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Changes in total factor productivity and efficiency of microfinance institutions in the developing world: A non-parametric approach

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Abstract

Applying the Färe-Primont index, this paper computes the total factor productivity (TFP) index for microfinance institutions (MFIs) in terms of its six individual components: technical change, technical, scale and mix efficiency changes and residual scale and residual mix efficiency changes. We use panel data of 342 MFIs from 61 countries covering the period 2003-2013. Results show that MFIs are operating at a low level of productivity with an overall annual rate of decline in TFP of 1.7 percent. Although technical progress, technical efficiency change and mix efficiency change components of TFP have increased over the study period, overall, TFP actually declined over time due to declining scale efficiency, residual scale-efficiency and/or residual mix efficiency changes. We found variations in regional performance with Sub-Saharan Africa experiencing the highest decline in TFP despite improvements in technical and mix efficiency changes. In contrast, Eastern Europe, Central Asia and South Asian regions have experienced a growth in TFP. Policy implications of these results are that MFIs should continue to pursue technical progress and aim to improve technical, scale and mix efficiency components by reallocating resources optimally. As well, MFIs should operate at an optimal scale and derive economies of scope by changing input and output mixes.

Keywords: microfinance institutions; total factor productivity growth; Färe-Primont productivity index; technical, scale and mix efficiency changes; cross-country panel data; non-parametric approach.

JEL Classification: C23, G21, O43

1. Introduction

Microfinance is an important source of financial services for low income households. Through innovative contract designs, microfinance institutions (MFIs) aim to solve the adverse selection, moral hazard and strategic default problems which are pervasively present in credit markets worldwide. Microfinance loan contracts can therefore mitigate the problems of enforcement, screening and incentive associated with moral hazard and adverse selection (Armendariz and Morduch, 2010). Accordingly, microfinance is promoted as a key intervention for small businesses lacking access to mainstream finance (business microfinance) and also for improving the lives of vulnerable individuals (personal microfinance) (Pedrini et al., 2016).

MFIs need to increase their productivity over time in order to expand their services and develop organizational effectiveness (Bassem, 2014). Increased productivity is also needed as MFIs are constrained by their dual missions of poverty reduction (the social objective) and self-sustainability (the financial objective). But, MFIs face at least two major challenges that affect their efficiency and productivity (Rashid and Twaha, 2013). First, to attain the financial objective of becoming self-sustainable, MFIs require additional financial resources so that they can provide collateral-free small loans continuously (Conning, 1999). Second, focusing more on financial objective raises concerns over mission drift, since increased profit-motivation may lead MFIs to change their focus on serving the very poor (Xu et al., 2016; Kar, 2013; Mersland and Strom, 2010). Thus, maintaining high productivity—hence performance—through efficient operations is vital for the self-sustainability of MFIs in the long run.

MFI efficiency and productivity are measured by using either a parametric (e.g., stochastic frontier analysis (SFA)) or a non-parametric approach (e.g., data envelopment analysis (DEA)) both of which have advantages and disadvantages. SFA measures the relative efficiency of entities allowing multiple-input and multiple-output settings. To apply this method, however, we need to specify the functional form of the production structure which is often difficult to determine. In contrast, DEA measures relative efficiency allowing for multiple outputs without requiring any functional form of the production structure. Nonetheless, the DEA is basically a deterministic technique and does not account for the stochasticity of the data. Therefore, the results obtained through applying this approach are generally biased and contaminated with noise. Furthermore, input price data play an important role in measuring productivity and efficiency of an entity. Such data are of major significance for MFIs, since most of these institutions operate in developing countries where input price markets are often not sufficiently developed to indicate reliable prices (Rahman and Salim, 2013; Thirtle et al., 2003). Therefore, choosing an appropriate technique—DEA or SFA—is important as it is of particular importance in developing country contexts.

The Malmquist productivity index (MPI) is widely used within the DEA framework. Many authors, however, argue that this is a biased measure of change in regards to TFP[1] (Grifell-Tatjé and Lovell, 1995; Wheelock and Wilson, 1999; O'Donnell, 2010, 2012a, 2012b, 2014). To overcome this limitation, O'Donnell (2014) first proposed the Färe-Primont productivity index (Färe *et al.*, 1994) within the DEA framework. This TFP index satisfies all regularity conditions of index numbers—for example, multiplicative completeness and transitivity—and is free from restrictive assumptions on firms' production technology and optimising behaviour, structure of markets, returns to scale and/or price information (O'Donnell, 2014; Rahman and Salim, 2013)[2]. The Färe-Primont TFP indices also capture the effect of improvements in technology in the form of research and development over time (Mukherjee and Kuroda, 2003). As well, the Färe-Primont approach is a reliable means of comparing multi-temporal (multiple periods) and/or multi-lateral (multiple firms) indices of TFP and efficiency (O'Donnell, 2012a). Another advantage of the Färe-Primont index (FPI) is that it does not require any restrictive assumptions about the nature of production technology, price information, behaviour of the firms or the level of competition in the input or output markets (O' Donnell, 2012b). Thus, a higher Färe-Primont TFP index would not only imply more output through better utilization of resources and technology but also poverty reduction in rural areas (Fan et al., 2000). Therefore, it is

[1] However in the case of constant returns to scale and inverse homotheticity this may not be true.
[2] Although it does requires specification of the production technology (in the form of output and input distance functions.

particularly important to evaluate the long-term performance of MFIs using TFP given poverty reduction is the social objective of most MFIs. This will help devise appropriate policies for the expansion of the microfinance markets in developing economies.

A number of earlier studies have investigated productivity change of MFIs using different country-level samples. However, so far, no study has used the Färe-Primont TFP model to estimate changes in TFP and its six individual components (*i.e.*, technical change, technical efficiency change, scale-efficiency change, mix efficiency change, residual mix efficiency change and residual scale-efficiency change). The main objective of this paper, therefore, is to employ the Färe-Primont indices to evaluate changes in MFIs' TFP over time and its six components as mentioned above. We do this by means of a unique panel dataset that contains 3,479 observations of a cohort of 342 MFIs in 61 developing world countries covering an 11–year period (2003–2013).

The study contributes to the existing literature in at least two ways. First, previous studies have decomposed the TFP index into three components: technical change, technical efficiency change and scale-efficiency change. In contrast, our study applies the Färe-Primont TFP model in order to estimate changes in TFP and its six individual components as indicated above. Therefore, the analysis provides us with a more detailed and disaggregated information on the performance of MFIs by measuring their productivity growth over time and helps us evaluate the potentials of this sector to support future growth. Second, the dataset used in this study is significantly larger than previous studies (for instance, Mia and Soltane, 2016; Wijesiri and Meoli, 2015; Babu and Kulshreshtha, 2014; Bassem, 2014; Gebremichael and Rani, 2012). Hence, our analysis is more applicable to the present state of microfinance markets since several years of more recent data have been added.

The paper is organized as follows. Section 2 provides a brief literature survey of the measurement of productivity change which largely uses the DEA approach. Section 3 discusses the methodology employed to construct the TFP indices and associated efficiency decompositions. Section 4 describes the data, its construction and the variables used for the analysis. Section 5 reports and interprets the results of TFP growth and its components. Finally, Section 6 provides a discussion on the results and conclusions and draws policy implications.

2. Literature

The microfinance impact evaluation literature is extensive. However, the research literature on MFIs' performance (social and financial), efficiency and productivity is only now being developed and is summarized as follows.

2.1. Efficiency studies based on accounting ratios

The early study of Farrington (2000) identifies important financial ratios and variables—such as, the administrative expense ratio, loan officers to total staff ratio, number of loans per loan officer, composition of loan portfolio, loan size, sources of funds and salary structure—to assess MFI efficiency. Similarly, Baumann (2005) compared performance of selected MFIs focusing on poverty alleviation in South Africa and found that South African MFIs were comparatively less efficient. The financial ratio analysis of Lafourcade et al. (2005) finds that African MFIs incur the highest *cost per borrower*, but they enjoy the lowest *cost per saver*. They also found that regulated MFIs are more efficient than unregulated ones. In contrast, cooperative MFIs are least efficient with the highest *cost per borrower*. However, conclusions based on these accounting ratios can often be misleading since they only provide a partial view of efficiency. As discussed below, many studies have therefore alternatively applied frontier efficiency measures such as DEA (non-parametric) and SFA (parametric) to measure MFI efficiency.

