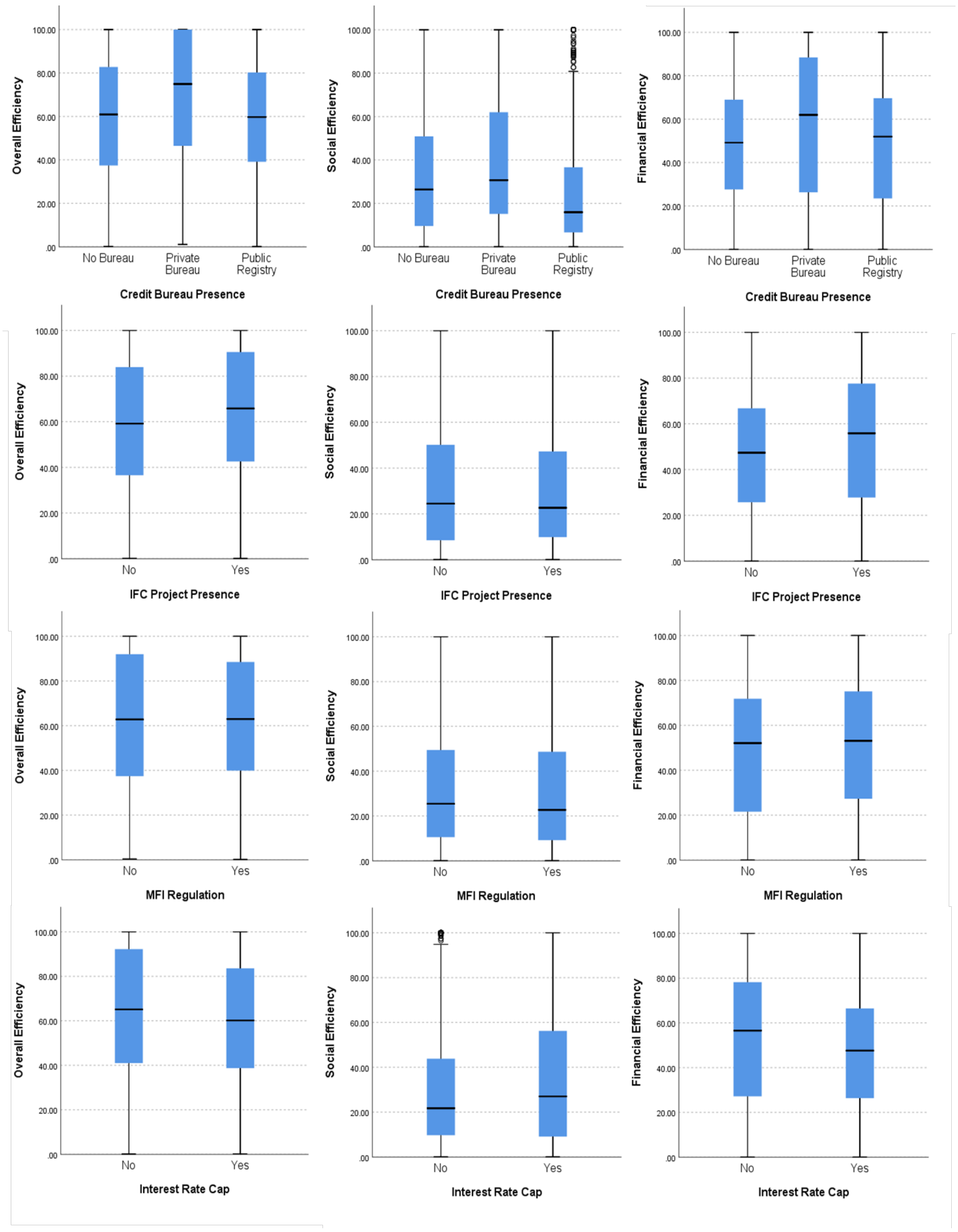

Figure 4.24: Mean Values of Meta-Frontier efficiency level's by categorized groups - economy level factors

4.5.4.2 DMU-level factors

The following DMU-level factors was analysed:

- Presence of a deposit scheme

- Prevailing product type
- SME Orientation
- Prevalence of female customers

Table 4.34 provides descriptive statistics of DMU-level factor distribution.

Year	Deposits		Product type			SME orientation					Gender orientation		
	No	Yes	3 mos plus	No Info	Up to 3 mos	No	No Info	Yes - Full	Yes - Partial	Balanced	Female prevail	Male prevail	No Info
2004	70%	30%	7%	71%	23%	99%	1%	0%	0%	0%	24%	0%	76%
2005	63%	37%	11%	62%	26%	100%	0%	0%	0%	0%	28%	0%	72%
2006	49%	51%	19%	49%	32%	100%	0%	0%	0%	0%	29%	0%	71%
2007	34%	66%	17%	36%	47%	99%	0%	0%	0%	0%	24%	0%	76%
2008	14%	86%	30%	15%	55%	48%	0%	34%	18%	17%	28%	25%	30%
2009	10%	90%	23%	20%	57%	29%	1%	47%	22%	16%	19%	19%	47%
2010	10%	90%	18%	33%	49%	45%	3%	28%	25%	9%	15%	6%	70%
2011	11%	89%	43%	32%	25%	57%	2%	20%	21%	12%	17%	10%	61%
2012	10%	90%	33%	25%	42%	52%	1%	23%	24%	17%	16%	11%	56%
2013	12%	88%	29%	24%	47%	57%	1%	18%	24%	8%	6%	11%	76%
2014	8%	92%	24%	26%	50%	54%	1%	15%	31%	13%	4%	19%	63%
2015	9%	91%	34%	18%	48%	40%	2%	21%	37%	11%	10%	11%	67%
2016	8%	92%	41%	18%	40%	26%	5%	25%	44%	17%	11%	19%	53%
2017	9%	91%	39%	13%	48%	22%	2%	38%	38%	19%	18%	24%	40%
Total	24%	76%	25%	33%	41%	63%	1%	18%	18%	9%	19%	10%	62%

