Central European Journal of Operations Research (2022) 30:449–477
https://doi.org/10.1007/s10100-021-00789-8

Microfinance in Sub-Saharan Africa: social efficiency, financial efficiency and institutional factors

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Accepted: 22 October 2021 / Published online: 22 November 2021

Abstract

There are two natural efficiency measures associated with microfinance banking: *social efficiency*, measuring to what extent the micro-capital becomes accessible to the smallest entrepreneurs with no previous access to external funding, and *financial efficiency*, measuring the sustainability of the microfinance business and its attractiveness for investors providing the funds. We study the relationship between the two objectives (which might be incompatible in some cases) on a panel of 579 microfinance institutions across 36 Sub-Saharan African countries in period 2004–2017, covering the Big Crisis, and identify determinants of both types of efficiency. The main analytic tool is data envelopment analysis. We also study further relations between the microfinance sector and institutional factors of the corresponding economy, such as the presence of the World Bank programs or mandatory caps on interest rates. The main findings are as follows. Microfinance institutions focusing on lending to small and medium enterprises demonstrate a higher level of efficiency (both social and financial). Gender focus of the lending institutions also has a significant influence on the efficiency. The presence of the private credit bureau on a market is associated with significantly higher efficiency levels in both social and financial aspects. Public credit registers, however, are not associated with a positive efficiency trend. The presence of general microfinance legislation shows no significant influence, however the mandatory interest rate cap seems to affect the performance. In general, the research indicated *no* strong evidence of mutual exclusiveness of the social and financial objectives.

The work was supported by the Czech Science Foundation Project 19-02773S.

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Keywords Microfinance · Social efficiency · Financial efficiency · Data envelopment analysis

1 Introduction

1.1 Social and financial efficiency of the microfinance business

The microfinance movement began with a very specific objective, differentiating microfinance from all other categories of financial services, 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 them an opportunity to become self-sufficient. Because of this fundamental objective of the microfinance industry, studies assessing performance of the business usually include some form of measurement of social impact, or *social efficiency*.

Financial efficiency, or *sustainability*, is another crucial performance measure as it determines the ability of an institution to continue providing services over time. Generally, there is a question whether or not the goals—social and financial efficiency—are compatible: on the one hand, the business can achieve high interest margins, but conversely, such specific loans are associated with high risks which are difficult to diversify.

In modern literature researchers measure the performance of microfinance institutions focusing on two main objectives: outreach and financial sustainability (Morduch 1999). *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 ("MFI") to pay its employees, lenders, suppliers and to produce a profit from operations. The crucial question 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 Lensink et al. (2008) for instance. Cull et al. (2007) conducted an empirical study and have indicated "mission drift" phenomenon: higher loan amounts are 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. The current research mostly investigates both objectives separately, and compares the results in striving to answer the question of whether the two objectives are mutually exclusive.

1.2 Measures of efficiency

As there is no unified 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, micro-

finance rating agencies and voluntary organizations (such as International Finance Corporation) to measure microfinance performance (CGAP, The Consultative Group to Assist the Poor, Annual Report, 2003, Von Stauffenberg et al. 2003) and have been used in numerous studies, e.g. in Koveos and Randhawa (2004), and Nanayakkara and Iselin (2012). Balkenhol (2008) 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. In this study we focus on *efficiency* as the ratio of outputs to inputs, where we take into account *both* targets: financial and social dimension.

1.3 External and internal factors affecting efficiency

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. 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. In the 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 rate cap. Other factors that this study has separated is the presence of a credit registry or credit bureau and presence of microfinance-focused development projects run by international organizations.

1.4 The main questions

This study addresses the following main questions:

- What is the financial and social efficiency of microfinance institutions across countries of the Sub-Saharan African region? Are social and financial objectives mutually exclusive? Has the industry witnessed a mission drift over time?
- What are the determinants of social and financial efficiecncies? Does the composition of products offered by institutions or target client group impact efficiency?
- Do regulations impact efficiency of the industry? Do infrastructural components such as credit registry, credit bureaus or presence of international development projects matter?

1.5 Why data envelopment analysis (DEA)?

We follow the basics and terminology of DEA according to Cooper et al. (2000). In this study, decision making units (DMUs) are also referred to as microfinance institutions (MFIs). Observe that the usage of DEA as a ranking tool under multiple goals is natural in our context. For example, should an MFI produce two kinds of outputs—profit for an investor and social outreach—it is virtually impossible to find their price equivalent in the form "a dollar of earnings per share (= measure of financial efficiency) is equivalent to a certain level of social outreach". Thus, the DEA-aggregation of the two goals is appropriate.

1.6 Hyperbolic DEA

Most DEA models are either input oriented or output oriented. However, there is an interesting concept by Färe and Lovell (1978), called *hyperbolic non-oriented DEA*, which allows us to remove the necessity of orientation in the model was proposed; see also Färe et al. (1985) and Halická and Trnovská (2018, 2019, 2021). The version of Färe-Lovell's model used in this study assumes variable returns to scale. Its optimization formulation has the form

$$\min_{\substack{\theta,\phi\in\mathbb{R}_+\\ \lambda\in\mathbb{R}_+^N}} \theta \text{ s.t. } \sum_{j=1}^{N}\lambda_j x_{ij} \le \theta x_{it},\ \sum_{j=1}^{N}\lambda_j y_{rj} \ge \phi y_{rt},\ \sum_{j=1}^{N}\lambda_j = 1,\ \phi\theta = 1, \qquad (1)$$