2.2. Efficiency studies based on the non-parametric DEA technique

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 (VRTS). Guitierrez-Nieto et al. (2007) utilised data from 30 Latin American MFIs to measure their efficiency. In their multivariate analysis with two inputs (*credit officers* and *operating expenses*) and three outputs (*interest and fee income*, *gross loan portfolio (GLP)* and *number of loans outstanding*), they found that four principal components represented 97 percent of the variation of MFI efficiency. Bassem (2008) analysed the efficiency of 35 MFIs in the MENA region and found only eight were efficient. This study also found that size negatively affects MFI efficiency and that MFIs' success greatly depends on establishing a relationship of trust with clients as it may reduce transaction costs. Hassan and Sanchez (2009) sampled MFIs in three regions: Latin America, the Middle East and North Africa (MENA) and South Asia. They compared technical and scale efficiency and found that formal microfinance is technically more efficient than informal microfinance and that the source of inefficiency was largely technical rather than scale-based. To overcome a missing data problem, Pal (2010) used 3 years' (2007–2009) average data in a panel of 39 Indian MFIs. The study finds only two MFIs to be efficient under CRTS and only six MFIs to be efficient under VRTS modelling. Based on a sample of 39 MFIs located across Africa, Asia and Latin America, Haq *et al.* (2010) found no trade-off between efficiency and outreach. They also found that NGO MFIs were the most efficient under the production approach, while the bank MFIs were the most efficient under the intermediation approach. Nadiya and Ramanan (2011) utilised data from 88 Indian MFIs. Based on their finding that only 14 MFIs were efficient, they estimated that if all the sampled MFIs were efficient, 18.3 percent of inputs could be saved or outputs could be increased by 20.2 percent. Likewise, Ahmad (2011) analysed the efficiency of MFIs in Pakistan considering both input oriented and output oriented methods under the assumption of CRTS. Islam et al. (2011) modelled inefficiency effects as a function of farm-specific variables to examine the efficiency of agricultural microfinance borrowers in Bangladesh. They found that land fragmentation, family size, household wealth, on-farm training and off-farm income share are the major determinants of inefficiency. Analysing data from 79 Indian MFIs, Babu and Kulshreshtha (2014) found that non-profit oriented and NGO MFIs are relatively more efficient compared to other types of MFIs and that most MFIs are operating with DRTS.

2.3. Efficiency studies based on the parametric SFA technique

Hasan and Tufte (2001) examined the determinants of the Grameen Bank's cost inefficiency using branch level cost data. They estimated the average inefficiency score to be between 3-6 percent. They found that female branches to be more efficient and that the age and size of a branch were insignificant determinants of MFI efficiency. Likewise, Hermes *et al.* (2011) found that MFIs' outreach to the poor and efficiency are negatively correlated and that efficiency of MFIs is higher if they focus less on the poor and/or they reduce the percentage of female borrowers. Similarly, Oteng-Abayie *et al.* (2011) used panel data from 135 MFIs in Ghana covering the period 2007-10. They found an average economic efficiency of 56 percent and indicated that age, saving indicators of outreach and productivity and cost per borrower are the major determinants of economic efficiency of MFIs. In this stream of literature, Nghiem *et al.* (2006) is the only study that applied both the parametric and non-parametric approaches. They noted that both approaches lead to similar estimates of MFIs efficiency.

2.4. Productivity studies using the Malmquist productivity index (MPI)

Mia and Ben Soltane (2016) employed panel data from 50 South Asian MFIs for the years 2007-2012 to study MFI productivity. They found it improved by 2.1 percent per year primarily due to changes in technical efficiency. However, scale efficiency was another reason for the growth in MFI productivity. Mia and Chandran (2016) employed data on 162 Bangladeshi MFIs for the period 2007-2012. Their results indicate that, mainly due to enhanced managerial efficiency, MFIs in Bangladesh achieved a 4.3 percent improvement in productivity. Utilising nine years' (2003-2011) panel data on 85 South Asian MFIs, Bibi and Ahmad (2015) found an overall growth in TFP in the region. Bassem (2014) utilised a balanced panel dataset of 33 MFIs in the MENA region for the period 2006–2011 and confirmed MFIs' overall productivity regress in the study period. Babu and Kulshreshtha (2014) employed panel data of 34 Indian MFIs over the period 2005-2011 and found that, although technical efficiency increased due to improved managerial and operational effectiveness, MFIs' productivity declined over time. Rashid and Twaha (2013) applied the empirical Bayesian technique for utilizing unbalanced panel data to 64 Indian MFIs covering the period 2005-2011. They found ambiguous effects of institutional characteristics and outreach on MFI productivity – being both positive and negative. But, they found an inverse linkage between efficiency and productivity. Likewise, Gebremichael and Rani (2012) examined the TFP change in 19 Ethiopian MFIs using a balanced panel dataset of 114 observations over the period 2004-2009. Their results indicate overall productivity progress and that the main source of TFP growth can be attributed to technical efficiency change. Similarly, Sufian (2007) investigated productivity changes in Malaysian non-bank financial institutions (NBFI) during the period 2000-2004. Results show that Malaysian NBFIs exhibited productivity regress largely attributed to technological change rather than technical efficiency change.

2.5. Studies on TFP decomposition

Several studies have examined TFP decomposition relating to a number of different contexts. For instance, Salim and Kalirajan (1999) assess TFP growth of Bangladesh food processing firms. They decomposed TFP into the change in productive capacity realization (PCR) and technical progress (TP). They found evidence of TP in many of the food processing firms, although output growth was mainly due to input growth because of low capacity realization. Le et al. (2018) found low productivity among SMEs in Vietnam and that current outputs could be increased by eight percent using the same quantity of inputs. Lee (2013) applied the MPI to Singapore data finding that the quality of workers clearly affects technical efficiency, but product assortment and competition have adverse impacts on efficiency. Nghiem *et al.* (2011) employing MPI, decomposed productivity growth in Queensland public hospitals into technical efficiency changes, technological changes and scale changes. The results revealed an average of 1.6 per cent growth in TFP in the study period. The main component contributing to this modest improvement in TFP was its growth at an average of 1.0 per cent. Kuosmanen and Sipilainen (2009) using the Fisher ideal TFP index, decomposed TFP into technical change, technical efficiency, scale efficiency, allocative efficiency and price effect and applied these decompositions to a panel data of 459 Finnish farms over the years 1992–2000.

It is clear from the above literature review that most of the studies were confined to a single region or a single country (except that of Hassan and Sanchez, 2009), consisted of relatively small samples of MFIs and were typically observed over periods of between 3–6 years. In contrast, our study utilizes information from 342 MFIs covering a much longer period of 11 years (2003–2013) and spans 61 developing world countries all of which offers a major improvement in terms of representativeness of MFIs.

3. Methodology

In the analysis, a non-parametric DEA linear program (LP) approach is used to estimate the production technology of MFIs and associated measures of productivity and efficiency. These are: (a) technical change (i.e., movements in the production frontier); (b) technical efficiency change (i.e., movements towards or away from the frontier); (c) scale efficiency change (i.e., movements around the frontier surface to capture economies of scale); and (d) mix efficiency change (i.e., movements around the frontier to capture economies of scope) (O'Donnell, 2010).

3.1. The Färe-Primont index of Total Factor Productivity

The TFP growth for a multi-input multi-output farm can be defined as (O'Donnell, 2010):

$$TFP_{it} = \frac{Q_{it}}{X_{it}} \qquad (1)$$

where $Q_{it} = Q(q_{it})$ is an aggregate output, $X_{it} = X(x_{it})$ is an aggregate input, and *Q*(.) and *X*(.) are non-negative, non-decreasing and linearly homogeneous aggregator functions. The associated index number that measures TFP of firm *i* in period *t* relative to TFP of firm *h* in period *s* is given by (O'Donnell, 2011a, 2011b):

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \frac{Q_{it} / X_{it}}{Q_{hs} / X_{hs}} = \frac{Q_{hs,it}}{X_{hs,it}} \qquad (2)$$

where $Q_{hs,it} = Q_{it} / Q_{hs}$ is an output quantity index and $X_{hs,it} = X_{it} / X_{hs}$ is an input quantity index.