Table 4.34: Descriptive Statistics of DMU-level factor distribution

At the beginning of the observation period in 2004, only 30% of microfinance institutions in the sample were providing deposit schemes to its customers. This number increased to 91% in 2017. Regarding the prevailing product type, proportions of institutions providing sort-term loans (loans with duration up to 3 months) and longer-term loans (loans with duration 3 and more months) remained relatively stable across the observation period with no significant trend over time. Meanwhile, more institutions started focusing their operations on granting loans to small and medium enterprises. Almost no DMUs were providing SME loans during 2004-2007 and by 2017, 76% of DMU were partially or fully focused on SME lending. With regards to the gender-based focus of institutions, female-focused institutions existed during the entire observation period, however, their proportion decreased from 24% in 2004 to 18% in 2017. It is also fair to note, that a significant number of DMUs did not provide gender data on their customer base.

Table 4.36 presents results of the Kruskal-Wallis test. As before, the table provides p-values - the probability of obtaining a result at least as extreme, given that the null hypothesis was true. The significance level of 5% is used. We therefore interpret results as follows: reject the null hypothesis if $p < 0.05$ and accept the null hypothesis if $p \geq 0.05$.

Categoriser	Asymptotic Significance - Overall Efficiency	Asymptotic Significance - Social Efficiency	Asymptotic Significance - Financial Efficiency
Deposits	0.678	0.076	0.170
Prevailing product type	0.000	0.000	0.000
SME Orientation	0.000	0.000	0.004
Female Customer Prevailing	0.004	0.000	0.696

Table 4.36: Independent-Samples Kruskal-Wallis Test - DMU level factors

- Presence of deposit scheme

The Kruskal-Wallis test indicated no significant difference in the efficiency scores across groups differentiated by the presence of a deposit scheme. The test suggests retaining the null hypothesis for all three efficiency specifications(p-values equal 0.678, 0.076 and 0.170 for overall, social and financial efficiency specifications respectively). This finding contradicts general opinion, that deposit-taking leads to higher financial efficiency of an institution. When comparing mean values in the table 4.37, higher mean social efficiency is observed for the DMU in the group "No" with peak values of 69% in 2015 a 50% in 2017. However, the p-values equal 0.076 suggesting retention of the null-hypothesis and therefore the conclusion is that there is no strong evidence confirming that the presence of deposit scheme has significant differentiation on the efficiency level. This might be related to the fact, that there is a low number of DMU's in group "No" (8%-9% during 2014 - 2017).

- Prevailing product type

The Kruskal-Wallis test indicated a significant difference in the efficiency scores across groups differentiated by indicating the prevailing product type (p-values equal 0.000 for all three efficiency specifications). The study found that a group of DMUs focusing on short-term loans (up to 3 months) were associated with increased mean efficiency level than the overall group. The Kruskal-Wallis test results, however, could have been impacted by the group "No info" and the true significance of the results is thus questionable. In order to answer this question,

	Overall Efficiency		Social Efficiency		Financial Efficiency	
	No	Yes	No	Yes	No	Yes
2004	-5%	11%	3%	-6%	-6%	14%
2005	-1%	2%	7%	-12%	-3%	5%
2006	-1%	1%	14%	-13%	-4%	4%
2007	4%	-2%	19%	-10%	3%	-2%
2008	12%	-2%	15%	-3%	1%	0%
2009	17%	-2%	24%	-3%	15%	-2%
2010	22%	-2%	38%	-4%	26%	-3%
2011	15%	-2%	28%	-3%	18%	-2%
2012	26%	-3%	42%	-5%	25%	-3%
2013	4%	0%	28%	-4%	6%	-1%
2014	12%	-1%	39%	-3%	9%	-1%
2015	16%	-1%	69%	-6%	26%	-2%
2016	16%	-1%	39%	-2%	23%	-2%
2017	1%	0%	50%	-4%	-1%	0%

Table 4.37: DMU Level results - Deposits

pairwise comparisons were conducted. For the pair "3 months or more - Up to 3 months" the p-value of the Kruskal-Wallis test is 0.026, which is lower than 0.05 and this, therefore, confirms a significant difference between these two groups.

	Overall Efficiency			Social Efficiency			Financial Efficiency		
	Up to 3 months	3 months or more	No info	Up to 3 months	3 months or more	No info	Up to 3 months	3 months or more	No info
2004	14%	14%	-6%	-12%	14%	3%	17%	14%	-7%
2005	4%	-1%	-2%	-18%	-12%	10%	8%	2%	-4%
2006	4%	2%	-3%	-19%	-4%	14%	10%	3%	-7%
2007	3%	-8%	-1%	1%	-28%	11%	3%	-3%	-3%
2008	9%	-2%	-28%	4%	8%	-30%	10%	-2%	-33%
2009	-1%	2%	2%	-4%	21%	-12%	0%	0%	1%
2010	11%	-1%	-16%	14%	6%	-24%	9%	-9%	-9%
2011	3%	2%	-5%	17%	4%	-19%	0%	0%	1%
2012	12%	-1%	-19%	15%	1%	-27%	12%	1%	-22%
2013	4%	2%	-11%	7%	13%	-29%	5%	3%	-13%
2014	4%	-5%	-3%	17%	-2%	-32%	6%	-6%	-6%
2015	2%	-7%	9%	1%	-2%	3%	3%	-8%	7%
2016	-5%	3%	5%	-10%	8%	8%	-2%	0%	5%
2017	-1%	0%	2%	6%	-7%	5%	-3%	2%	6%

Table 4.38: DMU Level results - Product Types

- SME Orientation

The Kruskal-Wallis test indicated a significant difference in the efficiency scores across groups differentiated by client group orientation for all three efficiency specifications (p-values equal 0.000 for overall and social efficiency specifications and 0.004 for financial). The positive efficiency trend is observed for the DMUs fully focusing on SME lending. For the rest of the groups, results are not easily interpretable. The issue of missing information on the target client group for some of the institutions, unfortunately, reduces the robustness of the results. For the period 2004 - 2007, the information was almost completely missing, and as a result, their years are not included in the table below.

