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Convergence of the performance of microfinance institutions: A decomposition analysis[☆]

Lin Yang Li^a, Niels Hermes^{b,*}, Aljar Meesters^c

^a Northwest University, China

^b University of Groningen, the Netherlands

^c Copernica, the Netherlands

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ABSTRACT

In this paper, we focus on investigating whether and to what extent patterns of performance microfinance institutions converge over time. In particular, we analyze whether patterns of performance are related to changes in operating efficiency, capital deepening, and/or technological change for a large international sample of microfinance institutions for the period 2003–2012. We apply intertemporal Data Envelopment Analysis, a methodology that has been used extensively in the literature explaining patterns of economic growth, but has not been applied yet in microfinance research. We decompose performance changes into operating efficiency changes, changes in capital intensity and/or technological change and find that capital deepening is the most important source of improved performance, especially during the first half, while capital deepening and technological innovations are important during the second half of the period. We also find strong evidence for convergence of performance between microfinance institutions. These trends concur with important changes in microfinance, such as increased commercialization, competition with commercial banks, and involvement of private investors.

1. Introduction

Poor households in emerging economies are excluded from access to the formal financial system, such as commercial banks. Yet, having access to financial services is crucial for the poor as this helps them to smooth their consumption, generate business opportunities, and improve their inclusion in the formal economy in the long run (Collins et al., 2009). This also explains why financial inclusion has been high on the agenda of both academics and policy makers, especially during recent years (see, e.g., Demircü-Kunt and Klapper, 2013; Brown et al., 2015; Ho and Mallick, 2017; Ahamed and Mallick, 2019; Li, 2018).

Since the late 1970s, the poor in emerging economies have increasingly gained access to financial services offered by so-called microfinance institutions (MFIs). Especially since the late 1990s, these MFIs have shown significant growth rates in terms of providing financial services to poor households. Whereas in 1997 these MFIs had around 10 million clients, in 2010 this number had grown to over 200 million (Maes and Reed, 2012). It has been estimated that around one billion poor people have been directly or indirectly affected by the access to microfinance

(Lützenkirchen and Weistroffer, 2012).

This rapid growth has been accompanied by significant changes in the daily operations of MFIs. Important changes in this respect have been an increased focus on financial sustainability next to social impact and performance (Hermes et al., 2011), modifications of business models towards a stronger focus on commercialization of activities (Cull et al., 2007; Mersland and Strøm, 2010), and the development and introduction of new lending and management technologies (Kapoor et al., 2007). These changes may have exerted a profound impact on the financial (i.e. being efficient in terms of cost efficiency and generating revenues) and social performance (i.e. being efficient in reaching the poor) of MFIs (Fall, 2018).

In this paper, we shed light on whether and to what extent the changing of operations of MFIs has had an impact on the financial and social performance of MFIs. To do this, we investigate patterns of financial and social performance of MFIs over a time span of ten years and establish whether these patterns are related to changes in operating efficiency (i.e. increasing output by using existing inputs in a more efficient way), capital intensity (i.e. increasing the units of capital per worker), and/or technological change (i.e. improved methods to combine capital and labor into

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* Corresponding author. Faculty of Economics and Business, University of Groningen, PO BOX 800, 9700 AV, Groningen, the Netherlands.

E-mail address: c.l.m.hermes@rug.nl (N. Hermes).

outputs). In particular, we investigate whether and to what extent patterns of performance of MFIs converge over time.

Although MFI performance and its determinants has been studied before,¹ to the best of our knowledge, we are the first to provide an overview of the changing patterns of MFI performance, and capture the convergence of both financial and social productivity for a large international sample of MFIs over an extended period of time. Moreover, the decomposition analysis provides important insight into how the MFI's business model and operating mechanism contribute to the dynamic pattern of MFI performance. With respect to the decomposition analysis we are one of the few to focus on social productivity, next to financial productivity. Analyzing patterns of MFI performance over time and tracing the sources of performance convergence is important as the findings of such an analysis may be instrumental in understanding how MFIs are able to reach poor clients with better services at lower cost.

We apply intertemporal Data Envelopment Analysis (DEA), a methodology that has been used extensively in the literature explaining patterns of economic growth, but has not been applied yet in microfinance research to explain financial and social performance of MFIs. We use a balanced panel data set for 171 MFIs active in 59 developing countries over the period 2003–2012.

We find strong evidence for convergence of performance between MFIs. We also document that increasing capital intensity (that is, capital deepening) is the most important source of improved performance of those MFIs that are lagging behind in terms of their performance, especially during the first half of the period 2003–2012, while capital deepening and technological innovation become relatively more important during the second half of the period. We show that these trends concur with important changes in the microfinance landscape over the ten-year period, such as increased commercialization of the microfinance business, competition with commercial banks and involvement of private investors.

The remainder of this paper is organized as follows. Section 2 discusses the major changes the microfinance market has been experiencing since the late 1990s to the early 2000s and how these changes may be connected to the performance of MFIs. Section 3 discusses the methodology we use to analyze patterns of performance, and show how we decompose performance changes into operating efficiency changes, changes in capital intensity and/or technological change, following a methodology proposed by [Los and Timmer \(2005\)](#). Section 4 presents the results of our empirical analysis, followed by the conclusions in section 5.

2. Microfinance: structural change and performance

The microfinance movement started mid-1970s in Bangladesh. Since its emergence, it went through various structural changes. Most importantly, since the late-1980s microfinance experienced a paradigm shift from being impact oriented towards being more commercially oriented (see, e.g., [Hulme and Mosley, 1996](#); [Christen, 2001](#); [Hulme and Arun, 2009](#); [Cull et al., 2011a](#); [Lützenkirchen and Weistroffer, 2012](#)).

Initially, most MFIs were NGOs focusing on lending to the poor in rural areas, in many cases by using the so-called group-lending model. Microfinance mainly aimed at having an impact on reducing poverty and increasing outreach. MFIs charged interest rates that did not allow them to cover their costs of operation, which meant that in many cases, they were not financially sustainable. Therefore, many MFIs were supported by government and/or private donor funding.

From the mid-1980s, the neo-liberal model, emphasizing the role of markets instead of governments, started to become the dominant view in economics and politics. This also affected thinking about how to provide financial services to the poor through microfinance. The failure of the model of state intervention in rural credit markets added to this change in thinking about microfinance. Instead of focusing on subsidized finance to

the poor, several practitioners and academics advocated a more commercial approach that aims at combining financial sustainability with high outreach. They claimed that by charging market interest rates MFIs would be able to make profits, which could be used to grow lending activities. Moreover, the profitability would attract outside investment, which would further contribute to the growing the activities of MFIs. In the end, they claimed, due to the expansion of activities more poor households could be served. Thus, financial and social sustainability were seen as complementary.

The shift towards commercialization of microfinance was accompanied by a change in the type of MFIs providing financial services. Whereas initially non-profit NGOs dominated the market, especially from the mid-1990s the number of for-profit organizations steadily increased. First, a number of successful NGOs changed their legal status and became non-bank financial institutions (NBFIs), which allowed them to attract deposits, thereby increasing their funding base. Second, donor organizations increasingly set up new NBFIs, instead of transforming existing NGOs. Third, an increasing number of commercial banks entered the market, triggered by the success of the microfinance concept. Still, as of 2010, the share of NGOs and NBFIs in a sample of around 2000 MFIs for which information is available in the Mix Market,² was around one third each, whereas the share of commercial banks was less than 10 per cent.

Microfinance also changed in terms of the type of financial services that were offered. From the initial focus on group lending, MFIs gradually shifted towards individual lending. As a business model, individual lending is more promising as it can better accommodate the needs of the relatively more wealthy clients. Operating costs are generally lower for this type of clients. Finally, group lending is more difficult to use outside rural areas, because this lending model is based on social capital, which is generally much less developed among people living in urban areas.

Next to changing the lending model, over time MFIs broadened the scope of the financial services they provided. This also significantly changed the microfinance landscape. From focusing on lending only in the beginning, MFIs gradually shifted to offering payment services, saving accounts, insurance, etc. as it was recognized that the poor need more than just loans. In addition, some MFIs started to offer loans in combination with business and financial literacy trainings to increase the probability that the loans were successfully transferred into profitable investment projects. MFIs not only offered new types of services, they also changed the mode of offering services, for example by introducing ATMs, chip cards, point-of-sale (POS) devices, and mobile banking. These services not only benefit customers by providing convenience and lower transaction costs but also enable MFIs to reach more clients in remote areas, reduce operational costs, and increase financial security ([Rhyne and Otero, 2006](#); [Yimiga, 2018](#)).

Finally, the microfinance landscape changed, because especially since the early 2000s, MFIs started to raise capital from financial markets. Commercial investors – and especially those focusing on so-called socially responsible investments – became increasingly interested in funding microfinance activities. In 2008, foreign private investment funding to MFIs amounted to US\$3.9 billion. In 2009, this increased to US\$5.6 billion, or 30 per cent of the total funding (i.e. including public donor funding) MFIs received that year ([El-Zoghbi et al., 2011](#)). Yet, commercial funding also put more pressure on their business model, with more attention for achieving financial sustainability and profit orientation, next to aiming at reaching out to poor clients.