Thus, TFP change can be expressed as a measure of output change divided by a measure of input change as follows. Here we use the Färe-Primont aggregator function that is non-negative, non-decreasing and linearly homogenous (O'Donnell, 2011b):

$$Q(q) = D_O(x_0, q, t_0) \qquad (3)$$

$$X(x) = D_I(x, q_0, t_0) \qquad (4)$$

where *q* and *x* are vectors of input and output quantities and D_O(.) and D_I(.) are the output and input distance functions. The Färe-Primont TFP index is given by (O'Donnell, 2011b):

$$TFP_{hs,it} = \frac{D_O(x_0, q_{it}, t_0)}{D_O(x_0, q_{hs}, t_0)} \frac{D_I(x_{hs}, q_0, t_0)}{D_I(x_{it}, q_0, t_0)} \qquad (5)$$

The Färe-Primont TFP index can be computed by applying measuring distance functions using DEA developed by O'Donnell (2010, 2011a).

3.2. Measures of efficiency

The following measures of efficiency change are computed by decomposing TFP changes (O'Donnell, 2012b). These efficiency measures are defined and explained with reference to two different production frontiers. The first is where the mixes of outputs and inputs are held fixed and is called a mix restricted production frontier. The second is where both input and output mixes are allowed to change and is called an unrestricted production frontier (Rahman and Salim, 2013; O'Donnell, 2012b):

Output-oriented technical efficiency $OTE_{it} = \dfrac{Q_{it} / X_{it}}{\overline{Q}_{it} / X_{it}} = \dfrac{Q_{it}}{\overline{Q}_{it}} = D_O(x_{it}, q_{it}, t) \leq 1$ (6)

Output-oriented scale efficiency $OSE_{it} = \dfrac{\hat{Q}_{it} / X_{it}}{\tilde{Q}_{it} / \tilde{X}_{it}} \leq 1$ (7)

Output-oriented mix efficiency $OME_{it} = \dfrac{\overline{Q}_{it} / X_{it}}{\hat{Q}_{it} / X_{it}} = \dfrac{\overline{Q}_{it}}{\hat{Q}_{it}} \leq 1$ (8)

Residual output-oriented scale efficiency $ROSE_{it} = \dfrac{\hat{Q}_{it} / X_{it}}{Q^*_{it} / X^*_{it}} \leq 1$ (9)

Residual mix efficiency $RME_{it} = \dfrac{\tilde{Q}_{it} / \tilde{X}_{it}}{Q^*_{it} / X^*_{it}} \leq 1$ (10)

where $TFP^*_t = Q^*_{it} / X^*_{it}$ denotes maximum TFP that is possible using the technology available in period t; and $\overline{Q}_{it} = Q_{it} / D_O(x_{it}, q_{it}, t)$ is the maximum aggregate output possible when using a scalar multiple of x_{it} to produce q_{it}. . $\tilde{Q}_{it}$ and $\tilde{X}_{it}$ are the (output mix and input mix preserving) aggregate output and input quantities at the point of mix invariant optimal scale (MIOS), which refers to a point where a ray through the origin is tangent to the mix restricted production frontier. $\hat{Q}_{it}$ and $\hat{X}_{it}$ are the aggregate output and input obtained when TFP is maximized subject to the constraint that the output and input vectors are scalar multiples of q_{it} and x_{it}, respectively (O'Donnell, 2012b).

Eq. (6) presents the most common measure of output-oriented technical efficiency defined as the maximum aggregate output which is possible to produce from a given level of aggregate input. Eq. (7) presents another commonly used measure of output oriented scale efficiency, which is defined as the efficiency derived by varying the scale of firm operation size and therefore indicates economies or diseconomies of scale. Eq. (8) represents output oriented mix efficiency, which is a measure of the potential change in productivity when restrictions on input and output mixes are relaxed. Mix efficiency depends on the economies or diseconomies of scope in output produced. The pure mix efficiency is closely related to the familiar concept of cost allocative efficiency (Rahman and Salim, 2013). This is the ratio of TFP - at a technically efficient point on the mix restricted frontier - to TFP at a point on the unrestricted frontier. Eq. (9) represents residual scale efficiency which is the ratio of TFP - at a technically and mix efficient point to TFP at a point of maximum productivity and which is equivalent to a scale effect. Finally, Eq. (10) presents residual mix efficiency which is defined as the ratio of TFP - at a point on the mix restricted production frontier - to TFP at a point of maximum productivity. This involves movement from an optimal point on the mix restricted frontier to the optimal point on the unrestricted frontier (for full details of these measures see O'Donnell, 2012b).

3.3. The components of TFP change

The TFP indices presented in aggregate quantities in Eq. (2) are multiplicatively complete and can be decomposed as follows (O'Donnell, 2011b):

$$TFP_{hs,it} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}}\right)\left(\frac{OSE_{it}}{OSE_{hs}}\right)\left(\frac{RME_{it}}{RME_{hs}}\right) = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}}\right)\left(\frac{OME_{it}}{OME_{hs}}\right)\left(\frac{ROSE_{it}}{ROSE_{hs}}\right) \quad (11)$$

The technological component (TC) measures a shift of the production frontier during a period. Its calculation results from the identification of the economic unit *i* that shows the maximum level of TFP for a given period *t* (Le Clech and Castejon, 2017), which is TFP_t* in Eq. (11). The first term in parenthesis of the right-hand side of Eq. (11) is technical change which is measured as the difference between maximum TFP possible using the unrestricted technology in periods *t* and *s*. The value >1 indicates technical progress and <1 indicates technical regress. The other ratios are efficiency changes defined in equations (6) to (10) with values >1 indicating more efficiency and <1 indicating less efficiency relative to reference technologies in periods *t* and *s* (Rahman and Salim, 2013).

3.4. Empirical estimation using data envelopment analysis

The underlying assumption using DEA is that the (local) output distance function representing the technology available in period *t* takes the form (O'Donnell, 2011a):

$$D_0(x_{it}, q_{it}, t) = (q_{it}^{'}\alpha)/(\gamma + x_{it}^{'}\beta) \qquad (12)$$

The output-oriented problem involves selecting values of the unknown parameters in Equation (12) in order to minimize technical efficiency: $OTE_{it}^{-1} = D_0^{-1}(x_{it}, q_{it}, t)$. The resulting LP is:

$$D_0^{-1}(x_{it}, q_{it}, t) = OTE^{-1} = \min_{\alpha,\gamma,\beta}\{\gamma + x_{it}^{'}\beta : \gamma t + X'\beta \geq Q'\alpha : q_{it}^{'}\alpha = 1; \alpha \geq 0; \beta \geq 0\} \qquad (13)$$

where $\boldsymbol{Q}$ is a J x M_t matrix of observed outputs, $\boldsymbol{X}$ is a K x M_t matrix of observed inputs, t is an M_t *x 1* unit vector, and M_t denotes the number of observations used to estimate the frontier in period *t* (for details, see O'Donnell, 2011a). To compute the Färe-Primont aggregates, DPIN-V3 first solves the following LP (O'Donnell, 2011a):

$$D_0^{-1}(x_0, q_0, t) = OTE^{-1} = \min_{\alpha,\gamma,\beta}\{\gamma + x_0^{'}\beta : \gamma t + X'\beta \geq Q'\alpha : q_0^{'}\alpha = 1; \alpha \geq 0; \beta \geq 0\} \qquad (14)$$

The aggregated inputs and outputs of the Färe-Primont index are estimated as (O'Donnell, 2011a):

$$Q_{it} = (q_{it}^{'}\alpha_0)/(\gamma_0 + x_0^{'}\beta_0) \qquad (15)$$

$$X_{it} = (x_{it}^{'}\eta_0)/(q_0^{'}\phi_0 - \delta_0) \qquad (16)$$

where α_0, β_0, γ_0, δ_0, η_0, solve equations (15) and (16). DPIN-V3 uses sample mean vectors as representative output and input vectors in equations (15) and (16). For computational details to estimate indices of productivity and efficiency measures using the DPIN-V3, see O'Donnell (2011a).

4. Data and variables

The dataset used in this empirical exercise is constructed from two different sources. MFI level financial, portfolio and outreach performance data were collected from the MIX (Microfinance Information Exchange) market database and country-level macroeconomic data on exchange rates. Yearly inflation rates were used for the adjustment of certain variables and data on inflation rates were gathered from the World Development Indicators (WDI) database of the World Bank. At the time of data collection in 2015, we accumulated 15,132 data observations from 2426 MFIs in 119 countries covering a period of 18 years (1996-2013). The sampled countries are of varying magnitudes of population and GDP size. The extent of their footprint on microfinance sectors also varies and are representative of the microfinance markets currently in operation worldwide. Nevertheless, not all data relating to these MFIs could be utilised in the study due to the following reasons.