	Overall Efficiency				Social Efficiency				Financial Efficiency			
	Yes Full	No	Yes Partial	No Info	Yes Full	No	Yes Partial	No Info	Yes Full	No	Yes Partial	No Info
2004		0%		18%		1%		-100%		0%		27%
2005		0%		21%		0%		-99%		0%		35%
2006		0%		12%		0%		-99%		0%		27%
2007	20%	0%		-3%	-69%	1%		-99%	38%	0%		12%
2008	9%	-8%	4%	-8%	19%	-13%	2%	-100%	5%	-7%	9%	18%
2009	6%	-3%	-7%	2%	22%	-14%	-29%	13%	3%	-1%	-5%	8%
2010	13%	-12%	7%	7%	30%	-25%	5%	53%	5%	-9%	9%	23%
2011	15%	-3%	-7%	22%	38%	-13%	-6%	39%	2%	0%	-5%	37%
2012	10%	-9%	7%	64%	19%	-12%	3%	166%	10%	-11%	12%	90%
2013	-3%	1%	0%	-35%	18%	-4%	-3%	-70%	-8%	2%	1%	-31%
2014	11%	-1%	-4%	33%	39%	-7%	-7%	14%	5%	0%	-3%	43%
2015	14%	-8%	0%	7%	62%	-21%	-7%	-85%	12%	-6%	-1%	21%
2016	14%	-9%	-2%	-11%	50%	-17%	-14%	-26%	8%	-2%	-1%	-29%
2017	5%	-21%	6%	26%	45%	-27%	-27%	-10%	0%	-18%	10%	39%

Table 4.39: DMU Level results - SME Orientation

- Prevalence of female customers

The Kruskal-Wallis test suggests a rejection of the null hypothesis for the overall and social efficiencies (p-values equal 0.004 and 0.000 respectively), and retention of the null hypothesis the financial efficiencies (p-values equal 0.696) for the group separation based on the prevalence of customers' gender. Focusing on female borrowers is generally associated with an increased mean overall efficiency and with significantly increased social efficiency as per table 4.41. It does not, however, indicate any trend towards financial efficiency. Similarly to the SME orientation above, for the period 2004 - 2007 the information was almost fully missing, and thus their years are not included in the table below.

	Overall Efficiency			Social Efficiency			Financial Efficiency		
	Male prevail-ingly	Female prevail-ingly	Balanced	Male prevail-ingly	Female prevail-ingly	Balanced	Male prevail-ingly	Female prevail-ingly	Balanced
2004		5%			18%			7%	
2005		-6%			6%			-1%	
2006		-2%			11%			-3%	
2007		-3%			7%			-4%	
2008	-19%	17%	-11%	-28%	36%	-3%	-13%	8%	-19%
2009	-9%	9%	-14%	-11%	34%	-10%	-7%	5%	-12%
2010	-9%	9%	-6%	-46%	41%	0%	3%	6%	-2%
2011	-13%	12%	-8%	-18%	56%	-9%	-8%	9%	-6%
2012	-4%	13%	-11%	-2%	16%	-17%	-2%	15%	-4%
2013	-22%	3%	-11%	-18%	16%	-19%	-16%	-2%	-10%
2014	3%	2%	-7%	16%	39%	1%	8%	-4%	-6%
2015	22%	5%	-5%	-23%	39%	-40%	37%	1%	5%
2016	-13%	22%	-1%	-10%	64%	-17%	-10%	28%	-2%
2017	-2%	9%	4%	-16%	60%	-38%	4%	9%	12%

Table 4.41: DMU Level results - Gender

The figure 4.25 visualizes the mean efficiency levels utilized in the Kruskal-Wallis test.