These changes in the microfinance landscape do raise the question as to how they may have affected the activities and performance of MFIs over time. The exponential growth of the microfinance industry has prompted research on the performance of MFIs, using parametric methods such as Stochastic Frontier Analysis (SFA) and non-parametric methods such as DEA to measure their efficiency in transforming inputs (e.g. capital and labor) into outputs (i.e. financial services). Most

¹ For recent overviews of the literature, see [Fall et al. \(2018\)](#) and [Hermes and Hudon \(2018\)](#).

² The Mix Market is an internet-based data set providing financial and social performance information for MFIs.

studies investigating MFI performance have been published after 2010. The majority of these studies apply DEA using data for one country for one year. Of the fifteen papers published since 2014, which were included in a recent meta-analysis carried out by Fall et al. (2018), only four use SFA; five use data for more than one country; and only five use panel data. The main outcome of the meta-analysis shows that, overall, the efficiency of MFIs has increased over time (Fall et al., 2018).

A few recent studies focus on investigating changes in MFI productivity and its determinants. These studies use an extended version of DEA by applying the Malmquist productivity index approach. Gebremichael and Rani (2012) apply this approach to investigate changes in productivity of 19 Ethiopian MFIs for the period 2004–2009. Bassem (2014) uses data for 33 MFIs in MENA countries for the period 2006–2011 using a similar approach. The same holds for Mia and Soltane (2016) using data for 50 South Asian MFIs over the period 2007–2012, as well as for Wijesiri and Meoli (2015) who collect data for 20 Kenyan MFIs for the period 2009–2012. Finally, using the Malmquist total factor productivity approach, Mia and Chandran (2016) apply data for 162 MFIs in Bangladesh for the period 2007–2012, while Bibi and Ahmad (2015) apply data for 85 MFIs in South Asian over the period of 2003–2011 using the same approach.

Yet, these studies focus on examining changes in productivity for a limited number of MFIs in a single country or a small number of countries, using data for a relatively short period of time (that is, mostly up to five years). Thus, there is hardly any evidence on the changes in productivity in a global setting. Moreover, the sources of changing MFI performance and patterns of convergence of MFI performance remain largely unknown.

Instead, in our study we explicitly capture the convergence of financial and social performance of the microfinance market using a global dataset. Moreover, our data cover a relatively long time period of ten years, enabling us to provide a comprehensive picture of the performance dynamics of the microfinance industry. In addition, we identify the sources of MFI productivity change. In particular, we are interested in how changes in operating efficiency, capital deepening and application of technological innovations may affect MFI productivity. More specifically, based on convergence analysis, we decompose the convergence of MFI performance into three components and show to what extent these components contribute to financial and social performance convergence in the microfinance industry. In contrast, studies using the Malmquist decomposition approach only trace performance changes into technical efficiency (learning) and technological change.

In the following, we discuss how operating efficiency, capital deepening and technological innovations may affect MFI performance convergence over time.

Operating efficiency denotes the challenge of handing out loans to clients at the lowest possible costs of operations and funds (Armendáriz and Morduch, 2010; Prior and Argandoña, 2009). Increasing operating efficiency has become a hot topic in microfinance literature, because many MFIs face relatively high operating and administrative expenses compared with their revenues. The daily operations of MFIs are costly because they engage in numerous small financial transactions. Each transaction requires face-to-face interaction with poor borrowers to evaluate their creditworthiness and monitor their use of credit (Fernando, 2006). With the rapidly growing number of MFIs and commercial banks involved in lending to the poor, the microfinance market has become increasingly competitive. This competition has forced MFIs to reduce costs and improve financial sustainability (Rhyne and Otero, 2006).

Learning from leading MFIs is one way for less-developed institutions to improve operating efficiency (Caudill et al., 2009). Leading MFIs are more cost-effective because they have been offering financial services to clients for a longer time; their practical experience ensures high financial as well as social productivity. Less-efficient institutions may mimic the designs and operations of leaders by improving management structures, rearranging operational procedures, and installing better corporate

governance systems (D'Espallier et al., 2017). According to Caudill et al. (2009), learning from leaders is particularly important for MFIs that are seeking to improve cost efficiency and financial productivity. By adopting experience in lending practices from market pioneers (e.g., how to use lending strategies and deal with default risks of poor clients), lagging MFIs can reduce the effort and spending associated with trial and error.

Capital deepening refers to increasing the volume of capital per unit of labor (D'Espallier et al., 2017). With respect to MFIs, capital deepening means that loan officers handle a higher volume and/or value of loans. This may be achieved by using monetary incentives to motivate staff and promoting competitiveness in the market (Aubert et al., 2009). In a survey among 147 MFIs, McKim and Hugart (2005) found that the percentage of MFIs using staff incentive schemes increased from 6% in 1999 to 63% in 2003. Aubert et al. (2009) show that MFIs applying these schemes exhibit substantial improvement in productivity of their credit agents and overall financial performance. Capital deepening may also be achieved by training staff on issues such as dealing with delinquent clients, time management, operational risk management, accounting principles, and other soft skills (Sarker, 2013). Over the past two decades, MFIs have been motivated to increase capital deepening to ensure survival and better performance in an increasingly competitive and commercialized market setting.

Technological innovations in microfinance may relate new technology applied by MFIs includes software that supports internal systems to track transactions and client information, the use of credit scoring systems to evaluate the creditworthiness and repayment abilities of borrowers (Helms, 2006) and improved network connections between branches to exchange information and monitor transactions. Moreover, new technologies may involve services provided through ATMs, chip cards, point-of-sale (POS) devices, and mobile banking.

MFIs are motivated to deploy these technologies to boost performance. First, by using well-designed information systems, network connections, and credit scoring systems, MFIs are better able to capture accurate information on customers, monitor their use of credit, and reduce default risks. They also help in producing reliable information regarding their performance and increase transparency about their operations. This improved transparency may help attracting more external funding (Rhyne and Otero, 2006), which may be instrumental in increasing their revenues. Second, adapting new technology may reduce operating costs by simplifying and standardizing transaction procedures (Ketley et al., 2005), which may make them more competitive. Third, new types of financial services increase the potential of financial access for poor clients. These new services not only benefit customers by providing convenience and lower transaction costs, they also enable MFIs to reach more clients in remote areas, reduce operational costs, and increase financial security (Rhyne and Otero, 2006).

In summary, changing operating efficiency, capital deepening and technological innovations represent three potentially important changes in MFI daily operations over the last decade. We focus on these aspects because they may be linked to operating responses of MFIs to the changing environment of the microfinance market over the last decade or so, that is, these operations may be influenced by processes of commercialization and increased competition in microfinance (Rhyne and Otero, 2006; Armendáriz and Morduch, 2010). In the remainder of the paper, we investigate to what extent operating efficiency, capital deepening and technological innovation have contributed to changes in and possibly convergence of financial and social performance of MFIs over the period 2003–2012.

3. Data and methodology

3.1. Data

We use a balanced panel containing data from 171 MFIs around the world for the period of 2003–2012 to construct a global production

frontier. The data are drawn from the MIX Market Internet database.³ Using a balanced panel allows us to better analyze changes in MFI efficiency over time as compared to using an unbalanced panel. As was mentioned before, the aim of our analysis is to investigate the long-term financial and social performance convergence of MFIs and identify the main sources of performance convergence. To allow us to analyze this correctly, our sample should provide full information on MFIs' performance for the longest possible time period. Using an unbalanced sample may lead to incorrect specifications of the productivity frontier and its movement over time, as well as of the sources of these movements. This may be the case when the position and shift of this frontier is determined to a large extent by MFIs entering and/or leaving the dataset during the period 2003–2012. For instance, a newly established MFI during the ten-year period may have sufficient initial assets and may offer services to a large number of clients. This newly established MFI may then shift the frontier upward, but the shift can only be explained by the new MFI's sufficient initial funding rather than the operational progress made in the microfinance market as a whole. So, using an unbalanced panel may interfere with our analysis with respect to the source of the shift of productivity frontiers. Given the available data by MIX we optimize the data set for our analysis by taking a balanced sample of 171 MFIs for the period 2003–2012.

3.2. Methodology

Our study follows a two-step analysis. First, MFI performance, or productivity, is estimated by using the intertemporal Data Envelopment Approach (DEA).⁴ Second, we apply dynamic panel data analysis to trace out the sources of productivity improvements of MFIs' daily operations. In the second part, our focus is on the convergence of productivity of MFIs and its determinants.

3.2.1. Intertemporal Data Envelopment Analysis

We apply DEA to determine the global production frontier. An important feature of DEA is that MFI productivity can be estimated without imposing specific restrictions or a particular functional form (Färe et al., 1994), because DEA conducts a piece-wise linear function over the data based on linear programming methods (Los and Timmer,

2005). Thus, the productivity of each MFI is determined by the combination of inputs, which is reflected in the MFI's operating technology. The productivity frontier is driven by MFIs that attain the highest productivity based on their input combinations (or operating technology).

We assume constant returns to scale⁵ with two inputs producing a single output. When determining inputs and outputs, we follow the production approach. Based on traditional banking theory, MFIs efficiency may be evaluated using one of two main approaches, that is, the production approach and the intermediation approach (Berger and Humphrey, 1997; Fall et al., 2018). According to the production approach, MFIs are considered as production units using capital and labor as inputs to produce outputs of loans, deposits, etc. The intermediation model views MFIs as financial intermediaries collecting deposits from savers to channel them to borrowers as loans and other financial services (Bassem, 2014; Widiarto and Emrouznejad, 2015). Most studies on MFI efficiency follow the production approach (Gutiérrez-Nieto et al., 2007; Bassem, 2008, 2014; Haq et al., 2010; Wijesiri et al., 2015; Lebovics et al., 2016), since not all MFIs are allowed to collect savings from the general public (Gutiérrez-Nieto et al., 2007; Widiarto et al., 2017), which is a crucial assumption of the intermediation model. Therefore, the production approach is used in our analysis to maintain homogeneity as many MFIs in our sample are not collecting deposits.

