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Productivity growth, catching-up and technology innovation in microfinance institutions in India: evidence using a bootstrap Malmquist Index approach

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Abstract

Purpose – This paper aims to examine the total factor productivity (TFP) change and its components: efficiency change and technical change in microfinance institutions (MFIs) in India operating from 2005 to 2018. The study also scrutinizes the variations in productivity levels across the distinct organizational form and size groups of MFIs. In addition to this, the authors identify the contextual factors that determine TFP growth, catching-up and technology innovation in MFIs.

Design/methodology/approach – The study employs a smooth homogeneous bootstrap estimation procedure of Simar and Wilson (1999) for obtaining reliable estimates of Malmquist indices –productivity and its components – in a data envelopment analysis (DEA) framework for individual MFIs. In order to identify the determinants of productivity change and its components, the study follows Simar and Wilson's (2007) guidelines and applies a bootstrap truncated regression model. The double bootstrap procedure performs well, both in terms of allowing correct estimation of bias and deriving statistically consistent productivity estimates in the first and root mean square errors in the second stage of the analysis.

Findings – The empirical results reveal that the MFIs have shown average productivity growth of 6.70% during the entire study period. The observed productivity gains are primarily contributed by a larger efficiency increase at the rate of 4.80%, while technical progress occurs at 2.3%. Nonbanking financial companies (NBFC)-MFIs outperformed non-NBFC-MFIs. Small MFIs show the highest TFP growth in terms of size groups, followed by the large MFIs and medium MFIs. The bootstrap truncated regression results suggest that the credit portfolio, size and age of MFIs matter in achieving higher productivity levels.

Practical implications – The practical implication drawn from the study is that the Indian MFI industry might adopt the latest technology and innovations in the products, risk assessment and credit delivery to improve their productivity levels. The industry must focus on enhancing the managerial skill of its employees to achieve a high productivity level.

Originality/value – This study is perhaps the initial attempt to explain the productivity behavior of MFIs in India by deploying a statistically robust double bootstrap procedure in the DEA-based Malmquist Productivity Index (MPI) framework. The authors estimate the bias-adjusted productivity index and its decompositions, which represent more reliable and statistically consistent estimates. For contextual factors responsible for driving productivity change, the study deploys a bootstrap truncated regression approach.

Keywords Total factor productivity, Bootstrap Malmquist Productivity Index, Bootstrap truncated regression, Microfinance institutions, India

Paper type Research paper

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1. Introduction

The national governments of many developing economies have considered microfinance institutions (MFIs) as one of the most significant devices to fight against poverty (Hermes *et al.*, 2011; Widiarto and Emrouznejad, 2015). In particular, the MFIs serve the poor to enhance their livelihood and enable them to build economic assets, empower women and reduce the vulnerability to economic stress. These institutions provide capital to the financially backward section and empower them to come out of the vicious circle of poverty (Rosenberg, 2010; Imai *et al.*, 2010; Hermes and Lensink, 2011). In the recent decade, the substantial growth in MFIs has been observed worldwide, specifically in the developing economies (see, for instance, Louis *et al.*, 2013; Bassem, 2014; Wijesiri, 2016; Kar and Rahman, 2018; among others). The Indian MFI industry has also seen rapid changes due to regulatory reforms and technological innovations, new investment channels and new business models (PwC, 2019). The Andhra Pradesh crisis of 2010 and subsequent regulatory developments in the MFI industry might have brought significant variations in their efficiency and productivity levels. Also, the MFIs have recently started to outsource few activities or use efficient third-party software at different stages ranging from client onboarding to repayment mechanisms (Behl and Singh, 2014). In the light of the changing industry environment, the introduction of reform measures, technological developments and entry of financial technology (FinTech) and shift in the ownership structure, we may expect productivity changes (growth/no change/decline) to happen that might be due to either efficiency change (improve/decline) and/or technological change (progress/regress). We believe that, in response to regulatory changes, the Indian MFI industry might have experienced catching-up phenomenon and technology innovation to become sustainable in the long term.

These developments motivate us to investigate the productivity behavior of MFIs during the pre- and post-Andhra crisis periods in India. Moreover, the organization forms and size groups might also have experienced the cascading effects of such shifts in the industry. The present study thus addresses the following research questions: What are the trends of productivity levels in the microfinance industry as a whole and across organizational forms and size groups? Do ownership and size matter for the productivity of MFIs? Did the Andhra crisis affect the productivity behavior of Indian MFIs? What are the contextual factors that drive productivity and its components in the MFI industry? To answer the above research questions, we formulated the following three precise objectives. The first objective is to investigate the trends in productivity of Indian MFIs in response to the Andhra crisis. The reliable estimates of TFP and its components for individual MFIs are computed by bootstrapping of Malmquist indices using smooth homogeneous bootstrap estimation procedure of Simar and Wilson (1999). The chosen procedure allows us to correct estimation bias and derives statistically consistent productivity estimates through good approximation to the true sampling distribution. The empirical analysis in the study is confined to a period from 2005 to 2018, which encompasses the years of growth, crisis, regulation and institutional developments in the Indian MFI industry. Alongside the impact of the Andhra crisis on efficiency change and technological change, components are also assessed.

Another objective of the study is to assess the impact of the crisis and subsequent regulatory reforms by the Reserve Bank of India (RBI) on the productivity of Indian MFIs. In order to examine the impact of these changes on the productivity change and its components, we divide the entire study period into two sub-periods, namely first sub-period (2005–2010) and second sub-period (2011–2018). Third, the paper also explores how productivity varies across the distinct organizational forms of MFIs, i.e. nonbanking financial companies (NBFCs) and non-NBFC-MFIs. Postadoption of new regulatory reforms, the MFIs have started to register themselves and converted into NBFC-MFIs. NBFCs operate with professional and trained manpower; these MFIs have better technology and access to funds.

Therefore, their productivity level is expected to be high. Additionally, the productivity level can be different with the size of MFI. Therefore, we examine the disparities in the productivity change across MFIs operating at different scales: small, medium and large categories. For doing so, we rely on the Mix Market categorization of MFIs based on the gross loan portfolio (GLP). Finally, the study identifies the factors responsible for productivity change and its components. For the second-stage analysis, we follow Simar and Wilson's (2007) guidelines and apply a bootstrap truncated regression algorithm. We believe that the double bootstrap procedure adopted in the present study performs well, both in terms of deriving statistically consistent productivity estimates in the first stage and root mean square error in the second stage of the DEA analysis.