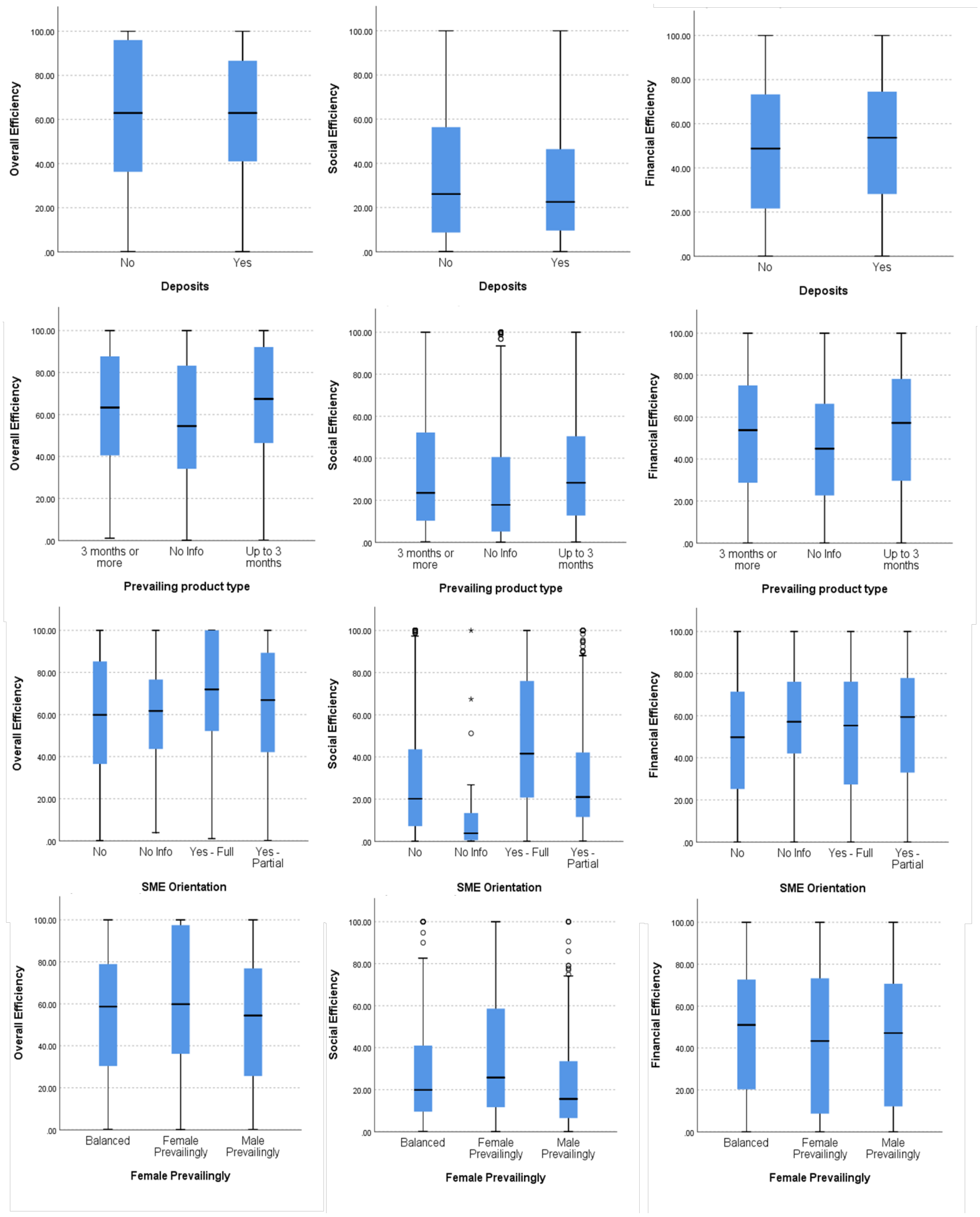

Figure 4.25: Mean Values of Meta-Frontier efficiency level's by categorized groups

4.6 Study questions answered

Question 1. What is the financial and social efficiency of microfinance institutions across developing countries of the Sub–Saharan African region? Do most institutions operate close to the efficiency frontier or away from it?
Financial and social efficiency of microfinance institutions changes over time, with the proportion of those that are overall efficient ranging from as low as 16% (2010) to as high as 32% . The proportion of socially efficient DMUs changes from 11% to 22% over time and the proportion of financial efficient DMUs from 12% to 28%.
To answer the question of whether institutions operate close to the efficiency frontier or away from it, a social-financial efficiency matrix was utilized. In 2004, the majority of units were having both social and financial efficiencies below 50%, indicating that their position is far from the frontier. In 2005, 2006 and 2007 more units are operating closer to frontiers for both social and financial efficiencies. In 2008, however, most of the units operate far from the efficiency frontiers (both social and financial) with a fair amount of units on the social efficiency frontier and very few units on the financial efficiency frontier. This is consistent with research findings of Efendic and Hadziahmetovic (2017), where the authors indicated that the crisis had a negative effect on both financial and social efficiency of microfinance institutions in Bosnia and Herzegovina. The following years are associated with DMUs operating closer to financial efficiency frontiers, and separate DMUs operating close to social efficiency frontier. 2013, 2014, 2015 and 2016 year charts display similar trends with the majority of units being placed in the first and the second quadrants of the SFE matrix, thus indicating prioritization of the financial objective over the social objective. When aggregated on a country level, SFE matrices are showing similar trends with most countries experiencing a severe shock in 2008 and moving toward the frontiers in the following years. Some years (2012, for instance) are associated with the very low social performance of the entire group, although in the following years - 2013, 2014, 2015, 2016 and 2017 - these countries operated closer the social efficiency frontier, which is good news in the context of poverty reduction.

Question 2. What is the productivity change over time periods? What is the change in the time of external shocks such as the 2008 global financial crisis?

Analysis conducted using the Ray-Desli Malmquist Index shows the deterioration of Technology Change during the period 2004-2007. During 2008, the industry frontier experienced a strong growth of 37% in comparison to 2007, which saw a drop of 38%. The frontier had a further 15% growth, after which followed 3 years of subsequent deterioration. A 12% growth was achieved in 2014 followed by two years of stability and a 12% deterioration in 2017. The Scale Efficiency Change shows a stable trend over the entire period with a slight increase of 11%, 6%, 9% and 6% over the period 2005-2009, which is associated with the beginning of operations for many institutions, and therefore it is expected for institutions to change the operational scale during the initial period of operations. Contrary to the SEC, the PEC shows a variable trend during the entire observation period. There is a strong increase of 42%, 39% and 34% in PEC during 2004-2007, followed by a 24% decrease in 2008. Almost all the following years, with the exception of 2016, are associated with a significant increase of SEC. The overall MI has positive change values during the entire period 2004-2017, demonstrating a year-by-year productivity increase.

Question 3. Social and financial objectives - are they mutually exclusive?