where $i = 1, \ldots, n$ ranges over the set of inputs, $r = 1, \ldots, m$ ranges over the set of outputs, N stands for the number of MFIs, x_{ij} is the ith input of the jth MFI and y_{rj} is the rth output of the jth MFI. Then, the optimal value θ is the input-minimizing efficiency for the MFI t under investigation and ϕ is output maximizing efficiency. The nonlinear constraint $\phi\theta = 1$ is often replaced by its first-order approximation $0 \le \phi = 2 - \theta$ yielding the LP form

$$\min_{\substack{0\le\theta\le 2\\ \lambda\in\mathbb{R}_+^N}} \theta \text{ s.t. } \sum_{j=1}^{N}\lambda_j x_{ij} \le \theta x_{it} (\forall i),\ \sum_{j=1}^{N}\lambda_j y_{rj} \ge (2-\theta) y_{rt} (\forall r),\ \sum_{j=1}^{N}\lambda_j = 1. \quad (2)$$

2 Empirical study: methodology of social and financial efficiency assessment

2.1 Related literature

The methodology used in the literature differs depending on the research objectives and available information. The common methodology that has hitherto been applied in measuring performance of microfinance institutions (MFIs) focuses namely on traditional financial ratios or indicators similar to those used in studies of main-

stream financial institutions. Several sets of financial indicators had been prescribed by groups of multilateral banks, microfinance rating agencies to measure MFI performance (Abrams and Ivatury 2003; Von Stauffenberg 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 Gutiérrez-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.

In literature, both parametric and non-parametric models are studied. Parametric approaches assume an *a priori* specification on the production function. These approaches are well-established in the literature, however, it is often difficult to argue that the production process follows the particular specification, e.g., Cobb-Douglas or Fourier (Emrouznejad and De Witte 2010). Non-parametric approaches do not require prior assumptions on the production function. They have more flexibility and let "data speak for themselves" (Stolp 1990).

The method of Free Disposal Hull, as proposed by Deprins et al. (1984), similarly to DEA constructs an efficiency frontier, but it relaxes the convexity assumption of basic DEA models. It is argued in the literature whether or not relaxation is appropriate. Stochastic semi-Nonparametric Envelopment of Data (StoNED), proposed by Kuosmanen and Kortelainen (2010), is able to estimate a 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 of mixing statistical noise and inefficiency (Skinner 1994). The approach assumes output to be scalar and therefore does not allow for the multiple input and multiple output production.

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

2.2 Input–output selection

Based on the conducted literature review, with respect to the availability of data in our sample, four inputs and three outputs reflecting the research key questions were selected for the model as displayed in Tables 1 and 2, including references to the existing literature discussing the selection of these inputs and outputs in studies on social and financial efficiency.

2.3 Dataset

The data for the study were obtained from two main data sources: (a) performance data on individual financial institutions were obtained from the Microfinance Information Exchange Market database ("MIX"); and (b) macro level indicators used in the post-

Table 1 Input–output configuration in DEA specifications

Efficiency type	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 2 DEA inputs and outputs and references

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 Emrouznejad (2015), Tahir and Tahrim (2013), Kipesha (2012), Gutiérrez-Nieto et al. (2009), Kabir 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), Gutiérrez-Nieto et al. (2007), Gutiérrez-Nieto et al. (2009), Kabir Hassan and Sanchez (2009), Haq et al. (2010), Ben Soltane (2014),Tahir and Tahrim (2014), 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), Kabir Hassan and Sanchez (2009), Sedzro and Keita (2009), Kipesha (2012), Haq et al. (2010), Fluckiger and Vassiliev (2007), Gutiérrez-Nieto et al. (2009), Gebremichael and Rani (2012), Ben Soltane (2014), Bibi and Ahmad (2015), Widiarto and Emrouznejad (2015), Mia and Chandran (2016), Efendic and Hadziahmetovic (2017), Widiarto et al. (2017)	Numeric

Table 2 continued

Variable	Role	Definition	Link with literature	Units
Financial revenue (F)	Output	Revenues from loan portfolio and other financial asset	Fluckiger and Vassiliev (2007), Kabir Hassan and Sanchez (2009), Gutiérrez-Nieto et al. (2007), Gebremichael and Rani (2012), Kipesha (2012), Ben Soltane (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)	Gutiérrez-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 (2014), Kabir Hassan and Sanchez (2009), Sedzro and Keita (2009), Widiarto and Emrouznejad (2015), Efendic and Hadziahmetovic (2017) and Widiarto et al. (2017)	Numeric

DEA analysis as well as for normalization of DEA input and output values were obtained from the World Bank database of World Development Indicators.

The study utilizes MIX data on the Sub-Saharan Africa region. Data on 579 microfinance institutions (MFIs) from 36 countries were extracted from the database. The dataset includes financial, operational, and social performance data on an annual basis. Annual data covering the period of 2004–2017 were utilized in the study. The full list of MFIs included in this study is available online from http://nb.vse.cz/~cernym/mfi.txt.

Table 3 summarizes the descriptive statistics of the data. In addition, a correlation analysis among inputs/outputs has been conducted, based on the Spearman correlation coefficient. Details are omitted; the conclusion of the analysis is that the variables used are not highly correlated (recall that it is a general recommendation in DEA methodology not to use highly correlated inputs/outputs).