Undoubtedly, the researchers have made numerous efforts to assess the efficiency level of MFIs in India (see, for example, Masood and Ahmad, 2012; Kumar and Sensarma, 2017; Sinha and Pandey, 2019; Khan and Gulati, 2019; Mohini and Vilvanathan, 2020). However, relatively few studies have examined the productivity behavior of Indian MFIs and rather none in the period after the Andhra crisis of 2010. The study by Babu (2016) examined the total factor productivity (TFP) of 34 Indian MFIs during the period 2005 to 2011 by employing the Malmquist Productivity Index (MPI) approach, as suggested by Färe *et al.* (1994). They found that Indian MFIs experienced a productivity loss due to the technical regress in the industry. Therefore, the Indian MFI sector requires significant innovations in production technology. On the contrary to this, Ambarkhane *et al.* (2019) observed TFP growth mainly attributed to technological advancement from 2012 to 2016. As discussed above, the Indian MFI industry has severely distressed by the Andhra Pradesh crisis in 2010 and confronted sea changes in their regulatory frameworks post2010. However, there is a lack of empirical evidence on how has MFI industry behaved in the wake of ongoing changes and whether the Indian MFIs have shown TFP gain or loss over the last one and a half-decade.

Our study differs from the previous studies of Babu (2016) and Ambarkhane *et al.* (2019) on the Indian context in two aspects. First, the investigation by Babu (2016) is limited to only the prereform period and Ambarkahne *et al.* (2019) based their analysis on postreform data. This study tries to capture the all-around productivity dynamics of MFIs before the Andhra Pradesh crisis (2006–2010) and the post-crisis and regulatory period (2011–2018). Second, previous studies on Indian MFIs have used the conventional DEA-based MPI to measure the productivity change. We note that the traditional DEA-based MPI has several downsides: (1) it does not account for measurement error or errors due to chance or environmental differences while estimations of MPI indices, (2) the estimates are sensitive to the random variations in the data (Simar and Wilson, 1999; Assaf *et al.*, 2010; Wijesiri and Meoli, 2015) and (3) provide statistically imprecise estimators (Wijesiri *et al.*, 2015). To overcome the above concerns, we followed Simar and Wilson's (1999) bootstrapped MPI algorithm to estimate the statistically consistent and bias-corrected productivity change and its decompositions for Indian MFIs. The idea behind bootstrapping of MFI indices and their decompositions is that it allows us to obtain a true estimator of TFP through a good approximation of the true sampling distribution (Balcombe and Rapsomanikis, 2008; Arjomandi, 2011).

All in all, the present study contributes to the infant literature in Indian MFI's productivity in many ways. First, the study is the first to investigate the dynamics in TFP levels and their decompositions for Indian MFIs in the light of new regulatory reforms initiated by the RBI after the Andhra Pradesh crisis 2010. Second, the study is a foremost attempt to obtain statistically reliable and bias-corrected estimates of productivity change and its decompositions by bootstrapping MPI indices. To the best of the authors' knowledge, no study to date has made this attempt in the Indian context. Fourth, the current study examines the productivity variations across distinct organizational forms and sizes of MFIs. Finally, we also identify the contextual factors responsible for the productivity change, catching-up phenomenon and innovation effect in the Indian MFI industry using a double-bootstrap procedure.

The rest of the paper unfolds as follows. Section 2 presents the growth and developments in the microfinance industry in India. Section 3 provides the relevant literature review on the subject matter. The methodological framework, data and input–output specification are discussed in Section 4. Section 5 reports the empirical results, and finally, section 6 concludes the study.

2. Microfinance institutions in India: growth and developments

The development of the Indian microfinance industry has happened in three distinct phases. The period from 1950 to 2001 that represents the formation of the Indian microfinance sector can be referred to as the first phase. In this phase, many nongovernment organizations (NGOs) were originated, mainly between 1992 and 2001, to provide microcredit services and innovations took place. However, this phase is better known as *low outreach and no sustainability* (MFIN, 2012). The second phase, 2002–2011, is known for the *growth and crisis*. This phase pursues the scaling-up and sustainability of MFIs. However, few MFIs were closed operations due to the unfortunate event of the Andhra Pradesh crisis. The third phase, 2012 onwards, emerged as the new era of responsible financial institutions.

2.1 Phase I: Formation of the microfinance industry (1950–2001)

Since the 1960s, the Government of India (GOI) has been continuously formulating and implementing various schemes and microcredit programmes, setting up MFIs for providing financial services to rural people, especially to the economically weaker section. India is among one of the first countries to adopt microfinance. The journey of Indian microfinance started with the NGO in Karnataka in 1968, called Mysore Rehabilitation and Development Agency (i.e. MYRADA). After a few years, in the 1970s, other NGOs get registered to offer microfinance services, which included the Self Employed Women's Association (SEWA) Bank (established in 1974 as a cooperative bank and become India's first MFI), the Annapurna Mahila Mandal (Mumbai based, established in 1975) and the Working Women Forum (Chennai based, established in 1978). The initiation of the microfinance industry is started with the establishment of SEWA Bank in the year 1974, which is considered one of the first MFIs in the Indian MFI industry. Later on, the National Bank for Agriculture and Rural Development (NABARD) initiated a programme on January 26, 1992, that links conventional banks and self-help group (SHG), known as SHG-Bank Linkage Programme (SBLP). Under the SBLP, banks maintain an account of SHG, accept their deposits and provide credit facilities to the group. The SBLP was considered a significant tool to alleviate poverty, and other government agencies also supported this wonderful idea. In the year 2002, the NABARD has initiated the provisioning norm for the unsecured lending to SHGs taken on par with the secured loans.