Accordingly, in our analysis, the MFI's capital (measured as the value of total assets) and labor (measured in terms of the total number of staff members) are chosen as our two inputs. In the evaluation of financial performance, our output measure is the value of the gross loan portfolio. When evaluating social performance, we use the number of female borrowers⁶ as our output measure.⁷

One important feature of our methodology is the use of *intertemporal* DEA as suggested by Tulkens and Van den Eeckaut (1995). This approach

³ See Appendix Table A.1 for definitions, explanations and data sources for all variables used in the empirical analysis. Appendix Table A.2 provides the descriptive statistics for the full sample (unbalanced) provided by the MIX Market and the sample used in our paper (balanced).

⁴ We acknowledge that DEA is a method that performs best when using data from relatively homogeneous samples of organizations in terms of the technologies employed. The data we use are from MFIs located in different countries. This may result in a sample of MFIs employing different business models and being subject to different institutions and regulations. In other words, our sample may be less homogenous in terms of production technologies used. In order to address the concern that a single global production frontier may not accurately capture the performance of MFIs using different business models and being subject to different institutions and regulations, we separate the MFIs in our sample into four regional groups (i.e. Latin America and the Caribbean, Eastern Europe and Central Asia, South East Asia and the Pacific, and Middle East and Africa) and construct regional frontiers for each group. According to the literature, countries in the same region share homogeneity in culture and social norms (Cull and Morduch, 2010), macroeconomic context (Ahlin et al., 2011), institutional framework (Cull et al., 2011b), and the level of financial sector development (Vanroose and D'Espallier, 2013), all of which may induce MFIs to share the same operational strategy, lending methods and financial technology (Cull and Morduch, 2010; Kar and Rahman, 2018; Fall 2018). Therefore, we calculate production frontiers based on MFIs located in different regions in the world based on the assumption that country differences are less pronounced between countries within the same region. This approach has been used in several other studies, see, e.g. Gutiérrez-Nieto et al. (2007), Widiarto and Emrouznejad (2015), Wijesiri et al. (2017), and Widiarto et al. (2017). We discuss the outcomes of these regional sub-samples later on in the results section of this paper.

⁵ The two most popular DEA models are the so-called CCR model, developed by Charnes, Cooper and Rhodes (Charnes et al., 1978) and the BCC model, developed by Banker, Charnes and Cooper (Banker et al., 1984). The CCR model assumes constant returns to scale (CRS); the BCC model assumes variable returns to scale (VRS). It is acknowledged that the VRS model is less restrictive than the CRS model. Nevertheless, our analysis employs the CRS model for the following reasons. First, the primary aim of this study is to decompose productivity change of MFIs and track the sources of productivity convergence in the microfinance industry. According to the literature, the CRS assumption is necessary for the productivity index to be considered as a valid measure of total factor productivity based on which decomposition can be realized (Färe and Grosskopf, 1996; Färe et al., 1997; Ray and Desli, 1997; Zhang et al., 2011). Additionally, as Casu et al. (2004) and Casu et al. (2013) point out, when decomposing productivity change, the literature has reached consensus that the decomposition is correctly measured by the ratio of the CRS distance function even when the technology exhibits VRS. Second, our decomposition approach is in line with Kumar and Russell (2002) and Timmer and Los (2005). Both studies stress the importance of assuming CRS in the analysis, in which case the benchmark technology set (production frontier) can be depicted in the (K/L, Y/L) space. That is, employing the CRS model enables us to reduce the problem to a one input (K/L) and one output setting (Y/L), reflected in the graphical analysis presented later in the paper in Figs. 1–3.

⁶ In the literature, the number of female borrowers is a standard measure of the MFI's depth of outreach; for example, see Bassem (2008), Gutiérrez-Nieto et al. (2009), Hermes et al. (2011), Kar (2012), Piot-Lepetit and Nzongang (2014) and Wijesiri et al. (2015). As a robustness check, we also used the number of active borrowers as a variable measuring the social performance of MFIs. This variable measures the so-called breadth of their outreach. The results of analyses using this alternative measure are qualitatively the same. They are available upon request from the author.

⁷ In some cases, MFIs did not report data on the percentage of female borrowers for some years, meaning that we cannot calculate the number of female borrowers as a social output variable for these years. To reduce the loss of observations, we use the method of Multiple Imputation (MI). This method is developed by Rubin (1976, 1987) and has been widely used for handling missing data. It imputes missing values in a dataset according to a probability distribution for the true values given the observed data.

has been used in a number of studies.⁸ Following this approach, when constructing the productivity frontier for year n , we adopt each MFI's input and output in previous years (before year n) as well as for year n as observations to estimate the frontier. In other words, we construct the productivity frontier of year n according to the most efficient observations in the period from the first year in our data (2003) up to and including year n , i.e. $n \in [2004, 2012]$. This approach thus results in estimating n sequential productivity frontiers. So, to determine the global production frontier for any year t , we assume that for any year $t (t = 1, \dots, T)$ we have an input vector defined as $x_{k,n}^t$, with $n (n = 1, \dots, N)$ denoting different kinds of input of MFI $k (k = 1, \dots, K)$ and an output vector defined as $y_{k,m}^t$, with $m (m = 1, \dots, M)$ different outputs. Furthermore, we assume that in the global microfinance market in any year t the technology of the previous year $t - 1$, is still feasible. In other words, all technologies available in periods before year t are also feasible in the current year t .

We apply intertemporal DEA for a number of reasons. First, by adopting historical data in our performance analysis we ensure that technological regress does not occur (Los and Timmer, 2005). By excluding the possibility of technological regress, we reflect reality: along with the accumulation of new knowledge, technological progress is achieved on the basis of current technology. A loss of technology or knowledge never occurs in practice.

Second, in line with Basu and Weil (1998), we assume that the transfer of technology and knowledge is possible around the globe, indicating that less productive MFIs are able to learn technological innovation from leading institutions in the industry. To take into account this learning process, historical data about efficient input combinations are essential for estimating the global productivity frontier. This assumes that all established technology is accessible for all MFIs in the global microfinance market, enabling lagging MFIs to provide their services more financially and socially efficient.

Finally and most importantly, by including the productivity history of MFIs in the estimation of the productivity frontier, we include information about their development paths, because any change of productivity in the past can be decomposed into technical efficiency change, capital deepening, and technological improvement. Therefore, this approach allows us to identify the sources of MFI productivity improvement. This is important information facilitating the development of approaches and strategies to help improve the performance of the microfinance industry.

3.2.2. Convergence of productivity

We analyze convergence of productivity by using a method that has been used frequently in the economic growth literature (Baumol, 1986). Recently, it has also been applied in research on the efficiency and competition in the banking sector (Mamatkakis et al., 2008; Casu and Girardone, 2010; Matthews and Zhang, 2010; Andries and Capraru, 2014). In particular, studies analyzing convergence of productivity focus on tests of so-called β -convergence and σ -convergence. We are the first to adopt β -convergence and σ -convergence tests for the microfinance industry.

β -convergence captures the *catching-up* effect of MFIs by testing the correlation between the change of the productivity growth rate and the initial level of productivity growth rate. If the change of growth rate is negatively correlated with the initial growth rate, this implies that initially less productive MFIs are accelerating and growing more rapidly than institutions with initially high growth rates, suggesting that a catching-up effect occurs and that MFIs overall are agglomerating to similar growth rates of productivity.

σ -convergence complements β -convergence by investigating the *dispersion* of productivity growth rate over time. σ -convergence is confirmed when the productivity growth of individual MFIs moves to the average level of growth rate of all MFIs in the sample (Weill, 2009). Our

analysis employs both β -convergence and σ -convergence to shed light on the dynamics of MFI productivity.

Equation (1) describes β -convergence of MFIs' productivity growth as follows:

$$\ln P_{i,T} - \ln P_{i,T-1} = \alpha_1 + \beta_1 \ln P_{i,T-1} + \gamma_1 (\ln P_{i,T-1} - \ln P_{i,T-2}) + \theta Z_{i,T} + \varepsilon_i, \quad (1)$$

where $P_{i,T}$ denotes the financial or social productivity of the MFI i in year T and $P_{i,T-1}$ is the productivity of MFI i in year $T-1$; i relates to MFIs and T refers to time periods. α , σ and γ are parameters to be estimated, and ε is the residual. The difference of the logarithm of productivity between two years (i.e. $\ln P_{i,T} - \ln P_{i,T-1}$) indicates the change of productivity growth rate. If the variation of MFIs' productivity growth is negatively correlated with its initial level of productivity growth rate ($\ln P_{i,T-1}$), MFIs with low initial productivity growth rates show a higher speed of improving productivity than those with high initial productivity growth rates. In other words, a negative β_1 is interpreted as the incidence of absolute catch-up effects of slowly growing MFIs; the larger the absolute value of the parameter, the greater the tendency of convergence. $Z_{i,T}$ is a vector of variables measuring MFIs' individual characteristics.