2.4 Outliers

Due to its inherent determinism, DEA models react sensitively to outliers in datasets (Emrouznejad and Thanassoulis 2010). Outliers that appear as efficient units then introduce bias into the analysis, misreporting truly efficient units as inefficient. Andersen and Petersen (1993) suitably tailored the DEA constrains to assess super-efficiency scores of efiicient units. This approach was applied in the current study and outliers indicated by super-efficiency models were removed from the dataset.

Table 3 Descriptive statistics of inputs and outputs for 231 MFIs 2004–2017

Input/output	2004		2005		2006		2007		2008	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
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

Input/output	2009		2010		2011		2012		2013	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
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

Table 3 continued

Input/output	2009		2010		2011		2012		2013	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
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

Input/output	2014		2015		2016		2017	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
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

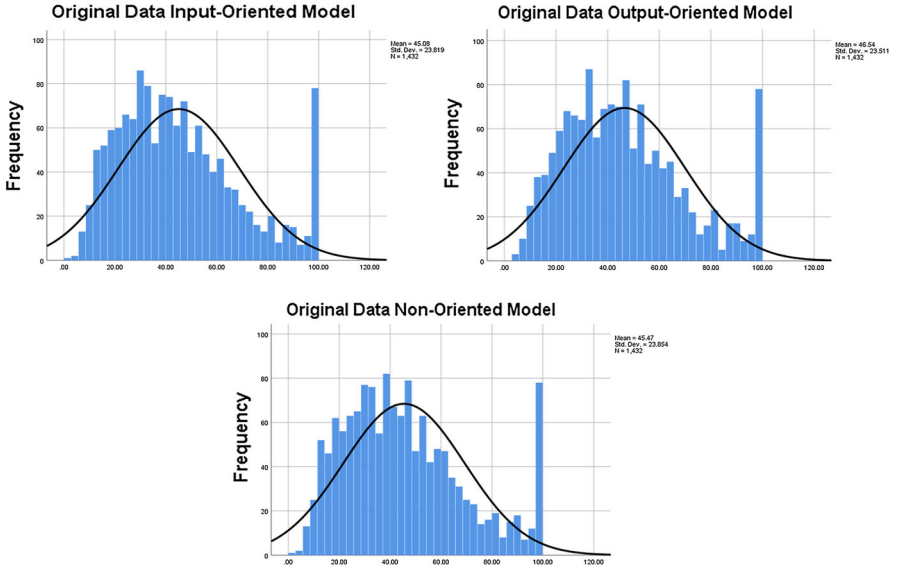

Fig. 1 Distribution of efficiency scores under various input–output orientations

2.5 Input–output orientation issues

This study is based on the hyperbolic DEA approach which does not require the choice of input–output orientation. Generally, models with different orientation can give different results. However, in case of this particular dataset, the choice of model orientation does not influence the results significantly. Figure 1 shows the distribution of efficiency scores under the hyperbolic non-oriented model compared to the input- and output-oriented model. Moreover, further robustness checks have been performed: for example, it turns out that 96% of units fall into the same efficiency quartiles regardless of the choice of the model orientation.

3 Results (part I): the overall picture and social-financial efficiency matrices

3.1 Social-financial efficiency matrices (SFEs)

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 via the Hyperbolic DEA, see (2). The analysis herein focuses on VRS non-oriented 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: "Q1" represents high social high financial efficiency

(the ideal quadrant where both objectives are relatively pursued concurrently), "Q2" represents high financial and low social efficiency, "Q3" represents low levels of both financial and social efficiencies and "Q4" represents high social efficiency and low financial efficiency.

3.2 Overall results

Table 4 displays aggregated results of the efficiency coefficient estimated by DEA models as well as number of observations for each period and number of removed outliers. The results are split into observation periods and by efficiency types.

The first row of Table 4 presents the dynamics of DMU counts observed in the dataset. 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.

The second row of the Table 4 presents the number of DMUs, which were flagged as outliers and therefore were excluded from the reference set. Rows 3–10 summarize the resulting DEA efficiency scores for each year of the observation period.

3.3 SFEs in 2004–2017 and the impact of the financial crisis

To understand the DMUs performance better on both scales of social and financial efficiency, Figs. 2, 3 and 4 present SFE matrices for the relevant periods. 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 fall 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 MFIs in Bosnia and Herzegovina. Another such result was reported in Di Bella (2011), that the global financial crisis affected MFIs 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

Table 4 Hyperbolic DEA non-oriented technical efficiency

Efficiency type	Indicator	Observation period													
		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
	SD	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
	SD	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

Table 4 continued

Efficiency type	Indicator	Observation period													
		2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
	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
	SD	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%