MIX data are voluntarily reported and represent MFI profiles collected from various sources including internal financial statements, management reports and audits of respective MFIs. The quality of data is then checked and data audit rules are applied to ensure accuracy. The MIX market ranking the MFI-data quality is denoted by the number of 'diamonds' on a scale of 1 to 5, where 5-implies the best quality. In this study, we only included MFIs with at least a level-3 disclosure rating to ensure that only high-quality data had been gathered. Indeed most of the organisations were ranked with 4 diamonds (around 60%)[3]. However in combining data from two different sources (MIX and WDI) a loss of observations resulted as information on several MFI-level performance variables and country-level macro-variables were not available for all MFIs and countries. In addition, due to missing variable values we had to drop a considerable number of MFIs from the initial dataset. Thus, after applying these two selection rules (availability and quality of data) before selecting an MFI, our final dataset was reduced to 3,479 observations drawn from 342 MFIs in 61 countries for the period 2003–2013[4]. The MFIs were all legally structured being in the form of non-profit NGOs, NBFIs, banks, rural banks, cooperatives/credit unions and others. The MFIs were distributed among all six global developing regions – East Asia and the Pacific (EAP), Eastern Europe and Central Asia (EECA), Latin America and the Caribbean (LAC), MENA, South Asia (SA) and Sub-Saharan Africa (SSA). However, the highest number of MFI-observations are from the LAC region (about 50%).

Consequently, the data were essentially unbalanced before imputation since all of the sampled MFIs did not have equal number of observations. Thus while some MFIs had 11 complete years of observations, others had only 3-10 years. We applied data imputation techniques to handle the unbalanced panel dataset as we needed to introduce duplicate observations and let the programme (DPIN V3) treat them as a balanced data set. In order to make the dataset balanced, we filled in the blanks with available data from adjacent observations. It must be emphasized that these 'replicated' observations were used only to fill in the missing information and had no effect on the calculations of the indices because the 'replicated' rows were removed from the final results page before calculating the indices[5]. However, we used a consistent approach in the replication by taking values either from the following observation (i.e., after the blank space) or preceding observation (i.e., before

[3] In the dataset, we had 737 (19.6%) observations with three (3) diamonds, 2,254 (59.9%) observations with four (4) diamonds and 770 (20.5%) observations five (5) diamonds. Diamonds information on only 1 observation was missing.

[4] For 2003, the dataset had observations on 201 MFIs. Similarly, for the years 2004-2013, the number of observations on MFIs for each year were 260, 307, 336, 338, 337, 338, 340, 340, 340 and 342 respectively.

[5] Confirmation of this approach to balancing a panel data set was secured through discussion with the developer of the FPI method of estimation and programmer of DPIN V3 software, Professor Chris O' Donnell.

the blank space) of the missing data cells. This replication of existing data to fill-in the missing values allowed us to prepare a balanced panel dataset with the total number of observations reaching 3,762 (= 342 MFIs × 11 years).

4.1. Specification of inputs and outputs

Defining inputs and outputs of financial institutions is not straightforward. However, the literature suggests three common approaches in this regard: the production approach, the intermediation approach and assets approach (Berger and Humphrey 1997; Gebremichael and Rani, 2012). In the intermediation approach, banks use labour and capital alongside financial liabilities—typically deposits—to produce loans and other means of financing. Here deposits are an input and returns are an output. The production approach, however, contains differences. It accepts that deposits are also a service offered to the customers of financial institutions together with loans. Thus, inputs should only cover labour and capital. Finally, since the creation of loans is the main function of financial institutions, the value of assets becomes the output in the assets approach.

Nevertheless, researchers have different opinions on the selection of input and output variables relating to financial institutions. MFIs are financial institutions of a special type and considered as quasi-banks. They provide products and services such as loans and deposits, which are treated as outputs under the production approach. In order to provide these services, MFIs use personnel and capital, which are treated as inputs. The number of transactions and documents processed in a given period can also be treated as output (Berger and Humphery, 1997; Kuussaari and Vesala, 1995). Thus, Berg *et al.* (1993) use labour, fixed assets and capital as inputs of banking organizations and total loan, saving balances, average loan size and number of accounts as outputs.

As stated above, MFIs accept donations and grants from numerous sources and also mobilize funds by borrowing from financial institutions. These funds are the assets that MFIs consequently use as inputs to conduct financial operations. However, for MFIs, data on all of these variables are generally unavailable. Hence, it is difficult to apply the production approach where personnel of the MFIs are inputs for providing loans and mobilizing their clients. According to the intermediation approach, MFIs' operating costs—i.e., expenses such as administrative charges, wages and salaries that are involved in MFI operations—are also regarded as inputs. Therefore, we consider personnel, administrative expenses and operating costs of MFIs as the inputs in our study. MFIs' social bottom line is to achieve high outreach by increasing loan services with the objective of serving the very poor. Therefore, we regard the GLP as an output of MFIs in our study. This also indicates the scale of operation of MFIs.

Bassem (2014) has used interest and fee income as an output of MFIs given it represents MFIs' income on GLPs. Thus, in view of the above description and the following illustrations of previous studies (e.g., Gutierrez et al., 2007; Bassem, 2014; Gebremichael and Rani, 2012), we selected three outputs for this study. They are: GLP, number of loans outstanding and nominal yield. Likewise, three inputs used in this exercise are number of personnel (employees), the administrative expenses to assets ratio and the operating expenses to assets ratio. However deposits cannot be used as an output variable in this study as many MFIs in our sample do not take deposits.

4.2. Variable adjustments

Following previous studies, both ratio variables and monetary variables have been used in the analysis. Since we used panel data which inherently includes time series, variables in monetary terms should be expressed in constant US dollar (USD) prices to overrule the inflationary impacts and exchange rate variations. That is, in TFP analysis we are estimating its net real growth. Thus the the value of GLPs needs to be at constant prices. We therefore adjusted the GLP variable as follows. We first multiplied each of the annual GLP observations by yearly exchange rates by country to get nominal GLP values - *i.e.*, the country specific current price values in local currency. The variable we used as a proxy for inflation—GDP deflator, annual percent—is measured by the annual growth rate of the GDP implicit deflator and shows the rate of price change in the economy as a whole. The GDP implicit deflator, however, is the ratio of GDP in current local currency to GDP in constant local currency. Consequently, we computed the adjusted GLP by adding the inflation rate × nominal GLP/100 to the nominal GLP which is still in the local currency of each country. Finally, we divided the adjusted GLP values in local currency – as computed by the country-specific annual exchange rates – to get the adjusted GLP in USD. The adjusted GLP (in USD) thus should be reasonably close to the original GLP (in USD) but not necessarily the same. This method automatically solves our negative inflation effect on GLPs as well, which is an added advantage. To note the ratio variables were not adjusted as they are unit free.

Descriptions on the variables are provided in Table 1. Table 2 presents summary statistics of the input and output variables used in the analysis. It is evident from Table 2 that the variables vary significantly within the sample. This indicates that the sample is comprised of large as well as small MFIs measured in terms of, for instance, GLPs and the number of outstanding loans.

5. Total factor productivity growth in MFIs

The multi-lateral multi-period TFP indices using the Färe-Primont approach (FPI) and their various components were calculated for each of the 342 MFIs covering the period 2003–2013. The results are summarized in Tables 3 and 4 for the overall sample. The regional performance of some selected measures of TFP and its components are presented in Figures 1 through 4 (for full details of all measures by regions, please see Appendix Tables 1 through 6). The average estimated TFP level is

0.13, which is very low. The average level of maximum TFP is estimated to be 0.66, mean technical efficiency is 0.59, scale-efficiency 0.61, mix efficiency 0.94, residual scale-efficiency 0.35 and residual mix efficiency 0.48 (Table 3). The implication of these results is that the MFIs are operating at a sub-optimal level and there remains ample scope to improve these measures of efficiency.

In terms of measuring changes in these indices, an index value greater than one for 'TFP change' and/or for 'efficiency change' indicates positive growth compared to the base year (2003). A value less than one indicates a decline in performance compared to the base period. Overall, TFP declined at the rate of 1.7 percent per annum (Table 4). This is a discouraging outcome given a positive growth of MFIs would allow them to continue to support the poor and alleviate persistent poverty in developing countries. MFIs did, however, experience a high level of technical progress at an annual rate of 4.2 percent followed by increases in technical efficiency change and mix efficiency change 0.85 and 0.47 percent per year respectively. But, overall, TFP was driven down largely by the 1.2 percent decline in scale efficiency change per annum and the 1.17 percent fall in annual residual mix efficiency (Table 4).