Equation (2) specifies the estimation of σ -convergence as follows:

$$\ln S_{i,T} - \ln S_{i,T-1} = \alpha_2 + \sigma \ln S_{i,T-1} + \gamma_2 (\ln S_{i,T-1} - \ln S_{i,T-2}) + \varepsilon_2. \quad (2)$$

We define $S_{i,T} = \ln(P_{i,T}) - \ln(\bar{P}_T)$, where $\bar{P}_T$ is the average productivity growth rate of all MFIs in our sample at year T . α , σ and γ are parameters to be estimated, and ε is the residual. By investigating the distance to the mean level of productivity over time, σ -convergence exhibits the variation of the gap of the productivity growth rate of individual MFIs relative to the average productivity growth rate of all MFIs in the sample. A significantly negative σ implies a narrowing dispersion. In our analysis, convergence is captured only when it meets the conditions of both β -convergence and σ -convergence.

3.2.3. Sources of productivity convergence

Next, we investigate the sources of financial and social productivity convergence. Here, we use Kumar and Russell (2002) to decompose each MFI's productivity growth. According to Kumar and Russell (2002), productivity growth of MFIs can be decomposed into a shift of productivity levels towards the frontier, a shift of productivity levels along the frontier, and a shift of the frontier itself. Fig. 1 illustrates an example of decomposing an MFI's productivity growth from year 0 to year 1. In Fig. 1, the global productivity frontiers in year 0 and year 1 are labeled $F_{(0)}$ and $F_{(1)}$ respectively.

The MFI's productivity growth (P_1 / P_0) can be decomposed as follows⁹:

⁹ See Los and Timmer (2005) and Timmer and Los (2005). On the right side of equation (3), the first term measures the operating efficiency ratio by calculating the Farrell Efficiency Index, where P_a and P_d represent the maximum values of productivity (best-practice) in year 0 and year 1 given MFI's capital labor ratios in respective years. As shown in Fig. 1, P_a denotes, given the capital-labor ratio of M_0 , the best-practice output can be reached on the frontier $F_{(0)}$, which is the intersection of frontier curve $F_{(0)}$ and the vertical dash line passing through M_0 . Similarly, P_d represents, given the capital-labor ratio of M_1 , the best-practice output can be obtained on the frontier $F_{(1)}$. According to Kumar and Russell (2002), measuring the capital intensity ratio (second term) and technological innovation ratio (third term) needs to adopt the 'Fisher ideal' decomposition because the vertical shift of the frontier can be observed both for vertical and horizontal movements from M_0 to M_1 . Hence, capital intensity ratio is calculated as the Fisher index of potential change in labor productivity resulting from a shift in the capital-labor ratio (Woltjer, 2013), where P_b represents MFI's potential output in year 1 using its capital-labor ratio in Year 0, and P_c denotes MFI's potential output in year 0 using its capital-labor ratio in year 1. In Fig. 1, P_b is the intersection of frontier curve $F_{(1)}$ and the vertical dash line passing through M_0 , while P_c is the intersection of frontier curve $F_{(0)}$ and the vertical dash line passing through M_1 . The last term measures the technological innovation ratio also by calculating the geometric average.

⁸ For instance, see Shestalova (2003), Timmer and Los (2005), Los and Timmer (2005), Casu et al. (2013) and Li and Lin (2015).

Fig. 1. Decomposition of an MFI's productivity convergence.

$$\frac{P_1}{P_0} = \underbrace{\left(\frac{P_1}{P_d} * \frac{P_a}{P_0}\right)}_{\text{Operating Efficiency Ratio}} * \underbrace{\left(\frac{P_c}{P_a} * \frac{P_d}{P_b}\right)^{\frac{1}{2}}}_{\text{Capital Intensity Ratio}} * \underbrace{\left(\frac{P_b}{P_a} * \frac{P_d}{P_c}\right)^{\frac{1}{2}}}_{\text{Technological Innovation Ratio}} \quad (3)$$

or:

$$(1 + \hat{P}) = (1 + \hat{P}^L)(1 + \hat{P}^C)(1 + \hat{P}^I) \quad (4)$$

Equation (4) is the simplified expression of equation (3). On the left-hand side of equation (4), $\hat{P}$ is the growth rate of productivity of year 0 to year 1. On the right-hand side, $(1 + \hat{P}^L)$ is the change of the operating efficiency ratio between year 0 and year 1. More specifically, $\hat{P}^L$ implies the change of the operating efficiency depicted as the change of an MFI's vertical distance towards the productivity frontier. Because the frontier represents the maximum attainable productivity for MFIs, narrowing the vertical distance to the frontier line implies that, *ceteris paribus*, lagging MFIs boost their operating efficiency by acquiring and applying available strategies and techniques from leading MFIs (Los and Timmer, 2005). This element reflects the process of learning from best practice MFIs (Timmer and Los, 2005), assuming that the lagging MFI has a capital intensity that is similar to that of the leading MFI. Therefore, we label $\hat{P}^L$ as the learning effect.

The second element $(1 + \hat{P}^C)$ reflects the horizontal movement of MFIs along the productivity frontier. This movement is facilitated by an increase of the capital intensity among MFIs that locate on the frontier. MFIs on the frontier have already exhausted their potential improvement of operating efficiency with current input combinations. By increasing capital intensity, such MFIs shift to a more advanced technology with a higher maximum attainable productivity level (Los and Timmer, 2005). Thus, because $\hat{P}^C$ measures the contribution of capital intensity to achieve higher levels of productivity, we refer to it as the capital deepening effect.

The third element $(1 + \hat{P}^I)$ depicts the shift of the productivity frontier itself. The vertical movement of the frontier is triggered by the incidence of technological innovation, which refers to the development of the technological context of the microfinance industry. The incidence of technological innovation not only endows MFIs on the frontier with higher productivity, but also benefits lagging MFIs in the industry with the technological spillover effect, because they can further increase their operating efficiency by applying the technological innovations. Therefore, a positive $\hat{P}^I$ represents the extent of technological innovation that is contributing to MFI productivity improvement. We refer to this as the innovation effect.

Next, we investigate the contributions of learning, capital deepening, and innovation to the convergence of productivity in the microfinance industry. Based on the decomposition results of each MFI's productivity growth, we employ the following regressions model, taken from Los and Timmer (2005), to evaluate the extent to which the three components contribute to the productivity dynamics of the microfinance industry for different time periods:

$$\text{Learning : } \hat{P}_i^L - \hat{P}_M^L = \alpha_L + \beta_L \left(\ln \frac{P_{i,0}}{P_{i,m}} - \ln \frac{P_{L,0}}{P_{L,m}} \right) + \varepsilon_{i,L}. \quad (5)$$

$$\text{Capital intensity : } \hat{P}_i^C - \hat{P}_L^C = \alpha_C + \beta_C \left(\ln \frac{P_{i,m}}{P_{L,m}} \right) + \varepsilon_{i,C}. \quad (6)$$

$$\text{Innovation : } \hat{P}_i^I - \hat{P}_L^I = \alpha_I + \beta_I \left(\ln \frac{P_{i,m}}{P_{L,m}} \right) + \varepsilon_{i,I}. \quad (7)$$

Equation (5) estimates the contribution of the learning effect to productivity convergence. $(\hat{P}_i^L - \hat{P}_M^L)$ is the difference of the learning effect contributing to productivity growth between MFI i and the MFI on the frontier with the same input combination (that is, the leading MFI). On the right side of the model, $P_{i,0}$ is the actual productivity level of MFI i , and $P_{i,m}$ is the maximum attainable level of the MFIs' productivity; $\frac{P_{i,0}}{P_{i,m}}$ indicates the growth rate of the ratio of MFI i 's actual and maximum productivity level, and $\frac{P_{L,0}}{P_{L,m}}$ is the growth rate of the leading MFI's productivity ratio. β_L is the parameter of interest. A negative value for β_L suggests learning from leading MFI's technology enables lagging MFIs to boost their operating efficiency and to converge to the leading MFIs. A larger absolute value of β_L indicates that MFIs with lower initial

Fig. 2. Evolution of the financial productivity frontier, 2003–2012.

productivity improve more from the learning effect. Equations (6) and (7) are analogous to equation (5); they focus on revealing the contribution of capital deepening and innovation to the productivity convergence in the industry.

4. Results

4.1. Dynamics of financial and social performance: descriptive analysis

We depict the global frontier of both financial productivity and social productivity every three years from 2003 to 2012, using intertemporal DEA. We map the frontier according to the locations of MFIs that attain the maximum feasible productivity level in a specific year. We indicate best practice MFIs by the pentagrams on the productivity frontier (see Figs. 2 and 3). Below the frontier, we plot the locations of less productive MFIs.

We also classify all MFIs in our sample into two types of institutions based on their profit status¹⁰. In particular, we classify non-profit MFIs as socially oriented MFIs, as they tend to focus on providing financial services and loans to the poor. We classify for-profit MFIs as financially oriented MFIs, since they tend to emphasize financial sustainability.¹¹ In

Figs. 2 and 3 below, squares represent socially oriented MFIs; stars refer to financially oriented MFIs.