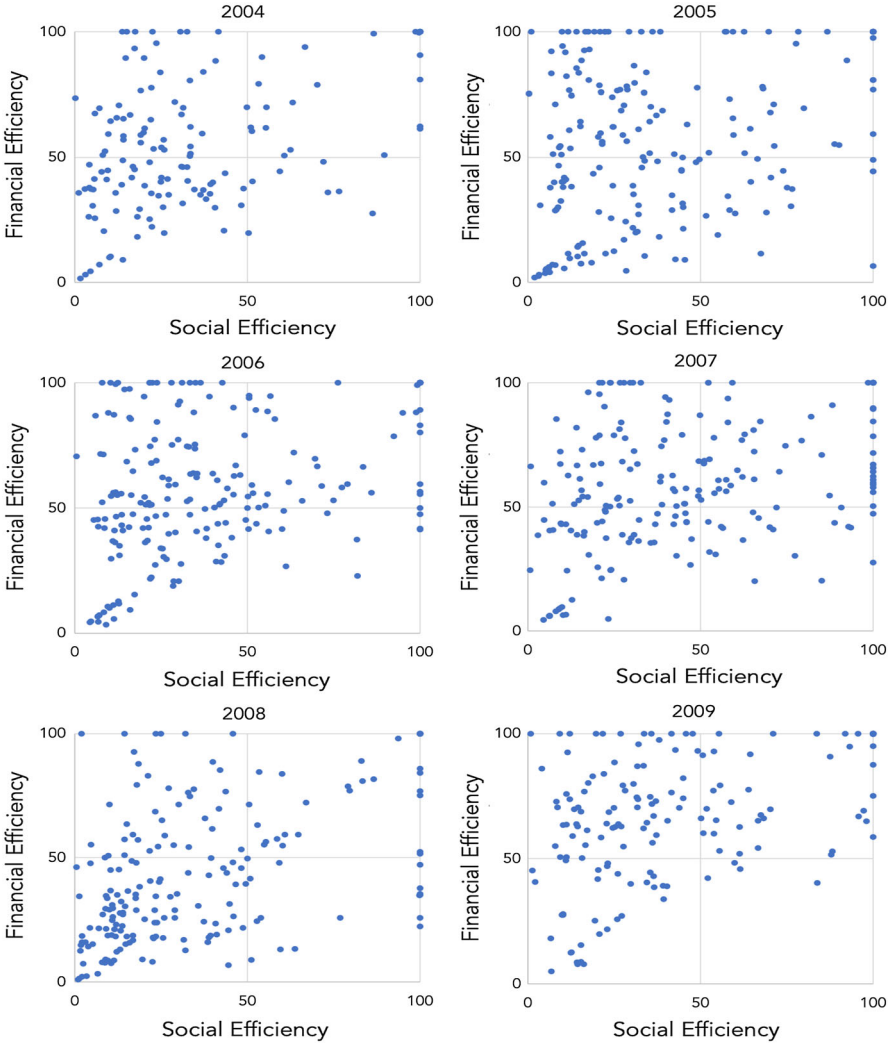

Fig. 2 Social-financial efficiency matrices in 2004–2009

debt financing to microfinance institutions is in foreign currency" (Reille and Forster 2008). Foreign investment in MFIs turns out to be more 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 5 aggregates the quadrant allocation of institutions in the SFE matrices between 2004 and 2017.

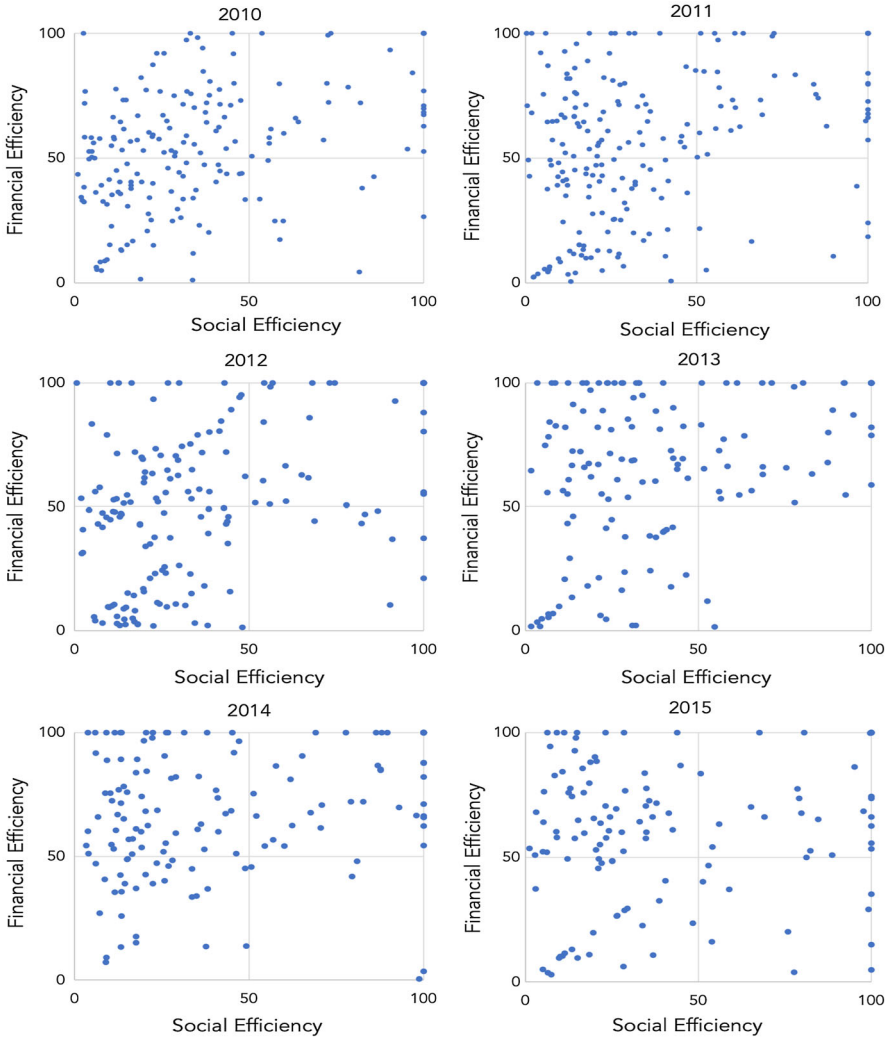

Fig. 3 Social-financial efficiency matrices in 2010–2015

3.4 SFEs by countries

After the analysis of DEA results at the DMU level from the previous section, 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. Figures 6, 7 and 8 illustrate the results for the 38 analyzed economies during 2004–2017.