In order to check the robustness of the results, we compared our FPI estimates with the MPI estimates. MPI is not strictly a comprehensive measure, but is widely used. However, this study uses a large sample following Lee (2013) which should provide more robust results, especially when the MPI is used. MPI results are presented in Table 5 which clearly show that although the overall conclusions are the same, the TFP measure is overestimated in the MPI approach. For example, the decline in TFP is estimated at 0.73 percent per annum. These results are on a par with those obtained by Le-Clech and Castejon (2017) who note that overall TFP growth in global agriculture was overestimated by the MPI as compared to the FPI approach. On the other hand, the MPI approach underestimated technical-progress and technical efficiency change at the rate of 1.88 and 0.17 percent yearly. Only the combined residual scale and mix efficiency measures are almost identical between the two approaches. Le-Clech and Castejon (2017) also noted the divergence in efficiency measures between FPI and MPI approaches and reported that the FPI measure provides more weight to efficiency components than the MPI measure. Furthermore, they concluded that the measures obtained using the FPI is more robust and reliable because it satisfies transitivity and multiplicative properties, which are not covered by the MPI approach.

Our TFP results are in agreement with the results of previous region-specific and country-specific studies of MFIs, such as those of Mia and Chandran (2016) (Bangladesh), Bassem (2014) (the MENA region), Babu and Kulshreshtha (2014) (India) and Sufian (2007) (Malaysia). The present study is a global one in terms of scope and coverage of countries, but similarity of the results with earlier studies indicates that region and country-specific trends are similar. Thus the global trend indicates there is scope to improve productivity of the MFIs.

Our results are comparable with Hassan and Sanchez's (2009) study of MFIs in the LAC, MENA and SA regions. However, they compared technical and scale efficiency by applying a different methodology and found that the source of inefficiency was more purely technical than scale-based. Again, our results are slightly different from those obtained by Bassem (2014) who noted a decline in technological change, but an improvement in technical efficiency, and Babu and Kulshreshtha (2014) who noted an increase in technical efficiency but a decline in productivity. One plausible explanation for these differences in the results is that the present study neither focuses only on MFIs from India nor only on the MENA region. In this study, the global dataset contains high and low-performing MFIs located worldwide. Also, unlike the above studies our dataset includes MFIs of all types including NGO MFIs, NBFIs, banks, rural banks and cooperatives. Another plausible reason for the differences is that employing data from all types of MFIs might have distorted the impacts of technical progress. However, the general implication of these results is that although the MFIs are operating at a declining level of technical efficiency and at sub-optimal scale, they are able to improve mix efficiency change or economies of scope by changing optimal input and output mixes over time.

5.1. Productivity performance by regions

When regional productivity performances are considered, we see they varied (Figures 1 through 4; Appendix Tables A1 through A6). A high level of regional variation was observed in the TFP indices with SSA experiencing the sharpest level of decline (Figure 1). The indices of technical change are identical for the regions as the technological frontier, given the construction of the FPI, is fixed at a constant value valid for all geographical regions (see Appendix Tables A1 through A6) (Le Clech and Castejon, 2017). The variation in the indices of technical efficiency change by region is small except for EAP, which is the leader with a high level of growth (Figure 2). The indices of scale-efficiency change is again highly variable as seen in case of the TFP indices. The highest level of decline is in SSA (Figure 3), implying that its MFIs are not generally operating at the optimal scale. However, it is interesting to see very similar variation in the indices of mix efficiency change across the regions (Figure 4), implying that MFIs are not very different in the way they derive derive economies of scope by varying input and output mixes - albeit with some fluctuation over time being experienced.

The magnitudes of the decline in productivity are similar to those found by Babu and Kulshreshtha (2014), but dissimilar to Mia and Chandran (2016) and Bibi and Ahmad (2015). For example, SSA experienced the highest decline in TFP - 6.53 percent p.a. - due to a sharp decline in scale-efficiency change of 5.4 percent p.a. despite improvements in technical and mix efficiency changes of 0.32 and 1.11 percent p.a. respectively. However these results do not lend support to an earlier study of Gebremichael and Rani (2012). The implication is that the MFIs in SSA are operating at a declining level of technical efficiency change and at a very low level of scale efficiency change. They therefore need to significantly improve mix efficiency change or derive economies of scope by adjusting input and output mixes over time.

In contrast, EECA and SA experienced growth in TFP of 0.64 and 0.34 percent p.a. respectively. But the sources of growth in TFP for these two regions are different. Productivity growth in SA was powered by technical progress and technical and scale efficiency changes whereas in EECA it was powered by technical progress and technical and mix efficiency changes. Nevertheless, technical progress remains the most dominant driver of TFP growth for both regions (Appendix Tables A1 and A4).

The decline in TFP of the MFIs of the LAC region is also high, declining by 2.33 percent p.a. This is mainly due to the high rate of decline in scale of 2.12 percent p.a., to efficiency changes (except improvements in mix efficiency change) of 1.06 percent p.a. and to technical efficiency change of 0.26 percent p.a. (Appendix Table A5). These results indicate that despite their loss of performance, MFIs in the LAC region are nevertheless able to improve economies of scope.

Although the EAP region was the leader in technical efficiency change with growth estimated at 3.78 percent p.a. and a marginal improvement in scale-efficiency change, the region experienced a decline in TFP of 0.36 percent p.a., mainly due to high rate of decline in residual mix and scale efficiency changes which offset any gains from the high level of technical efficiency improvements experienced by the MFIs in this region (Appendix Table A3).

The high rate of TFP decline in the MENA region of 1.85 percent p.a. is driven largely by a high rate of declines in residual mix efficiency change of 1.90 percent p.a. despite positive growth in technical efficiency change of 0.91 percent p.a. (Appendix Table A6). These results are similar to the results of Bassem (2014) who indicated an overall productivity regress of MFIs in the MENA region combined with a decline in technological change even though technical efficiency was improving.

6. Discussion, conclusion and policy implications

This study evaluates MFIs' long-term productivity performance using the Färe-Primont index (FPI) for a panel of 342 MFIs from 61 countries over the period 2003–2013. Inputs and outputs were chosen on the basis of social and financial objectives of MFIs. Results show that, overall, the TFP of MFIs actually declined by 1.70 percent per year. Over the study period, technical change, technical efficiency change and mix efficiency change components of the FPI grew respectively by 4.21, 0.85 and 0.47 percent annually, while yearly declines in FPI's scale efficiency, residual mix and residual scale efficiency components were 1.20, 1.79 and 1.17 percent respectively. All these contrasting values eventually led to an overall decline in TFP over the study period. However, regional performances were highly diverse. Among all the developing regions, SSA performed the worst recording the highest level of decline in TFP whereas EECA and SA recorded the top rate of TFP growth over time. The dataset used in this exercise is considerably more representative than previous studies given it includes a large sample of MFIs from the developing world. However, since these MFIs represent microfinance sectors in countries of varied levels of development, exogenous variables or other factors may have influences on the overall results (Golany and Roll, 1989). For robustness of the results, therefore, we compared the FPI estimates with those obtained by using the MPI which is commonly used in the literature. Results remain largely unperturbed, which underwrites the validity of the FPI estimates. Moreover, as suggested by Lee (2013), the application of the MPI to the large sample of this study provides additional robustness to the results.

Thus, it is evident from the analysis that MFIs, on average, are operating at a sub-optimal level of productivity and need to improve their scale efficiency. Also, the importance of technical advancement cannot be overemphasized. One way of shifting MFIs' production frontiers upwards is to upgrade their production technology (Bassem, 2014; Gebremichael and Rani, 2012). To achieve better economies of scale, MFIs may adopt innovative financial products and cost-effective service delivery methods (Mia and Ben Soltane, 2016). This could also help them to become more competitive in the market (Le et al., 2018). As well, easy access to key infrastructure is vitally important for scale efficiency of MFIs. It is therefore contingent on governments to fully examine and where appropriate, adopt such measures. Equally, to support and transmit innovations, governments need to ensure MFIs have easy access to infrastructure and proper working atmosphere (Hassan and Tufte, 2001; Hermes et al., 2011).

MFIs are commonly challenged by their twofold aims of being financially self-reliant (the financial objective) while serving the very poor (the social objective). A trade-off between social and financial objectives is called mission drift (Mersland and Strom, 2010; Kar, 2013). MFIs' declining technical and scale efficiency therefore require careful considerations so that attaining financial efficiency does not overly harm their social efficiency and thereby raise mission drift concerns. If increased profit orientation produces too greater risk in attaining the social objective of microfinance operations, MFIs should try to minimise costs of their operations and seek to become more efficient. This can be achieved through applying better management practices and low-cost loan delivery mechanisms (Mia and Ben Soltane, 2016; Babu and Kulshreshtha, 2014).