Fig. 2 presents the dynamics of *financial productivity* of the MFIs in our sample over the 2003–2012 period. As is shown in the figure, the frontier curve moved upward only after 2006. The movement was especially pronounced after 2009, suggesting that several technological innovations in the microfinance industry took place and became available after this year. Fig. 2 further suggests that many MFIs experienced a so-called catching-up process vis-à-vis the leading MFIs (that is, the ones located on the production frontier), resulting in overall financial productivity improvements. Similar to what has been described in the macroeconomic growth literature, this catching-up process involves two phases (Basu and Weil, 1998; Los and Timmer, 2005; Timmer and Los, 2005). In the first phase, MFIs experience capital deepening, that is, capital intensity rises due to higher levels of investment in capital. In the second phase, because of higher levels of capital intensity, they are better equipped to implement available technological innovation and improve their operational efficiency, resulting in a vertical move towards the efficient production frontier.

In 2003, most MFIs were located in the bottom-left corner of Fig. 2, suggesting relatively low levels of financial productivity and capital intensity at the beginning of the 2000s. In 2006, while the frontier curve remained unchanged, MFIs below the frontier, and in particular the profit-oriented institutions, showed a tendency to move horizontally towards the right. This indicates that these MFIs increased their capital intensity from 2003 to 2006. In the following years, many MFIs kept moving to the right, suggesting a further increase in their capital intensity, this time in combination with a more pronounced vertical move towards the efficient production frontier. This suggests they improved financial performance by combining capital intensity with available technological innovation, allowing lagging MFIs to further narrow their financial productivity gap with the leaders on the frontier. Interestingly, this move towards the upper-right corner of the figure was more pronounced for non-profit than for profit MFIs, suggesting that several non-

¹⁰ The information of profit status is offered in the MIX market data set.

¹¹ As a robustness check, we also classified MFIs into financially and socially oriented institutions based on the percentage of female borrowers served by the MFI. As was mentioned before, this widely used measure of outreach to the extreme poor (Cull et al., 2007; Hermes et al., 2011). Specifically, we label an MFI as socially oriented if its percentage of female borrowers is above the average percentage of female borrowers of the whole sample of MFIs (average percentage is 66%). We label an MFI as financially oriented when this percentage is below the sample average. The results remain consistent when we use this alternative criterion of classifying MFIs into financially and socially oriented. The results of this robustness check are available upon request from the authors.

Fig. 3. Evolution of the social productivity frontier, 2003–2012.

profit MFIs made more progress in improving their financial productivity than their profit-oriented counterparts.

Fig. 3 presents the dynamics of the *social productivity* of MFIs during the period 2003–2012. The figure shows that the social productivity frontier moved upward after 2006, suggesting that several technological innovations became available after this year, allowing MFIs (at least potentially) to become socially more efficient. Furthermore, it shows that MFIs operating on the social productivity frontier are located on the left-hand side of the production frontiers, suggesting that MFIs with the highest social performance are associated with relatively low levels of capital intensity. This suggests that, unlike financial productivity improvement (see Fig. 2), which is associated with more capital-intensive technology, increasing social productivity takes place with relatively low capital–labor ratios.

Overall, Fig. 3 shows that many MFIs remain located in the bottom-left, indicating that they show low progress in social productivity. Moreover, perhaps not surprisingly, as a general rule non-profit MFIs outperform for-profit MFIs in terms of social performance, although there are some exceptions to this rule. Thus, although for-profit MFIs have been moving horizontally to the right over the entire period, they show hardly any movement towards the efficient production frontier, that is, they have made only slow progress in terms of improving their social productivity.

To further support our results regarding the trends in performance as presented in Figs. 2 and 3, we split up our sample into four groups of MFIs based on their regional location. We include Latin America and the Caribbean (LAC), Eastern Europe and Central Asia (EECA), South East Asia and the Pacific (SEAP), and Middle East and Africa (MEA) as the regions. We assume that the determinants of the financial and social productivity frontiers are more similar for MFIs within the same region.¹²

¹² The results of the graph analysis using regional samples are available on request from the authors.

In general, the patterns of MFIs' performance for regional sub-samples are similar to those based on the global sample. That is, most profit-oriented MFIs develop into capital-intensive institutions improving their financial performance, but with limited improvement in social performance. In contrast, non-profit MFIs seem to improve both their financial and social performance over the 2003–2012 period.

At the same time, some interesting regional differences emerge. The strongest improvement of financial productivity is witnessed among non-profit MFIs in LAC, whereas several for-profit MFIs in MEA exhibit substantial progress of reaching the poor. When identifying the location of financial and social productivity frontiers for different regions, microfinance markets in LAC and EECA exhibit relatively higher levels of the financial production frontiers as compared to those in MEA and SEAP. This suggests that in these regions technologies available for improving financial productivity are more advanced. At the same time, however, for LAC and EECA the social productivity frontiers hardly shift upwards over the ten-year period. Such upward shifts are more pronounced for MEA and SEAP. This indicates that MFIs located in different regions lay distinct emphasis on operating techniques. That is, microfinance markets in LAC and EECA spend more efforts on improving financial self-sufficiency and overlook extending outreach to the extreme poor clients, while the markets in MEA and SEAP seem to behave in the opposite direction.

The dynamics of financial and social performance of MFIs that results from our descriptive analysis seem to be in line with important changes the microfinance industry experienced since the early 2000s. During this ten-year period, the microfinance industry experienced a process of commercialization. This has led non-profit MFI to transforming themselves into institutions characterized by seeking more private funding and emphasizing profitability and operating efficiency, next to being socially relevant (Christen, 2001; Mersland and Strøm, 2009). The process of commercialization also led to the entrance of commercial (profit-seeking) banks into microfinance, inducing competition in the microfinance market and pushing profit-oriented MFIs even more into

boosting capital intensity and promoting profitability than they previously did.

4.2. Convergence analysis

Table 1 displays results of estimating equation (1). In particular, in this table we report the results of testing for absolute (without controls) and conditional (with controls) β -convergence of financial productivity of the 171 MFIs in our sample during the period 2003–2012. In the conditional convergence tests (columns 4 to 6), we include control

variables measuring financial and social performance, the age of the MFI, regional location and type of ownership. The table shows that for the whole ten-year period and for two sub-periods, β coefficients (β_{WC} for convergence tests without controls and β_C for convergence tests with controls) are always consistently significant with negative signs, suggesting that initially less financially productive MFIs increased their performance more rapidly than highly financially productive MFIs at the initial stage. In other words, MFIs that were below the productivity frontier showed a more rapid pace of movement towards the frontier than those located closer to the frontier. This provides evidence of the

Table 1
 β -convergence of financial productivity (global sample).

Independent Variables	Dependent Variable: $\Delta \ln P_{i,T}$					
	Convergence without Control (β_{WC})			Convergence with Controls (β_C)		
	(1)	(2)	(3)	(4)	(5)	(6)
	03–12	03–07	08–12	03–12	03–07	08–12
$\ln P_{i,T-1}$ (β)	−0.075*** (0.01)	−0.052*** (0.01)	−0.063*** (0.01)	−0.094*** (0.01)	−0.073*** (0.01)	−0.091*** (0.01)
$\Delta \ln P_{i,T-1}$	0.0310 (0.06)	0.0390 (0.03)	−0.0440 (0.11)	−0.0280 (0.06)	0.0150 (0.03)	−0.127 (0.12)
Outreach To The Poor						
ALBPBGNI				0.044*** (0.01)	0.034* (0.02)	0.033** (0.02)
PFB				−0.099** (0.04)	−0.096* (0.06)	−0.112** (0.05)
Financial Performance						
Write-Off Rate				−2.115*** (0.36)	−1.330*** (0.51)	−1.823*** (0.44)
Return of Equity				0.0130 (0.04)	−0.0240 (0.04)	0.134*** (0.05)
Location (Reference Group: SEAP)						
LA				−0.0220 (0.03)	0.0250 (0.03)	−0.0300 (0.04)
MEA				−0.00400 (0.02)	0.100*** (0.03)	−0.057*** (0.02)
EECA				−0.072*** (0.03)	−0.0180 (0.04)	−0.086** (0.03)
No. of Clients (Reference Group: Small Outreach)						
Medium Outreach				0.0220 (0.02)	0.076*** (0.03)	−0.0350 (0.02)
Large Outreach				0.0210 (0.02)	0.050* (0.03)	0.00400 (0.02)
Age (Reference Group: New)						
Young				0.175*** (0.07)	0.144** (0.06)	−0.097** (0.05)
Mature				0.0190 (0.02)	−0.0120 (0.03)	−0.0610 (0.05)
Ownership (Reference Group: NGO)						
CUCO				0.0210 (0.02)	−0.0430 (0.04)	0.063** (0.03)
NBFI				0.0110 (0.03)	−0.00500 (0.04)	0.0210 (0.03)
Bank				0.0140 (0.02)	−0.00800 (0.02)	0.0240 (0.03)
Constant	0.922*** (0.09)	0.741*** (0.13)	0.758*** (0.12)	1.207*** (0.14)	0.982*** (0.19)	1.179*** (0.18)
No. of Observations	1368	513	855	1231	463	768
R^2	0.0720	0.0500	0.0480	0.167	0.161	0.188
Adjusted R^2	0.0710	0.0470	0.0460	0.156	0.131	0.171
F statistics	46.81	10.10	17.53	10.72	4.920	16.75

Notes: 1. $\Delta \ln P_{i,T} = \ln P_{i,T} - \ln P_{i,T-1}$; $\Delta \ln P_{i,T-1} = \ln P_{i,T-1} - \ln P_{i,T-2}$.