According to Fig. 6, in 2004 and 2005, 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,

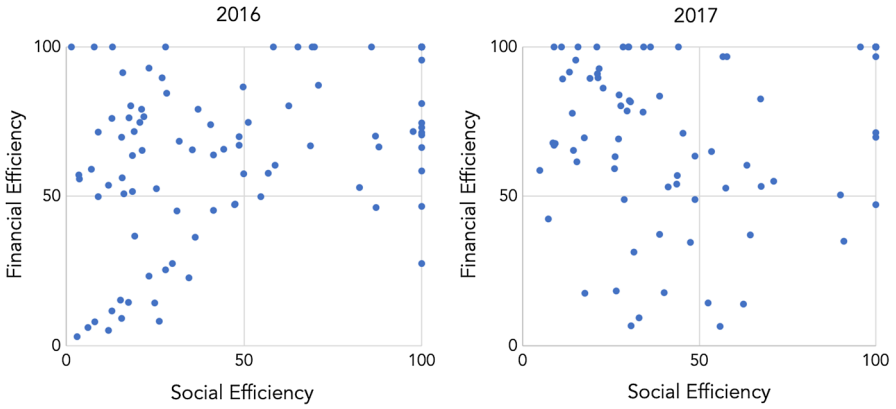

Fig. 4 Social-financial efficiency matrices in 2016–2017

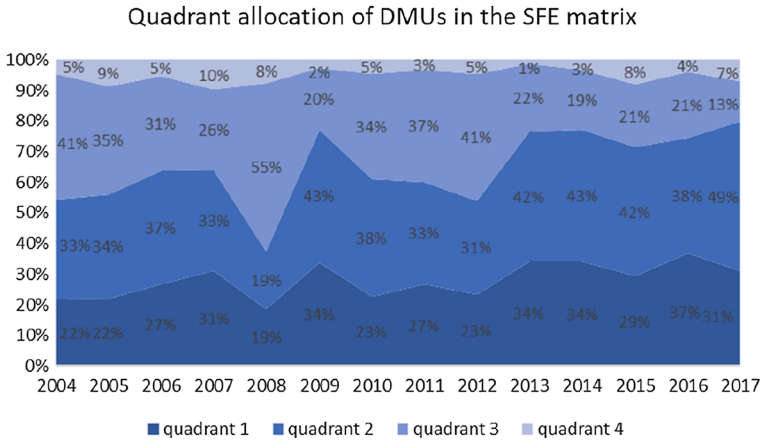

Fig. 5 Quadrant allocation of institutions in the SFE matrix

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 towards 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 achieving high financial efficiency. The trend is 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.