2.2 Phase II: Expansion, growth and crisis (2002–2011)

The initial years of the second phase are known for growth and expansion in the microfinance sector. Irrespective of a geographic region and outreach, the industry experienced steady growth during the period from 2000 to 2010. As per the Sa-Dhan report, the 129 reported MFIs confirmed their GLP of INR 4275 crores and client outreach of 8.23 million at the end of 2007. The average operating cost reported a decline to reach 11.76% in 2007, from 15.05% as at the end of 2005 (Sa-Dhan, 2007). During this period, the MFIs were primarily dependent on external borrowings, and the capital base was not huge as MFIs. In particular, during the years 2000–2005, the Indian MFIs have grown rapidly, and this growth was mainly driven by credit demand. In March 2006, the Government of Andhra Pradesh temporarily closed the operation of more than 57 branches of Spandana Sphoorthy and SHARE Microfin MFIs operating in the Krishna district. The number of defaulters had risen, and complaints about coercive collection practices were at their peak. The protest by borrowers has started, even allegations on the MFIs included kidnapping to coerce the parents for loan repayments (Mader, 2013). These incidents, coupled with increasing suicide by borrowers, led the government to enact the "Andhra Pradesh Micro-finance Institutions Regulation of Money Lending Act, 2010". According to Microfinance Institutions Network (MFIN) report 2012, total defaults were INR 7,200 crore microloans by 90 lakh borrowers in Andhra Pradesh. It became a national issue, and bankers have stopped issuing loans to MFIs. This led to a decline in the outreach of the MFI industry all over India. As of March 31, 2012, the loan disbursement and borrowers have declined by 38 and 17%, respectively (MFIN, 2012).

At the end of the second phase, the Indian MFI industry faced several challenges, which eventually lead to the launch of regulatory reforms for MFIs in the industry: (1) the industry faced criticism of charging high-interest rate; (2) only large size MFIs had access to the capital market; (3) absence of adequate regulatory framework; (4) dependency on the bank and financial institutions for funding their lending operations; (5) the pressure of aggressive growth plans; (6) lack of skilled and professional workforce; (7) absence of directory of existing MFIs; (8) there was no code of conduct for the MFI industry; (9) approximately 75% of credit portfolio of MFIs was concentrated in the four southern states: Andhra Pradesh, Karnataka, Kerala and Tamil Nadu; (10) most of the credit portfolio was held by nonprofit MFIs; (11) absence of a standardized reporting system; (12) there were no accounting guidelines and prudential norms, which led to highly leveraged balance sheets of MFIs and lack of uniformity and (13) most of the MFIs were dependent upon subsidy and financial assistance: the MFI used to look at social investments in their lending operations.

2.3 Phase III: Institutional changes and regulatory reforms (2012 onwards)

The current phase demonstrates the capacity of MFIs to evolve as self-sustainable financial institutions. The RBI has responded strongly after the Andhra Pradesh crisis, and the MFI industry turns to be more mature and sustainable afterward. In November 2010, the RBI formed a committee headed by Y.H. Malegam to study the issues and concerns of the MFI industry in India. Based on the committee's report, the RBI came with a new regulatory framework for the MFI industry with effect from January 2011. Various regulatory amendments have been recommended to govern the industry in the past decade. It has been made mandatory by the RBI for the MFIs to have a minimum net-own fund of INR 50 million (and INR 20 million for the North East region), and the capital requirements were fixed at 15% of its aggregate risk-weighted assets. RBI came with the provision that lending to the MFIs, with effect from April 1, 2011, will be considered priority sector lending, and they were given the recognition as the tool for financial inclusion by the GOI. The upper limit on interest rate was fixed at 26%. To protect the borrowers from high interest rates, the RBI has fixed the margin cap not to exceed 10% for large MFIs for the portfolio exceeding INR one billion and 12% for other MFIs. In 2014, the RBI allowed only three components to calculate the loan price (a) processing fees not exceeding 1%, (b) interest charge and (c) insurance premium. The MFIs are also directed not to impose any penalty on delaying the installments. To prevent clients' overindebtedness, the RBI has raised the limit on maximum loan from INR 35,000 to INR 60,000 in the first cycle and from INR 50,000 to INR 1,00,000 in the subsequent cycles by the MFIs in 2015. In addition, the MFIs are required to be a member of the Credit Information Bureaus (CIBs) and should follow the RBI's Fair Practice Code while operating the microfinance business. In 2017, the RBI issued the direction to NBFCs operating as MFIs for peer-to-peer lending and other operating guidelines.

3. Literature review

In the past two decades, the performance assessment of MFIs has gained tremendous popularity among policy researchers. Initially, the researchers have employed ratio analysis to assess the performance of MFIs (Lafourcade *et al.*, 2005; Baumann, 2004). The quantitative information from the financial statements and/or balance sheets was being used to assess the liquidity, productivity, profitability and solvency of MFIs. However, traditional ratio methods give an incomplete picture, and the performance results were not well comparable among the MFIs within the industry. Therefore, only relying on the ratio analysis that does not have a feature of comparison or any other indicators is not sufficient enough to make any decision (Widiarto and Emrouznejad, 2015). The contemporary literature spells the use of the frontier techniques as the most celebrated methods to assess the efficiency and productivity of MFIs (see the survey article of Fall *et al.*, 2018; Hermes and Hudon, 2018 for detailed review). Therefore, the researchers have gradually shifted their focus to the frontier methods – both parametric (i.e. stochastic frontier analysis [SFA]) and nonparametric (i.e. data envelopment analysis [DEA]) – to gauge the relative efficiency and productivity of MFIs in the industry. These frontier measures are fair enough to perform performance benchmarking and compare the performance of MFIs. To our knowledge, Hassan and Tufte (2001) is the first study on MFI efficiency that examines the cost efficiency of branches of the Grameen Bank (a Bangladeshi MFI) using the SFA for the period 1988–1991. Since then, the researchers have conducted a plethora of studies employing traditional DEA models for efficiency measurement. Fall *et al.* (2018) present an excellent meta-survey of 38 studies on MFI efficiency using frontier methods. However, the research efforts on investigating the productivity behavior of MFIs are at the embryonic stage. We listed the existing studies on the measurement of the productivity of MFIs across nations in Table 1.

Hassan *et al.* (2012) is perhaps the first study to estimate the productivity performance of MFIs in the Middle East and North Africa (MENA) region employing the DEA-based MPI as proposed by Färe *et al.*'s (1994). They observed technical progress/regress as the primary source of TFP gain/loss for MFIs operating in the MENA region under the production and intermediation approaches. Gebremichael and Rani (2012) estimated the productivity change for the Ethiopian MFI industry and found that TFP grew on average by 3.80% over the study period. Olasupo *et al.* (2014) examined the productivity change in South-West Nigerian MFIs from 2006 to 2010. Using the data from 2006 to 2011, Bassem (2014) reexamined the productivity of MFIs in the MENA region and found efficiency increase as the main driver of TFP gain during the study period. Mia and Chandran (2016) deploy the DEA-based output-oriented MPI to assess the growth in the TFP of 162 Bangladeshi MFI during the years 2007–2012. Their results confirm that the productivity level of Bangladeshi MFIs has improved by 4.30% and is mainly contributed by managerial efficiency change. In contrast, Azad *et al.* (2016) concluded that the pure technical efficiency change significantly contributed to the TFP gain in Bangladeshi MFIs. Jaiyeoba *et al.* (2018) observed that the TFP levels of Bangladeshi and Indonesian MFIs remain stagnant from 2007 to 2011.