The analysis doesn't show any strong indicators of mutual exclusiveness of financial and social efficiency. On the contrary, it shows that some economies (Burkina–Faso, for example) are positioned on the diagonal of the chart for the most of the time intervals, which indicates approximately equal levels of social and financial deficiencies when compared against the sample. The findings are consistent with microfinance sustainability and missing drift research conducted by (Kar and Rahman, 2018), where the author found that poverty alleviation and financial sustainability objectives can be achieved simultaneously.

Question 4. Is there mission drift in microfinance industry observed over time? During the period 2004-2007, strong prioritization of the financial objective over the social objective was observed for the majority of DMUs, during the latest years of the observation period, the focuses of DMUs became more diverse. While the majority of DMUs still prioritize the financial objective over the social objective, as reflected in aggregated results, when analyzed closely using social-financial efficiency matrices it is observed that separate DMUs are achieving a higher level of social efficiency than ever before. When country-level results are analysed, the conclusions are similar: while most economies giving higher priority to the financial objective, there are economies (Burkina-Faso, for instance), which balance the two objectives steadily over time. In 2016 and 2017 Senegal and South Africa entered the fourth quadrant of the SFE matrix, indicating a bigger focus on achieving high social efficiency.

Question 5. Does the composition of products offered by microfinance institutions affect efficiency? Where do the institutions focusing on support of small and medium business stand on the efficiency scale?
The research indicated a significant difference in the efficiency scores across groups differentiated by client group orientation for all three efficiency specifications (overall, social and financial). The positive efficiency trend is observed for the DMUs fully focusing on SME lending. This is a positive sign for the development of SME lending in the Sub–Saharan Africa region. Improvement of SME access to finance is crucial for economic development, especially in emerging markets.

Question 6.Are microfinance institutions providing deposit products in addition to lending products are more efficient than the ones providing only lending products?
The research found no significant difference in the efficiency scores across groups differentiated by the presence of a deposit scheme. Deposit-providing DMUs have a higher mean financial efficiency and lower mean social efficiency than the entire group when the mean efficiency values are compared. However, there is no strong evidence of significant difference supported by the Kruskal-Wallis test.

Question 7. Does gender orientation matter? Are woman financing microfinance institutions more efficient comparing to the overall sample?
The research found the there is indeed a significant difference in overall and social efficiencies across groups differentiated by the prevalence of customers'. DMUs focusing on female borrowers have higher mean financial and mean social efficiency levels than the overall DMU sample. However, there was no significant difference indicated for financial efficiency, indicating a relatively comparable financial performance of DMUs with regards to the prevalence of customers' gender.

Question 8. What increase in the consumer population could be if all microfinance institution under investigation were operation relatively efficiently?
The research indicates a significant gap between actual social objection values and target values. The gap decreases over time, except for a significant jump in 2015, where the portfolio offered by microfinance institutions could have been increased by 25-26% (depending on what efficiency model was chosen). Overall, every year the number of consumers benefiting from microfinance services could increase by at least 10%.

Question 9. Do regulations have a reflection on the efficiency of the microfinance industry? Are institutions operating in the markets which are more regulated also more efficient?
There is no unambiguous answer to the questions as to whether regulations impact on the efficiency of the microfinance industry, and whether institutions operating in markets which are more regulated are also more efficient.
This research analysed two regulation components - microfinance-specific legislation and the presence of the interest rate cap for microfinance loans. While legislation has shown no significant differentiation, the interest rate cap is indeed associated with a change in performance. While the significance was indicated for all three efficiency specifications, it is interesting that the trend direction is different: for overall and financial efficiency, the presence of an interest rate cap is associated with reduced mean efficiency, and for social efficiency, the opposite trend is observed. For all time periods, DMUs operating in a market with an interest rate cap have a higher mean social efficiency than the mean efficiency of the sample.

Question 10. Do infrastructural components such as credit registry and credit bureaus matter? Are institutions operating on markets with credit bureaus more efficient compared to the institutions operating on the markets with no credit bureaus?
The analysis has shown that the presence of the private credit bureau has brought about a positive trend, although decreasing over time, for all three overall, social and financial efficiency specifications. The conclusion is consistent with both literature references and practical experience.
The existence of the only public registry on the market for most of the time periods is associated with a lower mean efficiency level than the sample according to the table. The trend changes from negative to positive for the separate time periods. It is interesting that for some of the time periods, the group "Public Registry" has a lower mean efficiency than the group "No Bureau".

Question 11. Does the presence of international funding projects focused on the improvement of microfinance environment associated with the higher efficiency?
The Kruskal-Wallis test indicated a significant difference in the efficiency scores across groups differentiated by the presence of IFC projects. However, this was true only for overall and financial efficiency specifications and not for social efficiency. For social efficiency, the trend is not clearly expressed, indicating a positive trend for some years and negative for others.

4.7 Conclusions, study contribution and future research direction

The current research contributes to the literature with its in-depth analysis of the social and financial efficiency of microfinance institutions operating in 38 markets in the Sub–Saharan African region, using nonparametric techniques of Data Envelopment Analysis. The empirical study covers the time period 2004-2017 and therefore allows for the observation of efficiency trends and their relation to external factors over time. The research indicates important findings. For instance, microfinance institutions focusing on lending to small and medium enterprises demonstrate a higher level of efficiency(both social and financial), which is good news for the development of small business in the region. Gender focus of the lending institutions also has a significant influence on efficiency, with female-focused DMUs being more efficient than the group mean in the social context, and less efficient then the group mean from a financial perspective. The presence of the private credit bureau on a market correlated with significantly higher efficiency levels in both social and financial aspects. Public registers, however, are not associated with a positive trend.