2. Robust Standard Errors in Parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table 2
 σ -convergence of financial productivity (global sample).

Independent Variables	Dependent Variable: $\Delta \ln S_{i,T}$		
	Global Average		
	(1)	(2)	(3)
	03–12	03–07	08–12
$\ln S_{i,T-1}(\sigma)$	−0.062*** (0.01)	−0.057*** (0.01)	−0.064*** (0.01)
$\Delta \ln S_{i,T-1}$	−0.003 (0.06)	0.0450 (0.03)	−0.051 (0.12)
Constant	−0.00800 (0.01)	−0.00600 (0.01)	−0.0100 (0.01)
No. of Observations	1368	513	855
R^2	0.0490	0.0600	0.0500
Adjusted R^2	0.0480	0.0560	0.0470
F statistics	29.88	12.54	17.48

Notes: 1. $\Delta \ln S_{i,T} = \ln S_{i,T} - \ln S_{i,T-1}$; $\Delta \ln S_{i,T-1} = \ln S_{i,T-1} - \ln S_{i,T-2}$.

2. Robust Standard Errors in Parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

catching-up effect in the microfinance industry during the period of 2003–2012.

When we split the data into two sub-periods, our results indicate that the absolute value of both β_{WC} and β_C for the second five-year period are larger than those for the first-five year period (0.052 and 0.063 for the convergence tests without controls and 0.073 and 0.091 for the tests with controls), suggesting that the catching-up effect was more pronounced in the second half of the period. This corroborates the results of our descriptive analysis with respect to the shape of the intertemporal frontier of financial productivity in Fig. 2, showing that most initially less productive MFIs have been catching up with MFI leaders since 2006. This finding may be explained as follows. During the first five-year period, less productive MFIs were mostly focusing on accumulating capital. After investing more in capital-intensive techniques, less productive MFIs benefited from technological spillover from productivity leaders, resulting in productivity convergence.

Table 2 displays the results of our investigation of the dispersion of MFI financial productivity towards the sample average. The negative and significant coefficients for all σ -convergence tests confirm that the dispersion of MFI financial productivity vis-a-vis the sample average is diminishing. Therefore, both the β -convergence and σ -convergence tests confirm a process of financial productivity convergence in the microfinance industry during the period of 2003–2012.¹³

Table 3 shows the results of β -convergence tests with respect to social productivity. Again, we display results for the absolute and conditional β -convergence test using the same set of control variables as for the financial productivity convergence analysis. The results are similar to the β -convergence tests for financial productivity. Both β_{WC} and β_C are statistically significant with a negative sign, indicating the incidence of β -convergence for the entire ten-year period as well as for both five-year sub-periods.

The results in Table 3 also show that the absolute values of both β_{WC} and β_C for the second five-year period are smaller as compared to those for the first five-year period (that is, 0.104 and 0.074 for the convergence tests without controls and 0.419 and 0.404 for the tests with controls). This suggests that the catching-up effect was less pronounced from 2008

to 2012 for both absolute and conditional social productivity convergence. This contrasts our findings for financial productivity. The slowdown of the catching-up effect with respect to social performance in the second five-year period may be explained by the commercialization of the microfinance industry. As argued previously, the process of commercialization may have adversely affected social productivity of MFIs during 2008–2012. Most profit-oriented MFIs, but also some non-profit MFIs focused on extending their business by taking up external funding and taking measures to improve their financial performance and profitability. This process is reflected by the strong increase of capital–labor ratios and the improvements in financial productivity. However, as discussed above, improvements in social productivity are largely insensitive to the capital deepening process. This may explain why there was only limited improvement of social productivity during the second five-year period.

Table 4 presents results of the σ -convergence test of MFIs' social productivity. The negative and significant coefficients for all σ -convergence tests in the table confirm that the dispersion of MFI social productivity vis-a-vis the sample average is diminishing. Therefore, both the β -convergence and σ -convergence tests confirm the incidence of social productivity convergence in the microfinance industry during the period of 2003–2012.¹⁴

4.3. Decomposition of financial and social productivity convergence

As a final step in the analysis, we decompose the absolute and conditional convergence of MFI productivity into operating efficiency change, capital intensity change, and technological change. As mentioned earlier, these components can be referred to as processes of learning, capital deepening, and innovation. We investigate the role of each of the three components in the convergence of both financial and social productivity over the ten-year period.

Table 5 provides evidence with respect to the determinants of financial productivity convergence. In the ten-year period, all the three components contributed to convergence of financial productivity, as their coefficients are negatively significant for both sub-periods.

The absolute value of the coefficients of learning effect is smallest among the three (0.112 for decomposition without controls; 0.092 for decomposition with controls), suggesting that less financially productive MFIs benefited least from adopting operating techniques from leading MFIs to move closer to the financial productivity frontier.

According to the results displayed in Table 5, capital deepening is most important in facilitating financial productivity convergence throughout the ten-year period (absolute coefficients are 0.470 for decomposition without and 0.463 for decomposition with controls). This suggests that MFIs lagging in financial productivity successfully narrowed their productivity gap with leading MFIs by enlarging their capital intensity. The strong efforts related to capital deepening confirm that because of the commercialization of the microfinance industry, especially in the period of 2008–2012, MFIs aimed at achieving higher financial productivity by focusing on more capital-intensive service delivery.

The relatively large absolute values of the coefficients of innovation indicate its importance in promoting financial productivity convergence

¹³ We also carried out β -convergence and σ -convergence tests for financial productivity using regional samples (LAC, EECA, SEAP and MEA). The results of these tests confirm that financial productivity convergence occurs in all regions over the ten-year period. The results of β -convergence and σ -convergence tests for financial productivity using regional samples are available on request from the authors.

¹⁴ As an additional analysis, we also implement β -convergence and σ -convergence tests for social productivity using the same regional samples used for analyzing the convergence of financial productivity. Both types of convergence are confirmed for all regions except for LAC. This result corroborates our findings based on descriptive analysis in the previous section. There we discussed that among the four regions, the social productivity frontier for MFIs in the LAC region remained unchanged throughout the ten-year period. The implication of this outcome is that the microfinance market in LAC made limited progress in reaching the extreme poor over the ten-year period, explaining the non-convergence of social productivity in LAC. The results of these tests are available on request from the authors.

Table 3
 β -convergence of social productivity (global sample).

Independent Variables	Dependent Variable: $\Delta \ln P_{i,T}$					
	Convergence without Control (β_{WC})			Convergence with Controls (β_C)		
	(1)	(2)	(3)	(4)	(5)	(6)
	03–12	03–07	08–12	03–12	03–07	08–12
$\ln P_{i,T-1}$ (β)	−0.095*** (0.03)	−0.104*** (0.02)	−0.074** (0.03)	−0.419*** (0.06)	−0.404*** (0.04)	−0.397*** (0.08)
$\Delta \ln P_{i,T-1}$	−0.168 (0.12)	0.00200 (0.04)	−0.290 (0.18)	−0.0920 (0.08)	0.0240 (0.03)	−0.176 (0.12)
Outreach To The Poor						
ALBPBGNI				−0.168*** (0.05)	−0.161*** (0.04)	−0.169*** (0.06)
PFB				1.002*** (0.13)	0.865*** (0.11)	1.025*** (0.17)
Financial Performance						
Write-Off Rate				−1.449*** (0.42)	−0.829 (0.88)	−1.282** (0.53)
Return of Equity				0.0340 (0.03)	0.0140 (0.02)	0.089** (0.04)
Location (Reference Group: SEAP)						
LA				−0.085*** (0.03)	−0.096** (0.05)	−0.069* (0.04)
MEA				−0.088** (0.04)	−0.077** (0.04)	−0.0780 (0.06)
EECA				0.059* (0.03)	0.096* (0.05)	0.0340 (0.04)
No. of Clients (Reference Group: Small Outreach)						
Medium Outreach				0.185*** (0.04)	0.222*** (0.04)	0.149*** (0.05)
Large Outreach				0.262*** (0.06)	0.276*** (0.04)	0.243*** (0.07)
Age (Reference Group: New)						
Young				0.235*** (0.08)	0.232*** (0.06)	−0.300 (0.37)
Mature				0.0400 (0.05)	0.0530 (0.03)	−0.122 (0.19)
Ownership (Reference Group: NGO)						
CUCO				−0.0260 (0.07)	−0.0370 (0.05)	−0.0200 (0.12)
NBFI				0.231*** (0.05)	0.238*** (0.07)	0.231*** (0.06)
Bank				0.088*** (0.02)	0.059* (0.03)	0.092*** (0.03)
Constant	0.398*** (0.13)	0.480*** (0.09)	0.274* (0.15)	1.048*** (0.20)	1.091*** (0.14)	0.928*** (0.27)
No. of Observations	1368	513	855	1231	463	768
R ²	0.0900	0.0720	0.133	0.322	0.373	0.337
Adjusted R ²	0.0890	0.0690	0.131	0.313	0.350	0.323
F statistics	6.809	12.76	2.669	10.36	8.004	5.926

Notes: 1. $\Delta \ln P_{i,T} = \ln P_{i,T} - \ln P_{i,T-1}$; $\Delta \ln P_{i,T-1} = \ln P_{i,T-1} - \ln P_{i,T-2}$.