Besides, Mia and Soltane (2016) examined the productivity of 50 MFIs operating in the South Asia region and found that the productivity of South Asian MFIs has increased and the technical efficiency contributed significantly to the productivity growth. Recently, Mia *et al.* (2018) assess the TFP growth of the 21 Chinese MFIs operating and find the productivity level remains stagnant over the period and due to the lack of technological advancements. More recently, Kar and Rahman (2018) use the Färe-Primont index developed by O'Donnell (2014) to assess the TFP change of 342 MFIs from 61 countries. They find that over the study period, the productivity level has declined by 1.70%. However, the MFIs operating in Eastern Europe, Central Asia and South Asian regions have shown growth patterns. We note that the empirical findings are mixed and depend largely on different choices in inputs and outputs variables, study period, sources of data and DEA models (Fall *et al.*, 2018).

Author (Year)	Period	N	Country	Methodology	TFP change	Sources of TFP gain/ loss
Hassan *et al.* (2012)	2000–2005	30	MENA region	DEA-based MPI	TFP gain = 14% (Production) TFP loss = (–) 20% (Intermediation)	Technical progress Technical regress
Gebremichael and Rani (2012)	2004–2009	19	Ethiopia	DEA-based MPI	TFP gain = 3.80%	Efficiency increase
Olasupo *et al.* (2014)	2006–2010	86	South West Nigeria	DEA-based MPI	TFP loss =(–) 8.10%	Technical regress
Bassem (2014)	2006–2011	33	MENA region	DEA-based MPI	TFP gain = 4.90%	Efficiency increase
Wijesiri and Meoli (2015)	2009–2012	20	Kenya	DEA-based bootstrap MPI	TFP gain = 7%	Technical progress
Babu (2016)	2005–2011	34	India	DEA-based MPI	TFP loss = (–) 3.70%	Efficiency decline
Mia and Chandran (2016)	2007–2012	162	Bangladesh	DEA-based MPI	TFP gain = 4.30%	Managerial efficiency
Wijesiri (2016)	2005–2011	298	Global	DEA based MLPI	TPF gain = 1.28%	Technical progress
Mia and Soltane (2016)	2007–2012	50	South Asia	DEA-based MPI	TFP gain = 2.1%	Efficiency increase
Azad *et al.* (2016)	2008–2012	15	Bangladesh	DEA-based MPI	TFP gain = 93.50%	Pure efficiency change
Jaiyeoba *et al.* (2018)	2007–2011	31	Bangladesh and Indonesia	DEA-based MPI	TFP stagnant (Bangladesh) TFP stagnant (Indonesia)	Technical progress
Mia *et al.* (2018)	2010–2012	21	China	DEA-based MPI	TFP stagnant	Technical progress
Kar and Rahman (2018)	2003–2013	342	Global	DEA-based MPI	TFP loss = (–) 1.7%	Scale efficiency decline
Ambarkhane *et al.* (2019)	2012–2016	21	India	DEA-based MPI	TFP gain = 19.90%	Technical progress
This study	2005–2018	44 in 2005–06 and 89 in 2011–12	India	DEA based bootstrap MPI	TFP gain = 6.70%	Efficiency increase

Note(s): (1) N = number of MFIs, (2) MPI = Malmquist Productivity Index, (3) DEA = data envelopment analysis, (4) MLPI = Malmquist–Luenberger Productivity Index, (5) TFP = total factor productivity and (6) MENA = Middle East and North Africa
Source(s): Authors' compilation

Table 1. Studies on the productivity of microfinance institutions: a survey of literature

A thorough investigation of the past literature on MFI productivity draws attention to the fact that most previous studies have employed the conventional DEA-based MPI approach to obtain productivity and its components for individual MFIs. As already discussed in the introductory section, the key limitations of traditional MPI are that it does not account for measurement error and provide statistically imprecise estimators. Also, the TFP estimates obtained from Färe *et al.*'s (1994) MPI approach are sensitive to the random variations in the data (Simar and Wilson, 1999; Assaf *et al.*, 2010), and as a result, the estimated indices using the traditional MPI approach may be biased and misleading. To overcome this concern, Simar and Wilson (1999) proposed the bootstrapping of MPI indices and its decompositions and suggested the computation of bias-corrected MPI estimates through a resampling procedure within the DEA framework. Recognizing these downsides of the conventional MPI, Wijesiri and Meoli (2015) adopted the bootstrap procedure of Simar and Wilson (1999) and computed the robust estimates of productivity change for 20 MFIs operating in Kenya during the period 2009–2012. Their results confirm TFP growth of 7% primarily driven by technological advancement. In addition, Wijesiri (2016) employed another variant of productivity measurement – the output-oriented Malmquist–Luenberger Productivity Index (MLPI) – as suggested by Chung *et al.* (1997), which accounts for undesirable output in the assessment of the productivity of 298 MFIs, and they reported the mixed results for distinct types of MFIs during the study period.

In the Indian context, the study conducted by Babu (2016) and Ambarkhane *et al.* (2019) are the only two studies that examine the productivity of MFIs (see Table 1). Babu (2016) examined the TFP of 34 Indian MFIs during the period 2005 to 2011 by employing the conventional MPI approach and found that Indian MFIs experienced a productivity loss due to technical regress. In contrast, Ambarkhane *et al.* (2019) employed output-oriented MPI and observed that TFP growth was mainly attributed to technological advancement from 2012 to 2016. The investigation by Babu (2016) is limited to only the prereform period and Ambarkahne *et al.* (2019) based their analysis on postreform data. Moreover, both the studies on Indian MFIs have relied on the conventional MPI as a potent approach to measure the TFP change.

From the deep scrutiny of the literature, the paper draws the following observations. First, the TFP literature on MFIs, mainly Indian MFIs, providing conclusive evidence is in the infancy stage, and there is a deficiency of research studies examining productivity change, its decompositions and determinants. Second, to the best of the authors' knowledge, none of the studies have examined the productivity behavior of Indian MFIs in the wake of the Andhra crisis and ongoing regulatory developments and across distinct organizational forms and sizes of MFIs. Third, from the methodological point of view, the existing studies duffer from methodological downsides and did not account for measurement error and generate statistically imprecise TFP estimates that are sensitive to the random variations in the data. Lastly, no efforts have been made to investigate contextual factors influencing the productivity change and its components in the Indian case, which makes this study distinct from the existing ones.