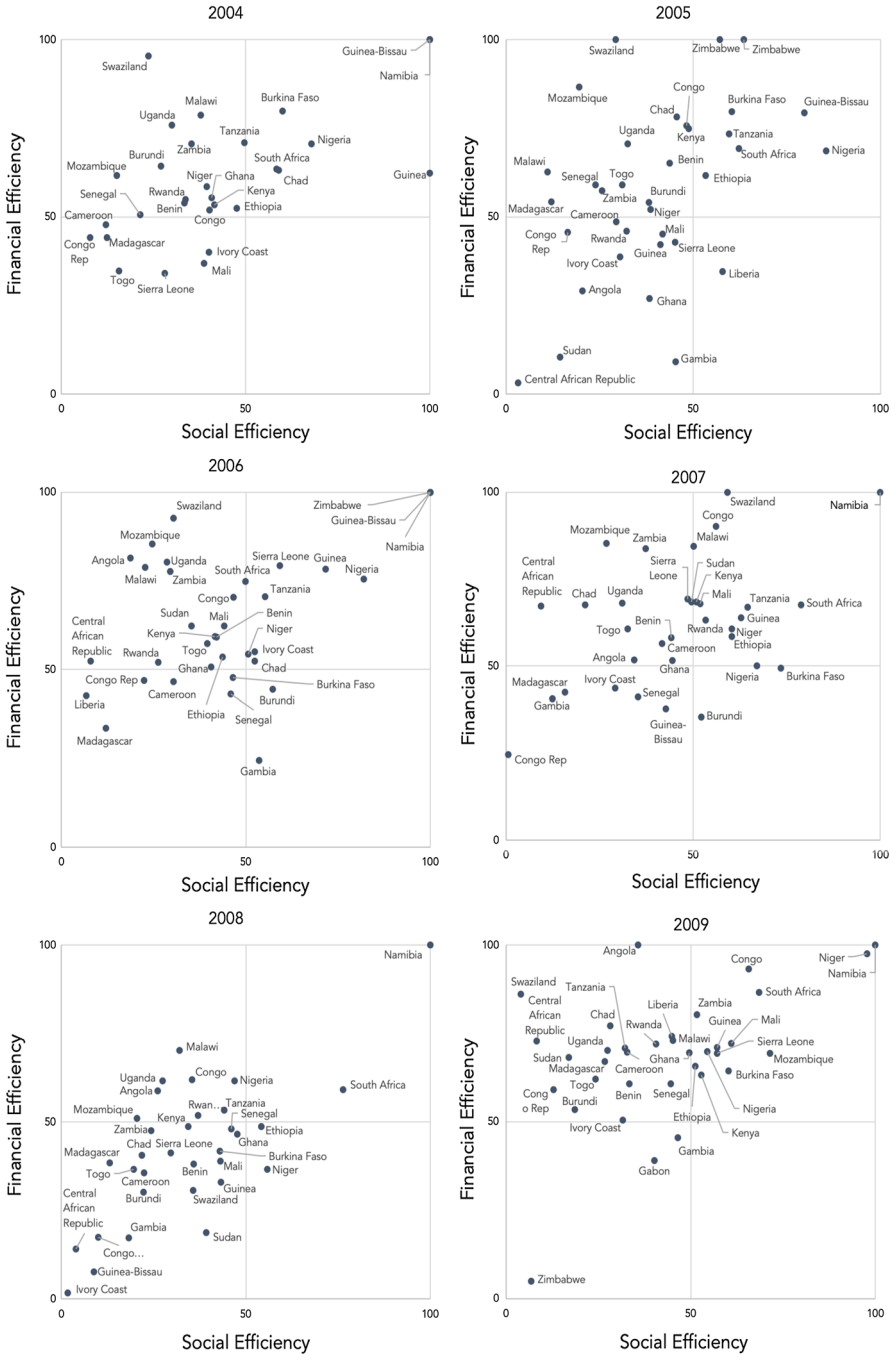

Fig. 6 SFE by countries in 2004–2009

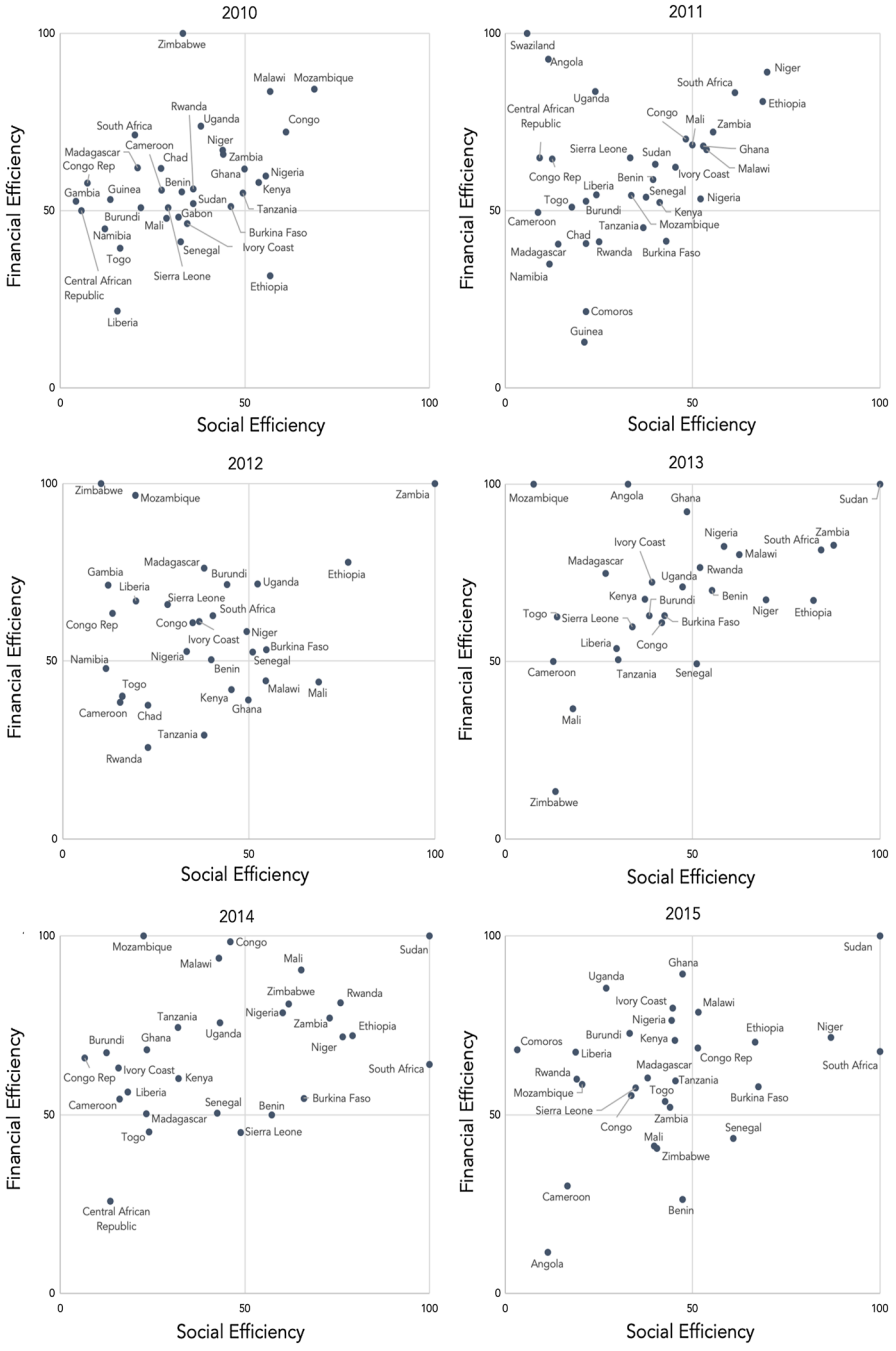

Fig. 7 SFE matrices by countries in 2010–2015

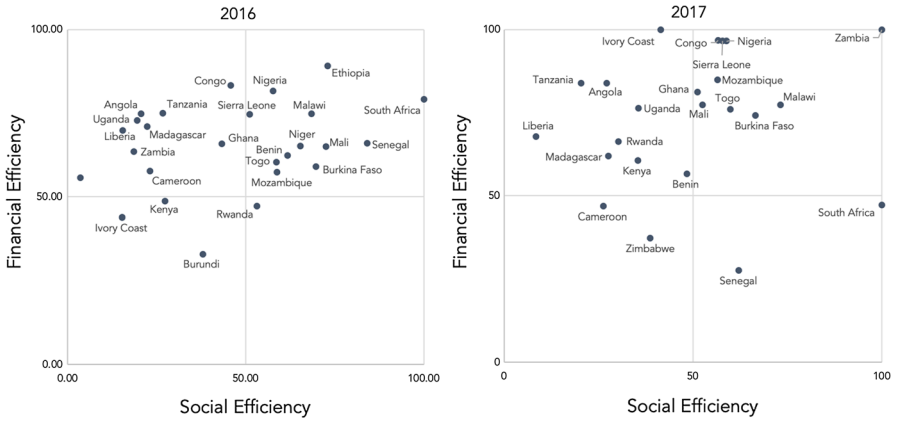

Fig. 8 SFE matrices by countries in 2016–2017

3.5 Are financial and social efficiency mutually exclusive? The case of Burkina Faso and South Africa

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 SFE matrix 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.

On the contrary, some economies indicate a shift of the focus over time. For example, DMUs operating in South Africa experienced a significant shift towards the highest social efficiency level in 2014–2017. 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.

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 indicate a lack of focus on the social objective.

4 Results (part II): potentially achievable targets and Malmquist analysis

4.1 Achievable social targets

Here we address the following question: *What could the increase in the number of served consumers be if all microfinance institutions under investigation were operating*

relatively efficiently? 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.

Table 5 provides the current and target overall volumes of consumers. 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. 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.

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 mean efficiency would become lower and targets thus higher leading to a higher estimation of the overall target.

4.2 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*

Table 5 Current and target overall volumes of consumers served by the financial institutions in the sample

	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 6 Overall efficiency: Desli–Ray Malmquist Index components for 2004–2017

Period	TC (ΔTC)	SEC (ΔSEC)	PEC (ΔPEC)	MI (ΔMI)
2004–2005	0.81 (−21%)	1.01 (1%)	1.52 (42%)	1.24 (22%)
2005–2006	0.99 (−1%)	1.11 (11%)	1.48 (39%)	1.62 (49%)
2006–2007	0.97 (−3%)	1.07 (6%)	1.41 (34%)	1.46 (38%)
2007–2008	1.45 (37%)	1.1 (9%)	0.79 (−24%)	1.25 (22%)
2008–2009	0.69 (−38%)	1.06 (6%)	1.54 (43%)	1.17 (16%)
2009–2010	1.16 (15%)	1.03 (3%)	1.02 (2%)	1.22 (20%)
2010–2011	0.96 (−4%)	1.01 (1%)	1.16 (15%)	1.13 (12%)