The important question of regulation and its relation to the efficiency levels was divided into the analysis of separate components, which is different from the approach employed in previous studies, and thus contributes to the field with new empirical evidence. The presence of microfinance legislation has been shown to have no significant influence, although an interest rate cap is indeed associated with a change in performance. Strong differentiation was indicated for all three efficiency specifications: for overall and financial efficiency, the presence of an interest rate cap was associated with reduced mean efficiency. For social efficiency, efficiency was increased. For all time periods, DMUs operating on the market with an interest rate cap have a higher mean social efficiency than the mean efficiency of the sample.

The frequently discussed question of mutual exclusiveness between social and financial objective was also studied in this research, and no strong evidence of the mutual exclusiveness was indicated. On the contrary, some countries have shown the ability to balance two objectives over time, which sets a positive example and motivation to other economies. In general, the priority focus of the microfinance industry remains on the achievement of financial objectives, although some movement towards the higher social efficiency has been observed over the most recent years of the observation period, which is a positive sign in context of poverty reduction.

The presence of projects led by international agencies and focused on the development of microfinance infrastructure indicated a positive impact on financial efficiency, but no impact on social efficiency. This is an interesting finding, as such projects are usually focused on the creation of microfinance infrastructure with the final goal of improving the social impact of the industry.

These results are important for investors, international organizations, regulatory entities and all stakeholders contributing to the development of the microfinance industry and poverty reduction. For these stakeholders, the research gives an indication of areas requiring development and areas worth prioritizing, as they are associated with a high level of efficiency.

The research contributes to the literature with several separate studies to ensure the robustness of the DEA models. Analysis of missing data issues was conducted, where several alternative approaches to replacing missing data were tested, and the results of the DEA model were compared against the DEA model built on the original dataset with no missing values. The Expectation-Maximization algorithm and strategic substitution have shown high performance, while regression substitution and record removal have shown low performance for our dataset.

A study of model orientation was conducted to answer the question of how the resulting efficiency estimations can change depending on the selection of model orientation. The empirical results show that on average 96% of DMUs remain in the same efficiency band, which indicates that efficiency levels are not particularly sensitive to the selection between input-oriented, output–oriented and non-oriented DEA models, at least in case of the dataset used for this research.

The research continues in several directions:

- Study of DEA model robustness toward changes in input-output variable construction;
- Extension of the set of environmental factors studied in the research;
- Analysis of the role of the microfinance sector in the customer transition to traditional banking services.

Chapter 5

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Appendix A

An Appendix

3A Entreprises (Guinea)
AAR Credit Services (Kenya)
AB Bank Rwanda (Rwanda)
AB Bank Zambia (Zambia)
AB MfB (Nigeria)
Abamuhoza SACCO (Rwanda)
ABF (Burkina Faso)
ABIDJAN CREDIT (Cote d'Ivoire (Ivory Coast))
AccèsBanque Madagascar (Madagascar)
AccessBank - LBR (Liberia)
AccessBank - TZA (Tanzania)
Accion MfB Nigeria (Nigeria)
ACDF (Kenya)
ACEP Burkina SA (Burkina Faso)
ACEP Cameroon (Cameroon)
ACEP Madagascar SA (Madagascar)
ACFB (Benin)
ACFIME (Burkina Faso)
ACODE (Chad)
ACSI (Ethiopia)
Adansi RB (Ghana)
ADCSI (Ethiopia)
ADEFI (Madagascar)
Adok Timo (Kenya)
Advans Cote d'Ivoire (Cote d'Ivoire (Ivory Coast))
Advans Nigeria (Nigeria)
Advans Banque Congo (Congo)
Advans Cameroun (Cameroon)
Advans Ghana (Ghana)
AFRICA FINANCES (Benin)
AfricaWorks (Mozambique)
AGFS (Ghana)
Aggar (Ethiopia)
Ahantaman RB (Ghana)
Akiba (Tanzania)
Akuapem RB (Ghana)
ALIDE (Benin)
Alliance MFB (Nigeria)
AMANSIE WEST RB (Ghana)
Amasezerano (Rwanda)
Amizero SACCO Gisakura (Rwanda)
Amma Al Oumma (Niger)
AMZ (Zambia)
ANKOBRA WEST RB (Ghana)
APFI-Burkina (Burkina Faso)
ARD (Sierra Leone)
ARGENTIFERE (Cote d'Ivoire (Ivory Coast))
ASA - GHA (Ghana)
Asa Initiative (Ghana)
ASACASE CPS (Senegal)
Ascend Nigeria (Nigeria)
ASIENA (Burkina Faso)
Assilassimé Solidarité (Togo)
ASUSU SA (Niger)
ASUSUN RAYA KARKARA (Niger)
Atlas MFB (Nigeria)
Atwima Kwanwoma (Ghana)
AVFS (Ethiopia)
Awe MFB (Nigeria)
Azsa MFB (Nigeria)
Babura MFB (Nigeria)
Benishangul (Ethiopia)
Bessfa RB (Ghana)
BIMAS (Kenya)
BK (Rwanda)
BMF (Benin)
Bonzali RB (Ghana)
Borimanga RB (Ghana)
Bosumtwi RB (Ghana)
BRAC - LBR (Liberia)
BRAC - SLE (Sierra Leone)
BRAC - TZA (Tanzania)
BRAC - UGA (Uganda)
Bromalah (Cote d'Ivoire (Ivory Coast))
Bukinda (Uganda)
Burebero SACCO (Uganda)
Buusaa Gonofaa (Ethiopia)
Buyanja SACCO (Uganda)
CAC (Cameroon)
CACOEC Sududiawdi (Mali)
CAECE- Jigiseme (Mali)
CAF Isonga (Rwanda)
CAFODEC (Guinea)
CamCCUL (Cameroon)
CAMEC NATIONALE (Mali)
CAMTES (Benin)
CANARI (Cote d'Ivoire (Ivory Coast))
CAPES (Congo)
Capital Finance (Niger)
Capitec Bank (South Africa)
CAPPED (Congo Rep)
CARD Ghana (Ghana)
CAURIE Micro Finance (Senegal)
CBEC (Benin)
CCA (Cameroon)
CCML (Ghana)
CCOM (Mozambique)
CDM (Cameroon)
CDS (Cameroon)
CEC (Cameroon)
CEC/Boucle du Mouhoun (Burkina Faso)
CECA (Togo)
CECAD (Burundi)
CECAM (Madagascar)