4. Methodological framework and data

4.1 DEA based bootstrap Malmquist Productivity Index

As discussed above, this study utilizes bootstrapping algorithm of Simar and Wislon (1999) to measure the bootstrap MPIs and their decompositions in a DEA framework. It is noteworthy here that the nonparametric DEA-based MPI approach has been quite well popularized in the productivity measurement since (1) it does not require any price information for input and output variables, (2) it relaxes the behavioral assumption of profit maximization and cost minimization, (3) it does not pre-assume the production technology for the functional form and (4) allows the decomposition of MPI indices into efficiency change (i.e. catching-up) and technological change (i.e. innovation) (Coelli *et al.*, 2003). See the eminent surveys by Fried *et al.* (2008), Del Gatto *et al.* (2011) and Sickles and Zelenyuk (2019) for the developments in the field of TFP growth measurement. However, the traditional MPI suffers from serious downside as the TFP estimates are sensitive to the random variations in the data and thus may lead to less reliable estimation (Simar and Wilson, 1999; Assaf *et al.*, 2010; Wijesiri and Meoli, 2015). The bootstrapping of MPI indices in the present study overcomes the above limitations of traditional DEA models. Simar and Wilson (1999) suggested that bootstrap MPI not only corrects for statistical bias in productivity measurement by providing bias-corrected TFP scores and its components but also offers valid confidence intervals, which are more robust, consistent and reliable. For the second-stage analysis, we perform the bootstrap truncated regression to determine the contextual factors responsible for variations in the productivity levels and its decompositions.

In order to estimate the productivity change during t and $t+1$, we consider n MFIs that may produce s output by utilizing m inputs over the time period T. Normally, an MFI in the period t uses x_t inputs to produce y_t outputs, where in the period $t+1$ quantities of input and output can be defined as x_{t+1} and y_{t+1}, respectively. Therefore, the production possibility set at time t is

$$P_t = \{(x, y)|x \ \text{can produce}\, y\, \text{at time}\, t\}, \tag{1}$$

x represents the input vector, $x \in \Re^n_+$ and y represents the vector for output, $y \in \Re^m_+$ at time t. The output feasibility set for "o" MFI can be described as

$$y_{t+1}(x_{o,t}) = \left\{y \in \Re^m_+ |(x, y) \in P_t\right\}, \tag{2}$$

Shephard (1970) suggest the output distance function for "o" MFI at the time t is

$$D_{o,t|t+1} \equiv \inf\left\{\theta > 0|y_{o,t}/\theta \in y_{o,t+1}(x_{o,t})\right\} \tag{3}$$

$D_{o,t|t+1}$ estimates the distance from the oth MFI's position in the input–output space at the time t to the boundary of the production set at the time $t+1$, where inputs remain constant and θ is a scalar equal to the efficiency score. When t and $t+1$ are equal, it is a measure of efficiency relative to the technology at the same time and $D_{o,t|t}$. Two same periods $(D_{o,t|t}, D_{o,t+1|t+1})$ and two mixed period $(D_{o,t|t+1}, D_{o,t+1|t})$ distance functions are required to be computed. Based on Färe *et al.* (1992), the Malmquist index between periods t and $t+1$ for "o" MFI at constant returns-to-scale assumption is then defined as

$$M_o(t, t+1) = \sqrt{\frac{D^{CRS}_{o,t|t+1}}{D^{CRS}_{o,t|t}} \times \frac{D^{CRS}_{o,t+1|t+1}}{D^{CRS}_{o,t+1|t}}} \tag{4}$$

The $M_o(t, t+1)$ is defined as the geometric mean of two Malmquist productivity indices for t and $t+1$. If $M_o(t, t+1) > 1$, the total factor productivity change (TFPCH) has improved between periods t and $t+1$. If $M_o(t, t+1)$ <1, it indicates that the TFPCH has declined. And $M_o(t, t+1) = 1$ implies no change in the productivity level.

Note that the production possibility set P_t and all the defined distances remain unobserved. Therefore, the MPI and the distance functions should be measured. It requires the estimation of the production set, $\widehat{P}_t$, and the output feasibility set, $\widehat{y}(x)$ as in (5) and (6):

$$\widehat{P}_t = \left\{(x, y) \in \Re^{m+s}_+ |y \le Y_t\lambda, x \ge X_t\lambda, \lambda \in \Re^n_+\right\} \tag{5}$$

where $Y_t = [y_{1,t}, y_{2,t}, \ldots, y_{s,t}]$, signifies $(s \times 1)$ vector of observed outputs in t period, $X_t = [X_{1,t}, x_{2,t}, \ldots, x_{m,t}]$, signifies $(m \times 1)$ vector of observed inputs in t period, and λ is an intensity variable, respectively. We can define the output feasibility set $(\widehat{y}(x))$ as follows:

$$\widehat{y}_t^{CRS}(x) = \{y \in \mathfrak{R}_+^s | y \leq Y_t\lambda, x \geq X_t\lambda, \lambda \in \mathfrak{R}_+^n\}, \tag{6}$$

By replacing $\widehat{y}_t^{CRS}(x)$ for $y_t(x)$ in (6), the same period and mixed period distance functions can ultimately be obtained by solving the following linear programmings (7) and (8), respectively:

$$\left(\widehat{D}_{o,t|t}^{CRS}\right)^{-1} = \max\{\lambda | \lambda y_{o,t} \leq Y_t\lambda_o, x_{o,t} \geq X_t\lambda_o, \lambda_o \in \mathfrak{R}_+^n\}, \tag{7}$$

$$\left(\widehat{D}_{o,t|t+1}^{CRS}\right)^{-1} = \max\{\lambda | \lambda y_{o,t} \leq Y_{t+1}\lambda_o, x_{o,t} \geq X_{t+1}\lambda_o, \lambda_o \in \mathfrak{R}_+^n\}, \tag{8}$$

For the given estimates of the distance functions, the MPI can be measured by replacing the estimators for the corresponding true distance function values in (4):

$$\widehat{M}_o(t, t+1) = \sqrt{\frac{\widehat{D}_{o,t|t+1}^{CRS}}{\widehat{D}_{o,t|t}^{CRS}} \times \frac{\widehat{D}_{o,t+1|t+1}^{CRS}}{\widehat{D}_{o,t+1|t}^{CRS}}} \tag{9}$$