2011–2012	0.95 (−5%)	1.02 (2%)	1.32 (28%)	1.29 (25%)
2012–2013	0.85 (−17%)	1.01 (1%)	1.38 (32%)	1.18 (16%)
2013–2014	1.12 (12%)	1.07 (7%)	1.33 (28%)	1.59 (46%)
2014–2015	1 (0%)	1.05 (5%)	1.02 (2%)	1.07 (7%)
2015–2016	1 (0%)	1 (0%)	0.92 (−9%)	1.07 (7%)
2016–2017	0.88 (−13%)	1.03 (3%)	1.28 (25%)	1.16 (15%)

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. The index applied in the research is the Desli–Ray Malmquist Index (*MI*) proposed by Ray and Desli (1997). Recall that the index is a product of three components:

- *PEC* (Pure Efficiency Change) representing the change in a distance to frontier,
- *SEC* (Scale Efficiency Change) explaining how a change in the scale on which DMU operates impacts the overall productivity change, and
- *TC* (Technology Change) explaining the frontier shift in two subsequent time periods.

Table 6 displays the geometric mean values of the Desli–Ray 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, denoted by Δ, was calculated by taking logs of the original values. Table 6 shows the deterioration of TC during the period 2004–2007. During 2008, the industry frontier experienced a strong growth of 37% in comparison to 2007, followed by a drop of 38%.

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 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. 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 24% decrease in 2008. The overall MI has positive change values during the entire period of 2004-2017, showing a year-by-year productivity increase.

Table 7 Social efficiency: Desli–Ray Malmquist Index components for 2004–2017

Period	TC (ΔTC)	SEC (ΔSEC)	PEC (ΔPEC)	MI (ΔMI)
2004	0.87 (− 14%)	1.03 (3%)	1.38 (33%)	1.23 (21%)
2005	1.05 (5%)	1.12 (12%)	1.14 (13%)	1.33 (29%)
2006	0.77 (− 26%)	1.03 (3%)	1.37 (32%)	1.13 (12%)
2007	1.19 (18%)	1.07 (7%)	0.92 (− 8%)	1.28 (25%)
2008	0.8 (− 22%)	1.23 (21%)	1.38 (32%)	1.37 (31%)
2009	1.32 (28%)	1 (0%)	0.98 (− 2%)	1.25 (22%)
2010	0.89 (− 12%)	1.03 (3%)	1.56 (44%)	1.55 (44%)
2011	0.85 (− 16%)	1.09 (8%)	1.83 (61%)	1.78 (58%)
2012	0.74 (− 31%)	1 (0%)	1.42 (35%)	1.05 (4%)
2013	1.05 (5%)	1.03 (3%)	0.99 (− 1%)	1.08 (8%)
2014	1.13 (12%)	1.08 (8%)	1.15 (14%)	1.41 (34%)
2015	0.92 (− 9%)	0.99 (− 1%)	1.08 (8%)	1.04 (4%)
2016	0.97 (− 3%)	1.03 (3%)	1.13 (12%)	1.12 (11%)