CECAW (Cameroon)
CECIC S.A. (Cameroon)
CECM (Burundi)
CECPF (Togo)
CEC-PROM Mature (Cameroon)
CEDA Sierra Leone (Sierra Leone)
CEDEF (Ghana)
CEFA (Cote d'Ivoire (Ivory Coast))
CEFOR (Madagascar)
Centenary Bank (Uganda)
Century MFB (Kenya)
CETZAM (Zambia)
CFA Microfinance (Cameroon)
CFCC (Cote d'Ivoire (Ivory Coast))
CFE (Rwanda)
CFF (Ghana)
CGF (Cameroon)
Chikum MFB (Nigeria)
CICE (Cote d'Ivoire (Ivory Coast))
CLECAM Biruyi (Rwanda)
CLECAM Ejoheza Kamonyi (Rwanda)
CLECAM Zamuka (Rwanda)
CMBF (Burkina Faso)
CMCA (Central African Republic)
CMECEL (Cote d'Ivoire (Ivory Coast))
CMF Ngwinurebe (Rwanda)
CMF Twiteganyirize (Rwanda)
CMF Umurimo (Rwanda)
CMMB (Benin)
CMS (Senegal)
CNSEC (Benin)
CODES (Benin)
COECEPT (Togo)
COMUBA (Benin)
Coojad (Rwanda)
COOPEC Bosangani (Congo)
COOPEC CAHI (Congo)
COOPEC CAMEC Inkisi (Congo)
COOPEC CAMEC Lukala (Congo)
COOPEC CAMEC MN (Congo)
COOPEC CSPKI (Rwanda)
COOPEC Hinfani Dosso (Niger)
COOPEC Ingashya (Rwanda)
COOPEC ITI (Rwanda)
Coopec Kalundu (Congo)
COOPEC Nyawera (Congo)
COOPEC Twizigamire (Rwanda)
COOPEC/ACCO (Congo)
COOPEDU-Kigali (Rwanda)
CORILAC (Burundi)
COSPEC (Burundi)
COWAN (Nigeria)
COWEC (Benin)
CPC-ADIM (Guinea-Bissau)
CPEC (Benin)
CPEC Anfanin Gobir de Tibiri (Niger)
CPEC Ci Gaba d'Aguie (Niger)
CPEC KARHE (Niger)
CPEC MIYETTI ALLAH (Niger)
CPECG Yete Mali (Guinea)
CPF Ineza (Rwanda)
CPFCI (Cote d'Ivoire (Ivory Coast))
CPI (Cameroon)
CRAN (Ghana)
CRDB Bank Burundi (Burundi)
CREDIT FEF (Cote d'Ivoire (Ivory Coast))
CREDIT YA MPA (Congo)
CRENAC (Cameroon)
Crest MFB (Nigeria)
CRG (Guinea)
CT Murambi (Rwanda)
CT Rusizi (Rwanda)
CUMO (Malawi)
CVECA BM (Burkina Faso)
CVECA Kita/Bafoulab (Mali)
CVECA Pays Dogon (Mali)
CVECA San-Djenn (Mali)
CVECA SOUM (Burkina Faso)
Daasgift Quality Foundation (Ghana)
DEC (Nigeria)
DECSI (Ethiopia)
Diamond Bank (Nigeria)
Diaspora finances (Cote d'Ivoire (Ivory Coast))
DIFO s.a. (Burundi)
Dire (Ethiopia)
DIVUTEC (Guinea-Bissau)
DJOMEC (Senegal)
DRC Microfinance (Kenya)
DUKUZE (Burundi)
Duterimbere (Rwanda)
EBO SACCO (Uganda)
ECLOF - KEN (Kenya)
ECLOF - TZA (Tanzania)
EFC Tanzania (Tanzania)
EFC Uganda (Uganda)
EFC Zambia (Zambia)
Ejoheza (Rwanda)
ELDA (Ghana)
E-MFI (Zambia)
Empire Trust MFB (Nigeria)
ENCOT (Uganda)
Equity Bank KEN (Kenya)
Equity Bank Rwanda (Rwanda)
Equity Tanzania (Tanzania)
Equity Uganda (Uganda)
Eshet (Ethiopia)
Every Home Care (Ghana)
Excel MFB (Nigeria)
Express Finance (Cote d'Ivoire (Ivory Coast))
FAARF (Burkina Faso)
FAM (Congo Rep)
FAMER MICROFINANCE (Togo)
Family Bank KEN (Kenya)
Family Bank SDN (Sudan)
Faulu MFB (Kenya)
FBN MFB (Nigeria)
FCC (Mozambique)
FCPB - BFA (Burkina Faso)
FDM (Mozambique)
FECECAM (Benin)
FECECAV (Togo)
FENACOBU (Burundi)
FESPROD (Benin)
Fiaseman RB (Ghana)
Fidelity Bank Ghana Ltd. (Ghana)
FIDES Bank Namibia (Namibia)
FIDES MICROFINANCE Sénégal (Senegal)
FIDEVIE (Benin)
FIDRA (Cote d'Ivoire (Ivory Coast))
FINADEV (Benin)
FINADEV Guinea (Guinea)
Finaïr (Niger)
Finance Salone (Sierra Leone)
Finance Trust (Uganda)
FINCA - DRC (Congo)
FINCA - MWI (Malawi)
FINCA - TZA (Tanzania)
FINCA - UGA (Uganda)
FINCA - ZMB (Zambia)
FINCORP (Swaziland)
FITSE (Malawi)
FOCCAS (Uganda)
Fortis MFB (Nigeria)
FSCJ (Burundi)
FSTE (Burundi)
FSTS (Burundi)
FUCEC Togo (Togo)
GA Rural Bank (Ghana)
Gambaga RB (Ghana)
GAMIFI SA (Gabon)
Gasha (Ethiopia)
GAWFA (Gambia)
Gboko MFB (Nigeria)
GES-CI (Cote d'Ivoire (Ivory Coast))