Here $\widehat{M}_o(t, t+1)$ is the index of output-oriented total factor productivity (*TFPCH*) for the latest production unit given technology $t+1$ related to technology t. *TFPCH* can be decomposed into two components, efficiency change (*EFFCH*) and technological change (*TECH*) as

$$TFPCH = \widehat{M}_o(t, t+1) = \left(\frac{\widehat{D}_{o,t+1|t+1}^{CRS}}{\widehat{D}_{o,t|t}^{CRS}}\right) \times \left(\frac{\widehat{D}_{o,t|t+1}^{CRS}}{\widehat{D}_{o,t+1|t+1}^{CRS}} \times \frac{\widehat{D}_{o,t|t}^{CRS}}{\widehat{D}_{o,t+1|t}^{CRS}}\right)^{1/2} \tag{10}$$

where $EFFCH = \dfrac{\widehat{D}_{o,t+1|t+1}^{CRS}}{\widehat{D}_{o,t|t}^{CRS}}$ and $TECH = \left(\dfrac{\widehat{D}_{o,t|t+1}^{CRS}}{\widehat{D}_{o,t+1|t+1}^{CRS}} \times \dfrac{\widehat{D}_{o,t|t}^{CRS}}{\widehat{D}_{o,t+1|t}^{CRS}}\right)^{1/2}$

If the *EFFCH* is greater than unity, it represents efficiency improvement, and if *EFFCH* equals unity, it means productivity stagnation. However, less than unity represents the decline in the efficiency level. The term technological change (*TECH*) represents the technological progress (or regress) between t and $t+1$. The ratio greater than one indicates technological up-gradation, equals to unity represents no change in the technology and less than one indicates the degradation in the technology. Thus,

$$TFPCH = TECH \times EFFCH$$

where *TECH* represents the innovation effect from period t to $t+1$, *EFFCH* exhibits the catching-up between two time periods. The product of these two components represents the *TFPCH* during the period t and $t+1$. Though the MPI based on traditional DEA is very flexible and no need for predefined production technology, it still suffers from drawbacks. As indicated above, the traditional MPI does not determine whether productivity estimates are true or merely due to sampling noise (Simar and Wilson, 1999). Moreover, the estimates are inconsistent due to sampling variations (Simar and Wilson, 2000). Therefore, in this study, we followed Simar and Wilson (1999) to overcome these issues and bootstrapped MPI indices using the bivariate smooth homogeneous bootstrap procedure with 2000 replications to obtain the consistent estimates of *TFPCH* and its components for individual MFIs.

4.1.1 Bootstrapping procedure.

Step 1: Compute the MPI $\widehat{M}_o(t, t+1)$ for each MFI ($j = 1, 2, 3, \ldots, n$) in each time (t and $t+1$) by solving the linear programming problems in Equations (7) and (8).

Step 2: Estimate the pseudo sample $\{(x^*_{j,t}, y^*_{j,t}); j = 1, \ldots, n; T = t, t+1\}$ to get reference bootstrap technology by incorporating the bivariate kernel density estimation and bandwidth was selected as suggested by Silverman (1986).

Step 3: Obtain the bootstrap estimate of MPI for $\widehat{M}^*_o(t, t+1)$ each individual MFI ($j = 1, 2, 3\ldots, n$) by using the pseudo sample obtained in step 2.

Step 4: Repeat steps 2 and 3, B times (i.e. number of bootstrap replication, which we set as $B = 2000$ in our case) in order to compute the bootstrap sample.

Step 5: From the bootstrap sample obtained in step 4, calculate bias-corrected estimates and confidence interval for the MPI estimates.

The framework intended for estimation of the confidence intervals of the Malmquist indices that the distribution of $\widehat{M}_o(t, t+1)$ and $M_o(t, t+1)$ is unknown and can be estimated by the distribution of $\widehat{M}^*_o(t, t+1) - \widehat{M}_o(t, t+1)$, where $M_o(t, t+1)$ is the true unknown index. $\widehat{M}_o(t, t+1)$ is the estimate of the Malmquist index and $\widehat{M}^*_o(t, t+1)$ is the bootstrap estimate of the index. Thus, an estimated $(1-a)$ percentage confidence interval for the "o" MFI's Malmquist index is given by

$$\widehat{M}_o(t, t+1) + L^*_a \leq M_o(t, t+1) \leq \widehat{M}_o(t, t+1) + U^*_a \tag{11}$$

One may also correct for the possible finite-sample bias in the original estimators of the Malmquist indices by following Simar and Wilson's (1999) guidelines. The bootstrap bias estimate for the original estimator $\widehat{M}_o(t, t+1)$ is

$$bias_B[\widehat{M}_o(t, t+1)] = B^{-1} \sum_{b=1}^{B} \widehat{M}_o(t, t+1)(b) - \widehat{M}_o(t, t+1) \tag{12}$$

In a similar way, we can measure the bias-corrected estimates of $\widehat{M}_o(t, t+1)$ as

$$\begin{aligned} \widehat{\widehat{M}}_o(t, t+1) &= \widehat{M}_o(t, t+1) - bias_B[\widehat{M}_o(t, t+1)] \\ &= 2bias_B[\widehat{M}_o(t, t+1)] - B^{-1} \sum_{b=1}^{B} \widehat{M}_o(t, t+1)(b) \end{aligned} \tag{13}$$

Simar and Wilson (1999) pointed that the bias-corrected estimator should be considered only if the sample variance S_o^{2*} of the bootstrap values $\{\widehat{M}^*_o(t, t+1)\}_{b=1,\ldots,B}$ is less than one-third of the squared bootstrap bias estimate for the original estimator, i.e. $S_o^{2*} < \frac{1}{3}(bias_B[\widehat{M}_o(t, t+1)])^2$. Steps 1–5 can be repeated for components of MPI or TFPCH, i.e. *EFFCH* and *TECH* to obtain bootstrap estimates.

4.2 Data and specification of input and output variables

This study follows notable works by Piot-Lepetit and Nzongang (2014) and Wijesiri and Meoli (2015) and used a mix of both production and intermediation approaches to select inputs and outputs for productivity measurement and its decompositions for Indian MFIs.