From our results, we can draw several implications for policy formulation and practice. They are as follows. First, there is scope for increasing productivity for the sampled MFIs and this can be effected through an improved application of inputs (technical improvement) which does not lead to an increase in the quantity of inputs. Information and communications technology (ICT) helps to explain variability in TFP between institutions (Lee, 2013). So, to achieve economies of scale, particularly of larger firms, improving on ICT is very important. As technology is still highly relevant for productivity improvement, large MFIs would particularly benefit from investing in better use of ICT for more effective customer tracking, loan monitoring, service delivery and high financial performance. In this way MFIs can become more profitable, attain scale efficiency and meet the business objectives (Le et al., 2018).

As the MIX market does not report data on subsidies, donations and grants, our results need to be qualified by the limitation that we did not take them into account. Again, due to data limitations we could not include an analysis of the determinants of MFI productivity and efficiency. Moreover, identification of the determinants of TFP is greatly influenced by the approach used in measuring TFP and its components. Thus, the productivity performance of MFIs can depend on the type of organisation (e.g., NGO, non-bank financial institution, credit union or cooperative etc.) and also on profit orientation (for profit or non-profit). Future research should take these issues into account and compare the performance of different MFIs based on their legal types and profit orientation status using alternative approaches to measure TFP. While this study covers a dataset that has 11 years' of observations, future studies could further increasing the data coverage time frame. It is the intention of the authors to help address these issues by improved and purposively collected data in further studies.

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Table 1. Description and definition of variables used in the analysis

Variable name	Description
Input variables	
Personnel	Total number of staff members
Operating expenses	Ratio of 'operating expense' to 'assets'
Administrative expenses	Ratio of 'administrative expense plus depreciation' to 'assets'
Output variables	
Gross loan portfolio	All outstanding principals due for all outstanding client loans
Nominal yield	Ratio of interest and fee incomes on loan portfolio to gross loan Portfolio
Number of loans	Number of outstanding loans

Table 2. Descriptive statistics of input and output variables

Variable		2003	2004	2005	2006	2007	2008	2009
Gross loan portfolio	Observations	200	258	306	331	337	337	336
	Mean	6.59e+07	8.04e+07	7.08e+07	4.83e+07	5.33e+07	6.12e+07	6.29e+07
	Std. dev.	3.20e+08	4.23e+08	3.81e+08	1.38e+08	1.69e+08	2.12e+08	1.99e+08
	Min	0	9125.821	9289.028	9158.252	0	0	0
	Max	4.18e+09	6.12e+09	6.06e+09	1.43e+09	1.80e+09	2.52e+09	2.37e+09
Personnel	Observations	178	247	299	322	328	334	331
	Mean	209.0393	261.2146	283.9164	337.2143	432.1951	494.3623	910
	Std. dev.	1039.24	1278.164	1158.908	1498.473	2039.129	1683.577	6626.856
	Min	4	5	0	3	0	3	3
	Max	13534	18898	17271	24457	34841	26749	118000
Operating exp.	Observations	127	196	244	292	325	331	323
	Mean	0.2038	0.2195	0.2029	0.2023	0.1816	0.1872	0.1765
	Std. dev.	0.1077	0.1910	0.1492	0.1490	0.1437	0.1418	0.1253
	Min	0.0076	0.0225	0	0.0128	0.0078	0.0079	0.02
	Max	.6129	2.2154	1.5478	1.0797	1.0916	1.0527	0.9084
Admin. exp.	Observations	79	148	200	274	311	329	323
	Mean	0.0880	0.0893	0.0853	0.0882	0.0799	0.0811	0.0754
	Std. dev.	0.0509	0.0536	0.0673	0.0682	0.0712	0.0698	0.0577
	Min	0.0116	0.0122	0.0065	0.0026	0.0009	0.0073	0.0072
	Max	0.3152	0.3771	0.7876	0.6109	0.6866	0.6829	0.5167
No. of loans	Observations	80	162	216	286	320	331	324
	Mean	77002.10	56781.90	64053.89	79039.42	95013.26	115894.6	147575.50
	Std. dev.	402659.80	327688.70	308514.50	403182.60	498070.80	568638	669246.80
	Min	370	39	0	192	50	55	273
	Max	3600000	4100000	4200000	4700000	6500000	6800000	7500000
Yield	Observations	79	148	200	275	313	330	323
	Mean	0.3716	0.3735	0.3626	0.3630	0.3428	0.3599	0.3335
	Std. dev.	0.1248	0.1474	0.1353	0.1684	0.1681	0.1849	0.1543
	Min	0.1361	0.1181	0.0569	0.0453	0.0474	0.0032	0.0591
	Max	0.7260	0.9225	0.9455	1.0454	0.9939	1.1819	0.9519

Table 2. Descriptive statistics of input and output variables (continued)

Variable		2010	2011	2012	2013
Gross loan portfolio	Observations	340	339	340	342
	Mean	7.17e+07	7.50e+07	6.75e+07	7.34e+07
	Std. dev.	2.52e+08	3.00e+08	3.16e+08	3.75e+08
	Min	0	4139.252	3843.859	0
	Max	2.59e+09	3.68e+09	4.15e+09	5.15e+09
Personnel	Observations	334	336	333	342
	Mean	643.4641	653.5625	698.6126	749.4883
	Std. dev.	1731.604	1523.781	1497.126	1561.977
	Min	0	3	4	4
	Max	21719	18789	17700	17394
Operating exp.	Observations	328	331	323	342
	Mean	0.1788	0.1812	0.1757	0.1822
	Std. dev.	0.1155	0.1107	0.1160	0.1377
	Min	0.0211	0.0157	0	0.0087
	Max	0.7265	0.6699	0.7301	1.6312
Admin. exp.	Observations	328	323	321	342
	Mean	0.0738	0.0753	0.0718	0.0745
	Std. dev.	0.0528	0.0564	0.0528	0.0639
	Min	0	0.008	0	0.0055
	Max	0.3961	0.5016	0.4211	0.6493
No. of loans	Observations	331	335	336	342
	Mean	153912	148930.40	157059.50	170380.20
	Std. dev.	680784.50	647980.80	634131.10	659421.80
	Min	227	249	72	23
	Max	8200000	8500000	8700000	8600000
Yield	Observations	333	332	324	342
	Mean	0.3376	0.3288	0.3197	0.32440
	Std. dev	0.1602	0.1648	0.1633	0.1623
	Min	0.0525	0	0	0.0341
	Max	1.2118	1.1194	1.0977	1.0875

Table 3. TFP and efficiency levels (all regions)

Year	Maximum TFP level	Technical efficiency levels	Scale efficiency level	Mix efficiency levels	Residual scale efficiency levels	Residual mix efficiency levels	TFP levels
	1	2	3	4	5	6	7 = (1*2*3*6) = (1*2*4*5)
2003	0.8047	0.5834	0.6113	0.9059	0.3242	0.4805	0.1379
2004	0.8047	0.5867	0.6195	0.9111	0.3280	0.4824	0.1411
2005	0.8047	0.5655	0.5927	0.9533	0.3220	0.5178	0.1397
2006	0.8047	0.5690	0.6284	0.9304	0.3130	0.4635	0.1333
2007	0.5069	0.5407	0.7225	0.9267	0.5260	0.6746	0.1336
2008	0.4836	0.6321	0.6535	0.9507	0.4543	0.6609	0.1321
2009	0.4993	0.6254	0.6224	0.9792	0.4152	0.6533	0.1270
2010	0.4483	0.5877	0.6953	0.9734	0.4756	0.6658	0.1221
2011	0.6199	0.5870	0.5915	0.9494	0.3283	0.5270	0.1135
2012	0.7121	0.6396	0.4960	0.9311	0.2587	0.4856	0.1097
2013	0.9796	0.6201	0.4970	0.9461	0.1950	0.3712	0.1121
Geomean	0.6576	0.5935	0.6081	0.9413	0.3455	0.4805	0.1270

Table 4. TFP change and its components (all regions)