2. Robust Standard Errors in Parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table 4 σ -Convergence of social productivity (global sample).

Independent Variables	Dependent Variable: $\Delta \ln S_{i,T}$		
	Global Average		
	(1)	(2)	(3)
	03–12	03–07	08–12
$\ln S_{i,T-1}(\sigma)$	−0.095*** (0.03)	−0.104*** (0.02)	−0.075** (0.03)
$\Delta \ln S_{i,T-1}$	−0.174 (0.13)	0.00200 (0.04)	−0.291 (0.19)
Constant	−0.031** (0.01)	−0.024* (0.01)	−0.035** (0.01)
No. of Observations	1368	513	855
R^2	0.0940	0.0720	0.134
Adjusted R^2	0.0920	0.0680	0.132
F statistics	6.564	12.45	2.681

Notes: 1. $\Delta \ln S_{i,T} = \ln S_{i,T} - \ln S_{i,T-1}$; $\Delta \ln S_{i,T-1} = \ln S_{i,T-1} - \ln S_{i,T-2}$ .2. Robust Standard Errors in Parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).**Table 5**

Decomposition of financial productivity convergence (global sample).

Independent Variables	Decomposition without Controls			Decomposition with Controls		
	(1)	(2)	(3)	(4)	(5)	(6)
	Learning	Capital Deepening	Innovation	Learning	Capital Deepening	Innovation
$\log\left(\frac{P_{i,0}}{P_{i,a}} / \frac{P_{L,0}}{P_{L,a}}\right)$	−0.112*** (0.01)			−0.092*** (0.01)		
$\log(P_{i,a}/P_{L,a})$		−0.470*** (0.08)	−0.223*** (0.02)		−0.463*** (0.08)	−0.239*** (0.02)
Outreach To The Poor						
ALBPBGNI				−0.0110 (0.02)	0.0130 (0.01)	0.012* (0.01)
PFB				−0.176** (0.07)	−0.072* (0.04)	0.00100 (0.02)
Financial Performance						
Write-Off Rate				1.280** (0.52)	0.101 (0.30)	−0.328** (0.17)
Return of Equity				−0.116*** (0.03)	0.0280 (0.03)	0.00300 (0.02)
Location (Reference Group: SEAP)						
LA				−0.0390 (0.06)	−0.0640 (0.04)	−0.0140 (0.02)
MEA				0.0610 (0.04)	0.0270 (0.03)	−0.00600 (0.01)
EECA				−0.0300 (0.06)	0.00600 (0.03)	−0.0120 (0.02)
No. of Clients (Reference Group: Small Outreach)						
Medium Outreach				−0.0270 (0.04)	0.0250 (0.03)	0.0100 (0.01)
Large Outreach				0.101*** (0.04)	0.0260 (0.02)	−0.00400 (0.01)
Age (Reference Group: New)						
Young				−0.219*** (0.08)	−0.111 (0.08)	0.0180 (0.03)
Mature				−0.232*** (0.04)	−0.059* (0.03)	0.036** (0.02)
Ownership (Reference Group: NGO)						
CUCO				0.00800 (0.05)	0.038* (0.02)	0.0130 (0.01)
NBFI				0.103* (0.06)	0.049** (0.02)	0.0110 (0.01)
Bank				−0.0130 (0.04)	−0.0170 (0.02)	0.00400 (0.01)
Constant	−0.208*** (0.01)	0.876*** (0.03)	0.966*** (0.01)	−0.0770 (0.07)	0.911*** (0.05)	0.950*** (0.02)
No. of Observations	1539	1539	1539	1348	1348	1348
R^2	0.0710	0.250	0.290	0.111	0.271	0.318
Adjusted R^2	0.0700	0.250	0.290	0.101	0.263	0.311
F statistics	98.08	31.56	139.2	11.16	4.431	13.02

Notes: 1. Robust Standard Errors in Parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

(0.223 and 0.239, respectively), suggesting that technological innovations exhibited substantial effects on the convergence of financial productivity during this period.

Table 6 presents the results of the decomposition of social productivity convergence. The results suggest that learning and capital deepening are the main drivers of convergence, while technological innovation shows a limited contribution to convergence. During the ten-year period, capital deepening is clearly the most important driver of social productivity improvements (absolute coefficients are 0.598 for decomposition without and 0.667 for decomposition with controls). Learning from the most efficient MFIs explains both absolute and conditional convergence at least to some extent (absolute coefficients are 0.105 and 0.130, respectively).

These results seem to match earlier findings based on the descriptive analysis in the previous section. There, we discussed that the micro-finance industry made limited progress on social performance over the ten-year period. We identified a strong process of capital deepening experienced by most MFIs. At the same time, however, we recorded that

Table 6
Decomposition of social productivity convergence (global sample).

	Decomposition without Controls			Decomposition with Controls		
	(1)	(2)	(3)	(4)	(5)	(6)
	Learning	Capital Deepening	Innovation	Learning	Capital Deepening	Innovation
$\log\left(\frac{P_{i,0}}{P_{i,a}}/\frac{P_{L,0}}{P_{L,a}}\right)$	−0.105*** (0.01)			−0.130*** (0.01)		
$\log(P_{i,a}/P_{L,a})$		−0.598*** (0.08)	0.088*** (0.02)		−0.667*** (0.09)	0.044* (0.02)
Outreach To The Poor						
ALBPBGNI				−0.056** (0.03)	−0.0110 (0.03)	0.017* (0.01)
				0.0340 (0.08)	−0.0770 (0.08)	−0.063** (0.03)
Financial Performance						
Write-Off Rate				−0.663 (0.54)	1.718** (0.68)	−0.245 (0.17)
Return of Equity				0.00300 (0.04)	−0.0420 (0.03)	0.00300 (0.01)
Location (Reference Group: SEAP)						
LA				−0.0450 (0.05)	−0.0670 (0.06)	−0.0200 (0.03)
MEA				−0.072** (0.04)	0.0250 (0.05)	−0.00500 (0.02)
EECA				0.00800 (0.05)	0.00700 (0.05)	0.0260 (0.02)
No. of Clients (Reference Group: Small Outreach)						
Medium Outreach				0.063* (0.04)	−0.0630 (0.04)	0.00900 (0.02)
Large Outreach				0.118*** (0.04)	−0.0400 (0.04)	−0.0170 (0.02)
Age (Reference Group: New)						
Young				0.0250 (0.08)	0.0210 (0.10)	0.0230 (0.03)
Mature				−0.071* (0.04)	0.0330 (0.04)	0.0120 (0.01)
Ownership (Reference Group: NGO)						
CUCO				−0.0600 (0.05)	0.0670 (0.05)	0.033* (0.02)
NBFI				0.0160 (0.06)	0.0120 (0.06)	0.042** (0.02)
Bank				0.0440 (0.03)	−0.0290 (0.04)	−0.0120 (0.02)
Constant	0.078*** (0.03)	1.195*** (0.02)	1.010*** (0.01)	0.148** (0.07)	1.239*** (0.07)	1.040*** (0.03)
No. of Observations	1536	1020	1020	1345	911	911
R ²	0.0820	0.136	0.0200	0.100	0.177	0.0560
Adjusted R ²	0.0810	0.136	0.0190	0.0900	0.163	0.0400
F statistics	117.5	61.95	15.47	10.06	5.186	4.476

Notes: 1. Robust Standard Errors in Parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

the social performance of MFIs seems relatively insensitive to capital deepening. The outcomes of the decomposition of convergence suggest that MFIs generally indeed rely on capital deepening, rather than on learning from leading MFIs and/or upgrading technologies, to extend their outreach.

We also carried out decomposition analysis using regional samples to identify the sources of financial and social productivity convergence.¹⁵ The results indicate that for all regional samples capital deepening is the primary source of financial and social productivity convergence. Learning from leading MFIs is the second most important driving force of productivity convergence in most regions, especially when it comes to social productivity convergence. These results are largely in line with those using the global sample.

¹⁵ The results of these decomposition analyses are available on request from the authors.

5. Summary and concluding remarks

In this paper, we investigate whether and to what extent the changing landscape in microfinance during the period 2003–2012 has influenced MFI operations and their social and financial performance. We apply DEA using a balanced panel data set for 171 MFIs active in 59 developing countries over the period of 2003–2012 and analyze the patterns of financial and social productivity convergence of MFIs over the ten-year period, as well as two five-year sub-periods (2003–2007 and 2008–2012). Our analysis provides an innovative way to analyze the impact of major changes in the microfinance industry in the early 2000s.

Our findings indicate overall improvements in financial and social productivity. With regard to financial productivity, we find that MFIs were able to make remarkable improvements. In particular, we find that during the first part of the ten-year period, their capital intensity went up quite strongly. This process of capital deepening is an important prerequisite for enabling learning effects from applying available

technological innovations initiated by leading microfinance institutions. In our data, we observe such a learning process for later years. Moreover, we observe further technological innovations (i.e., upward shifts of the frontier) taking place in the industry after 2006. For social productivity, trends are similar but less pronounced. In general, social productivity improvements lagged behind those of financial productivity.

We interpret these trends in financial and social productivity as the result of the commercialization process in microfinance. A stronger focus on financial performance, resulting in part from an increased interest in and access to private funding, led MFIs to change the structure and organization of their financial service activities. These changes also shifted client portfolios from poor to relatively wealthier clients and has led to a focus on financial services with higher profit margins. In the microfinance literature, the shift from a focus on social to a focus on financial goals is coined as mission drift (Copestake, 2007; Mersland and Strøm, 2010). Our research seems to provide empirical evidence for such a shift.