Our inputs vector consists of (1) total assets, (2) operating expenses and (3) employees. The total assets (*input*) includes the total of all net assets, and this variable has been used by many researchers in the MFI literature (Hassan *et al.*, 2012; Babu and Kulshreshtha, 2014; Jaiyeoba *et al.*, 2018). The operating expenses (*input*) are widely used proxy for input in the production process (Hassan *et al.*, 2012; Bassem, 2014; Babu and Kulshreshtha, 2014; Wijesiri and Meoli, 2015; Kar and Rahman, 2018; Jaiyeoba *et al.*, 2018). The number of employees (*input*) represents the staff that is directly related to lending activities. Further, we consider three outputs, namely, (1) GLP, (2) financial revenue, as the proxy of financial performance, and (3) the number of borrowers, as the proxy for social outreach. The GLP (output) is the total of credit placed during the financial year and is considered one of the key activities of MFIs. The number of borrowers is the proxy to measure the social outreach (breadth of outreach) of MFIs and used by various researchers to estimate the productivity of MFI. Moreover, in this study, to estimate the productivity level, we select the outputs mix representing both the perspectives of microfinance, financial sustainability and social outreach.

The data on selected input and output variables are collected from the MixMarket database. The study is conducted on data of all the Indian MFIs operating over the period from 2005 to 2018, which represents an unbalanced panel of 900 observations that is the largest sample size taken for productivity measurement of Indian MFIs. The focus of the previous studies is on a sample of a balanced panel of MFIs. Our sample includes 466 observations for NBFC-MFIs and 434 observations for nonNBFC-MFIs (cooperatives, NGOs, trust, Section 8 companies). The variables are extracted in USD, which are comparable, and data on employees and the number of active borrowers are in actual numbers. In all, our sample size (n) is in accordance with the Cooper *et al.* (2007) guidelines, i.e. (1) the sample size used in the DEA framework must be $n \geq m \times s$ and (2) sample size must be greater or equal to three times of the number of outputs and plus the number of inputs, i.e. $n \geq 3(m + s)$. The descriptive statistics of input–output used in the DEA model is reported in Table 2.

To obtain reliable estimates, we have made several data adjustments. First, the inconsistent observations in the dataset could be possible candidates of outliers (Barnett and Lewis, 1994). If not detected and removed from the dataset, the outliers may shift the entire production frontier upward (or downward) (Bogetoft and Otto, 2010). Banker and Gifford (1988) and Andersen and Petersen (1993) suggested using the super-efficiency procedure in the DEA model to eliminate the over influential points from the production frontier. Therefore, in order to estimate the true production frontier, we first detect the outliers by using the procedure suggested by Banker and Gifford (1988) and Banker and Chang (2006). All the MFIs with a super-efficiency score greater than two is declared as an outlier and removed from the analysis. Second, the process of mean normalization is adopted for each data variable. Third, since our panel is unbalanced, therefore, in order to avoid any potential bias in the analysis, the estimates for TFPCH and its components have been obtained by separately running the model for a two-year period considering each case a balanced panel of

Model	Variables	Mean	Std. dev.	Min.	Max.
Inputs	Total assets (US$'000)	53278.135	162899.060	4.482	2278871.415
	Operating expenses (US$'000)	3788.162	11757.751	8.14	195366.945
	Labor (in number)	845.600	2008.938	10	22733
Outputs	Financial revenue (US$'000)	9755.957	30334.460	3.586	1974730.188
	Gross loan portfolio (US$'000)	50826	154001.278	0.609	444278.043
	Borrowers (in Number)	264.572	714.531	46	6242266

Source(s): Authors' calculations

Table 2.
Descriptive statistics of input and output variables

MFIs. A similar procedure is adopted by Gulati and Kumar (2016) to estimate the productivity and its components in case of an unbalanced panel.

5. Empirical results

5.1 Productivity change and its components in the Indian MFI industry

Table 3 exhibits the estimates of bootstrap MPI indices, i.e. *TFPCH* and its components: *EFFCH* and *TECH* for the Indian microfinance industry over the period 2005 to 2018. It is noteworthy here that the bootstrap value of productivity estimate *TFPCH* > 1 (= or <1) indicates the productivity growth (no change or loss), *EFFCH* > 1 (= or <1) reflect efficiency increase (no change or decrease) and *TECH* > 1 (= or <1) signifies technical progress (no change or regress). The year-wise trend in *TFPCH, EFFCH* and *TECH* during the period 2005–2006 to 2017–2018 can be observed from Panel A of Table 3 and visualized in Figure 1. It is worth noting here that the value of the index is greater than unity indicates TFP gain (either due to efficiency increase or technical progress). In contrast, the value less than unit represents TFP loss (either due to efficiency decline or technical regress), whereas unity means stagnant. From bias-corrected estimates of TFPCH, we note that, on average, Indian MFIs have shown productivity growth at the rate of 6.70% per annum during the entire study period. Our findings are corroborated by the empirical results by Ambarkhane *et al.* (2019),

Year	*N*	*TFPCH*	*EFFCH*	*TECH*
Panel A: Year-wise geometric means				
2005–2006	44	1.047	1.003	1.046
2006–2007	67	1.199	1.155	1.045
2007–2008	53	1.169	1.030	1.134
2008–2009	57	1.042	1.045	0.999
2009–2010	66	0.944	1.007	0.938
2010–2011	72	1.053	1.125	0.938
2011–2012	89	1.078	1.055	1.021
2012–2013	83	0.981	0.982	1.003
2013–2014	77	1.073	1.049	1.027
2014–2015	73	1.058	1.010	1.052
2015–2016	77	1.138	0.999	1.142
2016–2017	76	1.030	1.107	0.940
2017–2018	66	1.061	1.051	1.014
Panel B: Geometric mean for sub-periods				
Entire period (2006–2018)		1.067	1.048	1.023
First sub-period (2006–2011)		1.076	1.061	1.017
Second sub-period (2012–2018)		1.060	1.036	1.028
Panel C: Hypothesis testing across sub-periods				
H_o: $FSP_{distriution} = SSP_{distribution}$				
Kruskal–Wallis test		0.001 (0.980)	1.403 (0.236)	6.178 (0.012)**
Jonckheere–Terpstra test		971 (0.022)**	952 (0.236)	106 (0.013)**
Li Test		0.404 (1.00)	0.032 (0.554)	5.969 (0.002)***