GGEM Microfinance Services Ltd. (Sierra Leone)
G-Life (Ghana)
Gobarau MFB (Nigeria)
Goshen (Rwanda)
GRAINE sarl (Burkina Faso)
Grameen Ghana (Ghana)
Grassroot (Nigeria)
Greenland Fedha (Kenya)
Greenland MFB (Nigeria)
Grooming Centre (Nigeria)
Harbu (Ethiopia)
Hasal MFB (Nigeria)
Hekima (Congo)
HELP (Sierra Leone)
Hofokam (Uganda)
Hope Congo (Congo Rep)
HOPE FUND BURUNDI SA (Burundi)
Hope Micro (Sierra Leone)
Ibu-Aje MFB (Nigeria)
ICMFB (Nigeria)
ID Ghana (Ghana)
IDYDC (Tanzania)
IFECC (Cote d'Ivoire (Ivory Coast))
IFRA (Madagascar)
Ikire MFB (Nigeria)
Ikoyi-Ile MFB (Nigeria)
Ilobu MFB (Nigeria)
Ilora MFB (Nigeria)
IMF HOPE RDC (Congo)
IMFB (Nigeria)
Inkunga (Rwanda)
intercrec (Senegal)
Ipapo MFB (Nigeria)
Iperu MFB (Nigeria)
ISHAKA MICROFINANCE (Burundi)
Isonga SACCO (Rwanda)
ISSIA (Uganda)
Jamii Bora (Kenya)
Jemeni (Mali)
Jigiyaso Ba (Mali)
Juhudi Kilimo (Kenya)
Kaaseman RB (Ghana)
Kafo Jiginew (Mali)
Karis MFB (Nigeria)
KEEF (Kenya)
Keffi MFB (Nigeria)
KIJURA SACCO (Uganda)
Kintampo RB (Ghana)
KixiCredito (Angola)
Kokari (Niger)
Kondo Jigima (Mali)
Koshi Yomuti (Namibia)
Kozibi (Rwanda)
KPOSB (Kenya)
KSF (Ghana)
Kuyasa (South Africa)
KWFT MFB (Kenya)
KYAPS (Uganda)
La Community Bank (Ghana)
La Financière (Cote d'Ivoire (Ivory Coast))
La FRUCTUEUSE (Togo)
LAPO-NGR (Nigeria)
Leadcity MFB (Nigeria)
LEAP (Liberia)
Leap Credit Micro Finance (Ghana)
Letshego KEN (Kenya)
Letshego RWA (Rwanda)
Letta (Ethiopia)
LFH (Nigeria)
Liberty Finance (Liberia)
Life Vest (Congo)
LMI (Nigeria)
Lower Pra RB (Ghana)
LSK (Burkina Faso)
Luma (Sierra Leone)
MA2E (Cote d'Ivoire (Ivory Coast))
Maata-N-Tudu (Ghana)
Madfa SACCO (Uganda)
Makao Mashinani (Kenya)
MAMIDECOT (Uganda)
Marang (South Africa)
Mbaitoli MFB (Nigeria)
MBF (Tanzania)
Mbinga CB (Tanzania)
MBT (Zambia)
MC (Cameroon)
MCL (Kenya)
MCPC No pega nimba (Guinea-Bissau)
MCPEC (Niger)
MDB (Benin)
MEC AFER (Senegal)
MEC Delta (Senegal)
MEC FADEC NJAMBUR (Senegal)
MECAT - NIGER (Niger)
MECRA (Burkina Faso)
MECRECO (Congo)
MECREF (Niger)
Meklit (Ethiopia)
Mepe RB (Ghana)
Metemamen (Ethiopia)
MGPCC DEKAWOWO (Togo)
Micro Start (Burkina Faso)
MicroCred - CIV (Cote d'Ivoire (Ivory Coast))
MicroCred - MDG (Madagascar)
MicroCred - MLI (Mali)
MicroCred - NGR (Nigeria)
MicroCred - SEN (Senegal)
MICROFUND (Togo)
MicroKing (Zimbabwe)
Microloan Foundation Malawi (Malawi)
MicroLoan Foundation Zambia (Zambia)
MIGEC SA (Cameroon)
MIGUI (Guinea)
Miselini (Mali)
MMCB (Sierra Leone)
MMP (Ghana)
MODEC (Benin)
Moyofade MFB (Nigeria)
MPC AMID (Guinea-Bissau)
MRFC (Malawi)
MSFP (Benin)
MUCOBA (Tanzania)
MUCODEC (Congo)
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Nandom RB (Ghana)
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Oroke MFB (Nigeria)
Osogbo MFB (Nigeria)
Ospoly MFB (Nigeria)
Otiv Alaotra (Madagascar)
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