Second, we investigate to what extent productivity improvements converged, that is, whether lagging MFIs moved closer to leading MFIs with regard to financial and social output. Using tests of β -convergence and σ -convergence, we establish that processes of convergence within the microfinance industry took place from 2003 to 2012. Thus, lagging MFIs were able to make more significant improvements in productivity than

leading MFIs. This suggests the occurrence of spillover of successful strategies, which may also be the result of commercialization within the industry. Due to competition, MFIs have felt the pressure to look for ways to improve their performance.

Finally, we use decomposition analysis of the financial and social productivity convergence to evaluate the contributions made by improving operating efficiency, increased capital intensity and/or technological change. Our findings largely corroborate the analysis of trends in financial and social productivity convergence, that is, that capital deepening was the most important contributor to productivity convergence, followed by learning effects. The contribution of technological innovation was relatively small, especially for social productivity convergence.

Our analysis of the patterns of MFI performance over time and of tracing the sources of performance convergence may contribute to a better understanding of how MFIs are able to reach poor clients with better services at lower cost. As such, the outcomes discussed in this paper may help management of MFIs as well as donors, banks and other financiers of MFIs in the decision-making process about what type of activities of MFIs should be developed further in order to reach higher levels of their financial and social performance.

Appendix A

Table A.1
Variable Definitions and Sources

Variable	Definition
Assets	Total of all net asset accounts Source: The MIX Market
Personnel	Total number of staff members Source: The MIX Market
Gross Loan Portfolio	All outstanding principals due for all outstanding client loans. This includes current, delinquent, and renegotiated loans, but not loans that have been written off. It does not include interest receivable. Source: The MIX Market
Number of Active Borrowers	The number of individuals or entities who currently have outstanding loan balances with the MFI or are primarily responsible for repaying any portion of the Loan Portfolio, Gross. Individuals who have multiple loans with an MFI should be counted as a single borrower. Source: The MIX Market
Capital Per Worker	Capital intensity of the institution. Defined as the institution's total assets divided by its personnel. Source: Author's calculation.
Financial Productivity	The MFI's gross loan portfolio divided by its personnel. Source: Author's calculation.
Social Productivity	The total number of an MFI's active borrowers divided by its personnel. Source: Author's calculation.
Non-Bank Financial Institution	A dummy variable identifies an institution that provides similar services to those of a bank, but is licensed under a separate category. The separate license may be the result of lower capital requirements, limitations on financial service offerings, or supervision under a different state agency. In some countries this corresponds to a special category created for microfinance institutions. Source: The MIX Market
Credit Union/Cooperative	A dummy variable identifies a non-profit, member-based financial intermediary. It may offer a range of financial services, including lending and deposit taking, for the benefit of its members. While not regulated by a state banking supervisory agency, it may come under the supervision of a regional or national cooperative council. Source: The MIX Market
Non-Government Organization	A dummy variable identifies an organization registered as a non-profit for tax purposes or some other legal charter. Its financial services are usually more restricted and usually do not include deposit taking. These institutions are typically not regulated by a banking supervisory agency. Source: The MIX Market
Bank	A dummy variable identifies a licensed financial intermediary regulated by a state banking supervisory agency. It may provide any of a number of financial services, including deposit taking, lending, payment services, and money transfers. Source: The MIX Market
Latin America and The Caribbean	A dummy variable identifies an MFI locates in the Latin America or the Caribbean. Source: The MIX Market
Eastern Europe and Central Asia	A dummy variable identifies an MFI locates in the Eastern Europe or the Central Asia. Source: The MIX Market
South East Asia and the Pacific	A dummy variable identifies an MFI located in South East Asia or the Pacific. Source: The MIX Market
Middle East and Africa	A dummy variable identifies an MFI located in the Middle East or Africa. Source: The MIX Market

(continued on next column)

Table A.1 (continued)

Variable	Definition
Average Loan Balance Per Borrower Divided by the Gross National Income per Capita	This variable specifies MFI's average loan size adjusted by the local economic condition. The average loan size is calculated as the MFI's <i>Gross Loan Portfolio</i> divided by its <i>Number of Active Borrowers</i> . The <i>ALBPBGNI</i> is the ratio of average loan size to the GNI per capita within the country. Source: The MIX Market
Percentage of Female Borrowers	The number of active borrowers who are females divided by <i>Number of Active Borrowers</i> . Source: The MIX Market
Write-Off Ratio	Write-offs are the total amount of loans written off during the period. The Write-Off Ratio is defined as the write offs divided by the <i>Gross Loan Portfolio</i> . Source: The MIX Market
Return on Equity	The net operating income divided by the total equity. Source: The MIX Market
Small Outreach	Scale of outreach identifies the total number of clients an MFI served. Small Outreach is a dummy that equals 1 when the MFI serves less than 10,000 clients, otherwise 0. Source: The MIX Market
Medium Outreach	Medium Outreach is a dummy that equals 1 when the total number of clients the MFI serving is between 10,000 and 30,000, otherwise 0. Source: The MIX Market
Large Outreach	Large Outreach is a dummy that equals 1 when the total number of clients the MFI serving is over 30,000, otherwise 0. Source: The MIX Market
New	Age dummies specify the length of duration since the establishment of an MFI. New is a dummy that equals 1 when an MFI has been operating for less than 5 years, otherwise 0. Source: The MIX Market
Young	Young is a dummy that equals 1 when the age of an MFI is between 5 and 8 years, otherwise 0. Source: The MIX Market
Mature	Mature is a dummy that equals 1 when the age of an MFI is over 8 years, otherwise 0. Source: The MIX Market

Notes: [Table A.1](#) reports variable definitions and sources for all variables used in the paper. The first column reports the variable name, the second column reports detailed variable definition and sources.

Table A.2

Summary Statistics of the Full Sample (Unbalanced) and Current Using Sample (Balanced)

Variables	Using Sample (Balanced)					Full Sample (Unbalanced)				
	Number of Observations	Mean	Standard Deviation	Minimum	Maximum	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Assets	1710	1.96*10 ⁷	7.41*10 ⁷	2188	1.04*10 ⁹	14435	2.85*10 ⁷	1.45*10 ⁹	−3.96*10 ⁸	1.69*10 ¹¹
Labor	1710	680.7386	2471.08	5	34841	13799	395.2224	4184.128	0	263300
Gross Loan Portfolio	1710	6.10*10 ⁷	1.65*10 ⁸	19047	1.86*10 ⁹	15261	8.89*10 ⁷	5.96*10 ⁹	0	7.35*10 ¹¹
No. of Active Borrowers	1710	126939	617897.5	156	6710000	14042	60066.2	372501.9	0	1.42*10 ⁷
No. of Female Borrowers	1710	108035.9	609516.5	35	7805191	11031	44862.44	302285.8	0	6457033
Capital Per Worker	1710	26563.8	30120.57	61.87879	330132.6	13114	48065.6	734002.5	−674981.3	6.63*10 ⁷
Financial Productivity	1710	100766.1	100628.6	907	739469.9	13693	131643.9	2871010	0	2.88*10 ⁸
Social Productivity	1710	136.9187	89.41963	0.1018942	1387.943	13356	130.8686	206.9412	0	13708.81
ALBPBGNI	1704	0.5761437	0.6815565	0.0028	4.9041	13876	1.600276	42.90146	0	3827.531
PFB	1710	0.6589502	0.2350968	0.0025	1.250566	11031	0.6480831	0.280239	0	6.6891
Write-Off Ratio	1591	0.0185348	0.0302883	−0.0055	0.2999	9767	0.0247227	0.2906873	−0.1268	25.7114
Return on Equity	1644	0.1069002	0.437214	−9.8796	6.6009	11009	0.3167744	35.52013	−1651	2726.667
New	1710	0.0438596	0.2048427	0	1	15559	0.174947	0.379934	0	1
Young	1710	0.1573099	0.3641992	0	1	15559	.1965422	0.3973959	0	1
Mature	1710	0.7988304	0.4009918	0	1	15559	0.5509352	0.4974148	0	1
LA	1710	0.3859649	0.4869648	0	1	15559	0.26467	0.4411715	0	1
MEA	1710	0.1695906	0.3753826	0	1	15559	0.2734109	0.4457243	0	1
EECA	1710	0.2339181	0.4234446	0	1	15559	0.1789961	0.3833614	0	1
SEAP	1710	0.2105263	0.4078017	0	1	15559	0.2829231	0.4504338	0	1
NGO	1710	0.3976608	0.4895578	0	1	15559	0.3495083	0.47683	0	1
CUCO	1710	0.0701754	0.2555172	0	1	15559	0.1873514	0.3902059	0	1
NBFI	1710	0.374269	0.4840752	0	1	15559	0.307539	0.4614894	0	1
Bank	1710	0.1578947	0.3647489	0	1	15559	0.1435182	0.3506118	0	1

Notes: [Table A.2](#) provides descriptive statistics for the full sample provided by the MIX Market and the sample used in our paper. The full sample is an unbalanced panel covering 15,559 observations from 1995 to 2013. We make the original sample into a balanced panel covering 171 MFIs from 2003 to 2012.

Appendix B. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.econmod.2019.05.014>.

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