Year	Technical change	Technical efficiency change	Scale efficiency change	Mix efficiency change	Residual scale efficiency change	Residual mix efficiency change	TFP change
2003	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2004	1.0000	0.9946	1.0290	1.0047	1.0369	1.0124	1.0361
2005	1.0000	0.9636	0.9750	1.0514	1.0347	1.1157	1.0483
2006	1.0000	0.9692	1.0544	1.0514	0.9924	0.9896	1.0112
2007	0.6298	0.9316	1.2169	1.0344	1.6680	1.4178	1.0124
2008	0.6010	1.0989	1.1051	1.0583	1.4407	1.3798	1.0069
2009	0.6205	1.0796	1.0598	1.0813	1.3337	1.3608	0.9661
2010	0.5571	1.0284	1.1775	1.0925	1.4939	1.3860	0.9350
2011	0.7704	1.0054	0.9996	1.0460	1.0450	1.0935	0.8466
2012	0.8848	1.1025	0.8408	1.0256	0.8171	0.9967	0.8176
2013	1.2172	1.0651	0.8405	1.0450	0.6175	0.7678	0.8367
Growth rate (%)	4.2139	0.8536	-1.2005	0.4709	-1.7859	-1.1715	-1.6993

Table 5. Comparison of FPI and Malmquist TFP indices and selected components (all regions)

	Färe-Primont indices				Malmquist indices			
Year	Technical change	Technical efficiency change	Scale and residual mix efficiency change	TFP change	Technical change	Technical efficiency change	Scale and residual mix efficiency change	TFP change
2003	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2004	1.0000	0.9946	1.0418	1.0361	0.9902	1.0039	0.9494	0.9347
2005	1.0000	0.9636	1.0878	1.0483	0.9373	0.9646	0.9994	0.8988
2006	1.0000	0.9692	1.0434	1.0112	0.6842	1.0005	1.0884	0.8429
2007	0.6298	0.9316	1.7253	1.0124	0.7539	0.9582	1.2287	0.8753
2008	0.6010	1.0989	1.5247	1.0069	0.7034	1.1691	0.9926	0.8943
2009	0.6205	1.0796	1.4421	0.9661	0.8731	0.9910	1.0302	0.8914
2010	0.5571	1.0284	1.6320	0.9350	1.0049	0.9380	1.0051	0.9485
2011	0.7704	1.0054	1.0930	0.8466	0.8887	0.9989	0.9556	0.8807
2012	0.8848	1.1025	0.8380	0.8176	1.1916	1.0926	0.7351	0.9626
2013	1.2172	1.0651	0.6453	0.8367	1.0354	0.9668	0.8105	0.9146
Growth rate (%)	4.2139	0.8536	-1.3359	-1.6993	1.8795	0.1752	-1.3601	-0.7325

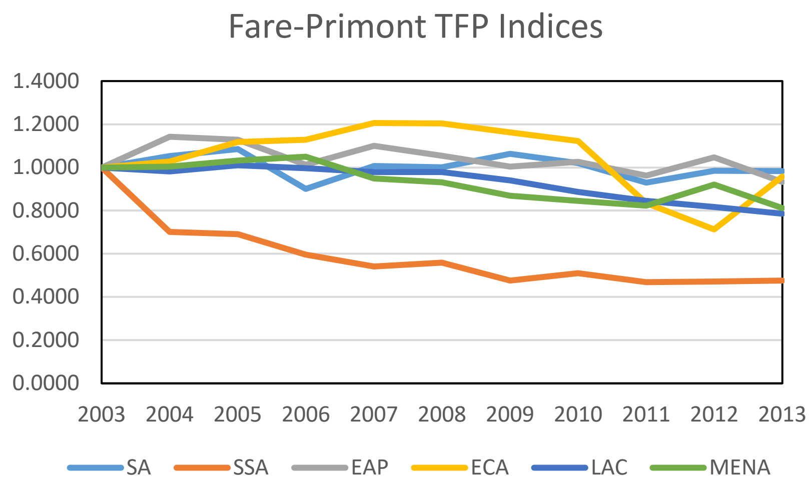

Figure 1. Fare-Primont TFP indices by region.

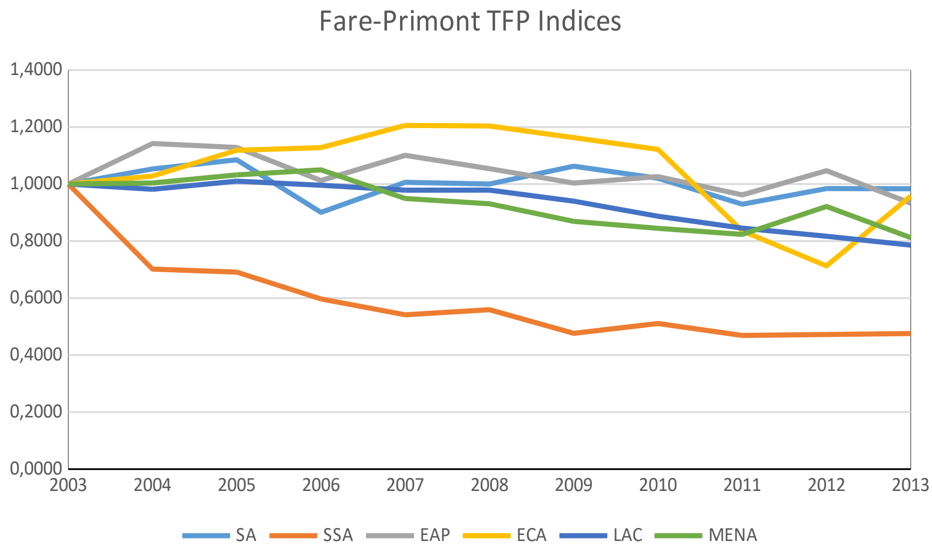

Figure 2. Technical efficiency change by region.

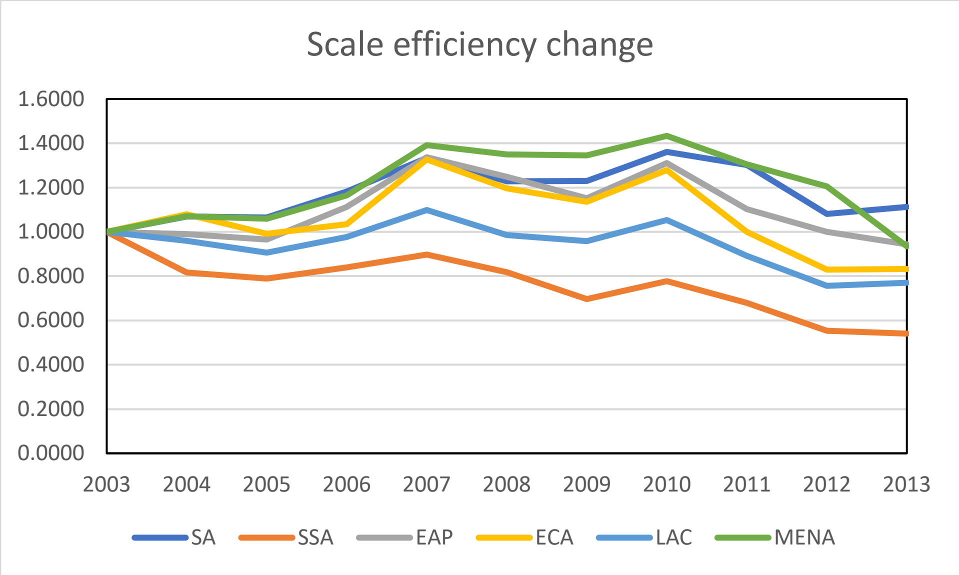

Figure 3. Scale efficiency change by region.

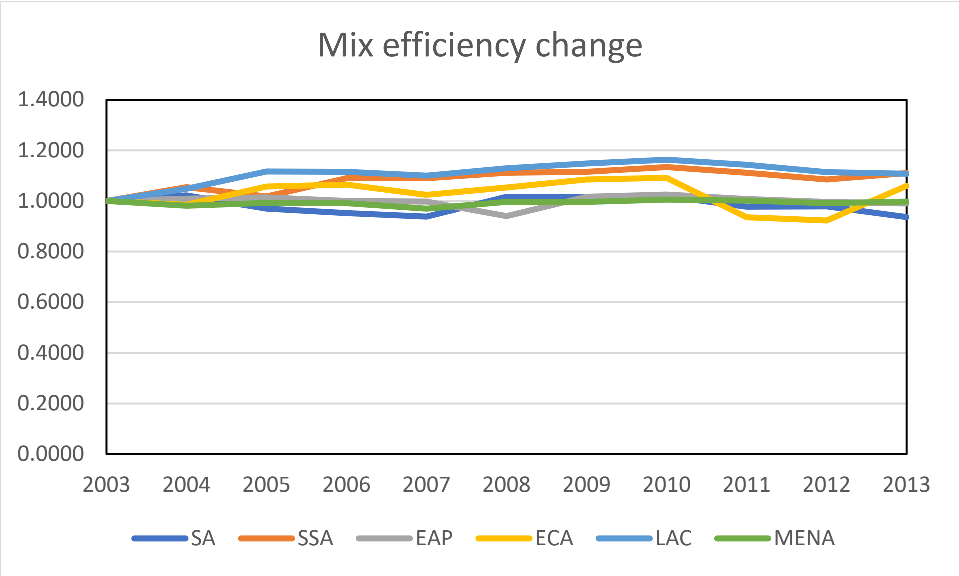

Figure 4. Mix efficiency change by region.