Table 8 Financial efficiency: Desli–Ray Malmquist Index components for 2004–2017

Period	TC (ΔTC)	SEC (ΔSEC)	PEC (ΔPEC)	MI (ΔMI)
2004	0.9 (− 10%)	1 (0%)	1.59 (46%)	1.43 (36%)
2005	1 (0%)	0.99 (− 1%)	2.37 (86%)	2.36 (86%)
2006	1.07 (6%)	1 (0%)	1.63 (49%)	1.74 (55%)
2007	1.81 (59%)	1.01 (1%)	0.67 (− 41%)	1.22 (20%)
2008	0.55 (− 59%)	0.99 (− 1%)	1.94 (66%)	1.05 (5%)
2009	1.12 (11%)	0.99 (− 1%)	1.06 (6%)	1.21 (19%)
2010	0.95 (− 5%)	1 (0%)	1.3 (26%)	1.23 (21%)
2011	1 (0%)	1 (0%)	1.56 (45%)	1.65 (50%)
2012	0.85 (− 16%)	1 (0%)	1.98 (69%)	1.7 (53%)
2013	1.22 (20%)	1 (0%)	1.03 (3%)	1.26 (23%)
2014	0.95 (− 5%)	0.99 (− 1%)	0.94 (− 6%)	0.94 (− 6%)
2015	1.1 (10%)	0.98 (− 2%)	1.03 (3%)	1.11 (10%)
2016	0.84 (− 18%)	1 (0%)	1.48 (39%)	1.25 (22%)

Tables 7 and 8 show an analogous analysis for the case of social and financial efficiency.

5 Results (part III): economy-level factors and DMU-level factors

5.1 Economy-level factors

We apply the Kruskal–Wallis test to detect the significance of influence of various factors. The following economy-level factors were analysed: presence of credit bureau, presence of the microfinance program led by the World Bank and International Finance

Table 9 Results of the Kruskal–Wallis test (p-values): economy-level factors

Categoriser	Overall efficiency	Social efficiency	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

Corporation (IFC), presence of legislation for the microfinance industry and presence of interest rate limitation for the microfinance industry. For each of the four categorisers, the null hypothesis *the distribution of E is the same across the categories* was tested for $E =$ "overall efficiency", "social efficiency", "financial efficiency". Table 9 presents the results of the Kruskal–Wallis test. The results are presented in terms of p-values: the null hypothesis is rejected at the significance level of 5% (say) if $p < 0.05$.

Presence of credit bureau The mean efficiency levels of MFIs are divided into three groups: "No credit bureau", "Public registry only" and "Private bureau (or both private and public)". 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) For the microfinance industry and Sub-Saharan region, IFC is one of the leading global investors in terms of volume, number of projects, longevity and extension of projects. Thus, the research separates programs led by IFC into a separate factor for analysis.

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 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

Table 10 Results of Kruskal–Wallis test (p-values): DMU-level factors

Categoriser	Overall efficiency	Social efficiency	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

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".

When presence of credit bureau considered, results in the Table 9 suggest rejection of the null hypothesis for all three efficiency sets. The presence of the private credit bureau on a market associated with significantly higher efficiency levels in both social and financial aspects. Public registers, however, are not associated with a positive trend. The test also 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. There is also an indication of a significant difference in the efficiency scores across groups differentiated by the presence of interest rate limitation for the microfinance loans.

There is 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. This finding is interesting in itself, although it is not surprising. Hartarska and Nadolnyak (2007) found that legislation involvement does not directly affect performance either in terms of operational self-sustainability or outreach.

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 in the further section, the presence of a deposit-taking scheme has no relation to the MFI efficiency level.

5.2 DMU-level factors

The following DMU-level factors was analysed using the same methodology as above: presence of deposit scheme (categories "Yes" and "No"), prevailing product type (majority of short-term loans with maturity up to 3 months or loans with longer maturity), SME orientation (prevailing orientation on small and medium-sized entities), prevalence of female customers. Results of the Kruskal–Wallis test, given in terms of p-values, are summarized in the Table 10.

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.

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.

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 higher average efficiency was observed for the DMUs fully focusing on SME lending.

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. It does not, however, indicate any trend towards financial efficiency.

6 Summary and conclusions

The current research contributes to the literature with its analysis of the social and financial efficiency of microfinance institutions operating in 36 markets in the Sub-Saharan African region. 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.

Financial and social efficiency of microfinance institutions changes over time, with the proportion of those that are overall efficient ranging from as low as 18% (2010) to as high as 35% (2016). The proportion of socially efficient DMUs changes from 13% to 23% over time and the proportion of financially efficient DMUs from 10% to 29%.

The analysis does not 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 "in the middle" of the Social-Financial Efficiency matrix 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.

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 associated with significantly higher efficiency levels in both social and financial aspects. Public registers, however, are not associated with a positive trend.

The analysis of the regulatory framework and its relation to the efficiency levels leads to the following conclusions. 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 a reduced mean efficiency. For social efficiency, an 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 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.

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