APPENDIX

Table A1 TFP change and its components (South Asia)

Year	Technical change	Technical efficiency change	Scale efficiency change	Mix efficiency change	Residual scale efficiency change	Residual mix efficiency change	TFP change
2003	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2004	1.0000	0.9297	1.0687	1.0221	1.1080	1.0597	1.0529
2005	1.0000	0.9320	1.0654	0.9698	1.2004	1.0928	1.0851
2006	1.0000	0.8807	1.1825	0.9527	1.0734	0.8647	0.9006
2007	0.6298	0.9042	1.3342	0.9381	1.8830	1.3240	1.0060
2008	0.6010	1.1008	1.2289	1.0171	1.4863	1.2301	1.0001
2009	0.6205	1.1220	1.2292	1.0159	1.5024	1.2417	1.0626
2010	0.5571	1.1715	1.3610	1.0195	1.5332	1.1484	1.0202
2011	0.7704	0.9769	1.3027	0.9778	1.2626	0.9477	0.9291
2012	0.8848	1.1135	1.0805	0.9791	1.0202	0.9245	0.9842
2013	1.2172	1.0755	1.1128	0.9365	0.8021	0.6750	0.9834
Growth rate (%)	4.2139	1.2424	1.4884	-0.5850	0.7823	-1.9243	0.1636

Table A2. TFP change and its components (Sub-Saharan Africa)

Year	Technical change	Technical efficiency change	Scale efficiency change	Mix efficiency change	Residual scale efficiency change	Residual mix efficiency change	TFP change
2003	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2004	1.0000	0.9162	0.8171	1.0551	0.7259	0.9372	0.7016
2005	1.0000	0.9619	0.7893	1.0174	0.7062	0.9103	0.6911
2006	1.0000	0.9344	0.8394	1.0906	0.5856	0.7609	0.5968
2007	0.6298	0.8248	0.8976	1.0897	0.9563	1.1609	0.5413
2008	0.6010	1.0009	0.8179	1.1119	0.8361	1.1366	0.5592
2009	0.6205	0.9860	0.6964	1.1159	0.6975	1.1176	0.4761
2010	0.5571	0.9873	0.7770	1.1341	0.8188	1.1950	0.5107
2011	0.7704	0.8599	0.6792	1.1111	0.6368	1.0417	0.4687
2012	0.8848	1.0238	0.5537	1.0854	0.4801	0.9411	0.4721
2013	1.2172	0.9732	0.5405	1.1106	0.3615	0.7426	0.4755
Growth rate (%)	4.2139	0.3230	-5.4015	1.1056	-6.7201	-1.3407	-6.5342

Table A3. TFP change and its components (East Asia and the Pacific)

Year	Technical change	Technical efficiency change	Scale efficiency change	Mix efficiency change	Residual scale efficiency change	Residual mix efficiency change	TFP change
2003	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2004	1.0000	1.0428	0.9904	1.0097	1.0849	1.1060	1.1422
2005	1.0000	1.1852	0.9650	1.0141	0.9388	0.9865	1.1283
2006	1.0000	1.1460	1.1131	1.0006	0.8828	0.7935	1.0123
2007	0.6298	1.1707	1.3371	0.9973	1.4970	1.1165	1.1008
2008	0.6010	1.3494	1.2491	0.9402	1.3822	1.0404	1.0539
2009	0.6205	1.2965	1.1515	1.0172	1.2263	1.0832	1.0035
2010	0.5571	1.2970	1.3114	1.0254	1.3849	1.0829	1.0261
2011	0.7704	1.3081	1.1029	1.0080	0.9470	0.8655	0.9619
2012	0.8848	1.4967	1.0002	0.9969	0.7930	0.7904	1.0470
2013	1.2172	1.4126	0.9437	0.9896	0.5482	0.5748	0.9328
Growth rate (%)	4.2139	3.7819	0.0579	-0.0517	-2.6131	-3.7819	-0.3644

Table A4. TFP change and its components (Eastern Europe and Central Asia)

Year	Technical change	Technical efficiency change	Scale efficiency change	Mix efficiency change	Residual scale efficiency change	Residual mix efficiency change	TFP change
2003	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2004	1.0000	0.9492	1.0796	0.9845	1.1001	1.0032	1.0280
2005	1.0000	0.9261	0.9907	1.0575	1.1420	1.2190	1.1184
2006	1.0000	0.9481	1.0348	1.0641	1.1179	1.1496	1.1279
2007	0.6298	0.9359	1.3272	1.0240	1.9976	1.5412	1.2058
2008	0.6010	1.1181	1.1961	1.0530	1.7011	1.4976	1.2036
2009	0.6205	1.0832	1.1354	1.0849	1.5947	1.5237	1.1628
2010	0.5571	1.0500	1.2795	1.0914	1.7568	1.4986	1.1217
2011	0.7704	1.0117	1.0005	0.9358	1.1455	1.0713	0.8354
2012	0.8848	1.0518	0.8295	0.9229	0.8300	0.9234	0.7129
2013	1.2172	1.0519	0.8327	1.0593	0.7065	0.8986	0.9582
Growth rate (%)	4.2139	0.7185	-0.8337	0.8322	0.2240	0.2470	0.6464

Table A5. TFP change and its components (Latin America and the Caribbean)

Year	Technical change	Technical efficiency change	Scale efficiency change	Mix efficiency change	Residual scale efficiency change	Residual mix efficiency change	TFP change
2003	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2004	1.0000	0.9808	0.9591	1.0488	0.9544	1.0437	0.9817
2005	1.0000	0.9221	0.9065	1.1171	0.9807	1.2085	1.0102
2006	1.0000	0.9330	0.9774	1.1153	0.9570	1.0920	0.9958
2007	0.6298	0.8908	1.0987	1.1006	1.5848	1.5874	0.9785
2008	0.6010	1.0389	0.9855	1.1298	1.3874	1.5905	0.9787
2009	0.6205	1.0205	0.9581	1.1484	1.2925	1.5493	0.9399
2010	0.5571	0.9331	1.0541	1.1632	1.4669	1.6187	0.8869
2011	0.7704	0.9517	0.8916	1.1434	1.0085	1.2933	0.8454
2012	0.8848	1.0447	0.7563	1.1135	0.7936	1.1684	0.8168
2013	1.2172	1.0010	0.7702	1.1071	0.5824	0.8372	0.7856
Growth rate (%)	4.2139	0.2626	-2.1164	1.0611	-2.3600	-0.0138	-2.3551

Table A6. TFP change and its components (Middle East and North Africa)

Year	Technical change	Technical efficiency change	Scale efficiency change	Mix efficiency change	Residual scale efficiency change	Residual mix efficiency change	TFP change
2003	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2004	1.0000	0.9501	1.0714	0.9814	1.0763	0.9859	1.0036
2005	1.0000	0.9528	1.0589	0.9931	1.0909	1.0231	1.0322
2006	1.0000	1.0413	1.1643	0.9913	1.0170	0.8658	1.0497
2007	0.6298	0.9034	1.3918	0.9697	1.7207	1.1988	0.9494
2008	0.6010	1.0897	1.3496	0.9969	1.4258	1.0532	0.9308
2009	0.6205	1.0774	1.3461	0.9968	1.3042	0.9658	0.8691
2010	0.5571	1.0308	1.4334	1.0054	1.4627	1.0260	0.8446
2011	0.7704	1.0464	1.3047	1.0014	1.0199	0.7828	0.8233
2012	0.8848	1.0155	1.2046	0.9917	1.1778	0.9695	0.9214
2013	1.2172	1.0570	0.9346	0.9981	0.6322	0.6752	0.8119
Growth rate (%)	4.2139	0.9149	-0.0403	-0.0092	-0.3220	-1.8971	-1.8548