Note(s): (1) *N* = number of MFIs, (2) *TFPCH* = total factor productivity change, *EFFCH* = efficiency change, *TECH* = technical change, (3) *FSP* = first sub-period, *SSP* = second sub-period and (4) ***,** and * indicate coefficients are significant at 1, 5 and 10% levels, respectively
Source(s): Authors' calculations

Table 3. Productivity change and its components for the Indian MFI industry

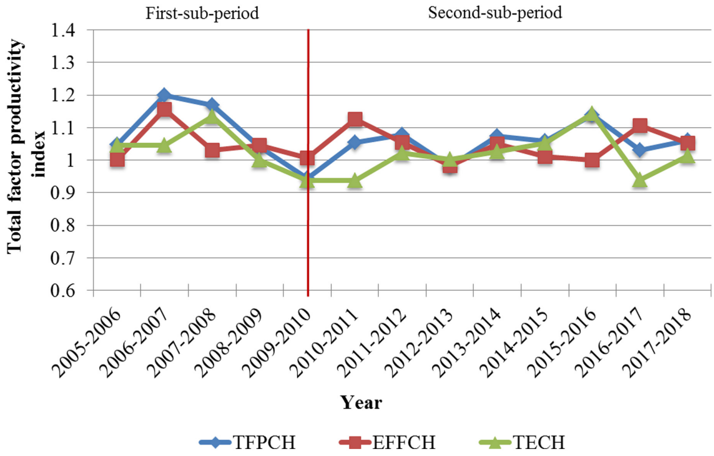

Figure 1.
Trends in TFP change and its components in the Indian MFI industry

who reported that the productivity of Indian MFI grew at the rate of 11.90% per annum during the year 2012–2016. Our findings are statistically more robust and reliable, as our annual growth rate estimates are relatively lower than other similar studies since estimates are bias-adjusted.

The observed TFP growth has been primarily contributed by efficiency improvement at the rate of 4.80% during the study period. At the same time, the technical progress occurred at a moderate rate of 2.3%. It has been observed that the period from 2005 to 2010 reflects a significant boom in MFIs lending activities, entry of new MFIs and the success of Swayam Krishi Sangham (SKS) IPO in the MFI sector. In addition to that, the subsequent period known for regulatory reforms has comforted the MFIs to convert themselves to NBFCs and get access to the funds and other benefits, innovative credit assessment and better delivery mechanisms, developments of new financial products and onboarding process, outsourcing of activities to FinTech firms, services offered from technology firms to the MFIs, etc. which might have drastically reduced their operating expenses and improved the overall performance of MFIs. Altogether, the efficiency improvement from both financial and social perspectives, credit boom, regulatory reforms coupled with the hiring of skilled and professional manpower, technological advancements through entry of FinTech firms in the MFI sector, etc. are the key contributing factors that might have driven the productivity growth.

5.2 Productivity change in response to regulatory reforms

After the Andhra Pradesh crisis in the year 2010, based on the recommendations of the Y.H. Malegam Committee Report, 2011, the RBI regulations were introduced in the Indian MFI industry. Therefore, we use the year 2010 as a reference year. We divided the study period into two sub-periods: the first sub-period (2005–2010) and the second sub-period (2011–2018) to investigate the impact of regulatory reforms on the productivity behavior of Indian MFIs. Panel B of Table 3 reports the geometric means of indices during the entire study period and for the two distinct sub-periods. We note that the TFP in the MFI industry grew at 7.6% annually during the first sub-period, mainly driven by efficiency improvement at the rate of 6.1%. Further, the results are in contrast with the findings reported by Babu and Kulshreshtha (2014). They reported a dip in the TFP levels of Indian MFIs during the period 2005 to 2011, which was mainly due to efficiency decline. Moreover, the findings of this study report that the productivity growth was lower in the second sub-period, which stood at 6% per annum as compared to 7.6% in the first sub-period.

Although the rate of catching-up has lowered by 2.5% (*EFFCH* = 1.036) per annum, the MFI industry experienced innovations or technological advancements in the second sub-period, particularly after the inception of new regulatory reforms by the RBI in 2011. It is evident that during the second-sub period, the Indian MFI industry records technical progress at a rate of 2.8% per annum (*TECH* = 1.028). The observed productivity gains could be attributed due to several reasons. First, the increased cap on borrowers' indebtedness from INR 50,000 to INR 100,000 led to an increase in the average loan size of borrowers by 58% during the financial year 2014–2016 (MFIN, 2018). Second, in addition to regulatory changes, priority sector lending norms, shifting customer base-from rural to urban (i.e. cut down operating cost and maximize operating efficiency), augmented availability of a variety of debt funds, increased data quality of borrowers (i.e. credit bureaus have supported in pre-and post-acquisition risk assessment) along with the technological investments might have permitted MFIs to experience efficiency gains and technical progress, and eventually, the productivity growth in the entire MFI industry during the sub-periods.

Our findings clearly indicate the positive impact of the new regulatory framework on adopting innovations or technological advancements in the MFI industry. The MFIs could have achieved more productivity growth since the regulatory reforms have broadened the outreach of the Indian MFI industry. However, relatively low efficiency increase limited the ability of MFIs to further enhance their TFP levels. The efficiency deterioration in the second sub-period might have happened because the RBI has fixed the interest rate charged by MFIs in 2013, which has curbed the financial revenue of MFIs and hence the efficiency has decreased, leading to a lower productivity level in 2012–2013 (see Figure 1). Another plausible reason behind this deterioration could be the decline in the repayment rate after the demonetization was announced in November 2016. The MFI industry faced major liquidity issues and a subsequent decline in efficiency during 2015–2016. However, the industry has recovered soon and did not face any other major consequences except a temporary decline in the repayment rates and efficiency levels.

We extend our analysis to statistically validate whether the variations in the *TFPCH, EFFCH* and *TECH* during the first and second-sub-period are statistically significant. For this, we conducted three tests: the Jonckheere–Terpstra test, the Li test and the Kruskal–Wallis test. The test results are reported in Panel C of Table 3. The Jonckheere–Terpstra test results suggest that the difference in productivity change and technology change during the first and second sup-periods are statistically significant at a 5% significance level. In addition, the estimates of the Kruskal Wallis test reflect that the differences in technological change are statistically significant only at a 5% level of significance. Even though the variations in efficiency change exist between the sub-periods, but these differences are statistically insignificant. Further, all three tests reject the null hypothesis in the case of the *TECH* component, implying the statistically significant difference in technological change across the two sub-periods. Moreover, the study concludes that reforms have stimulated the technology adaptation and innovations in products and business models, sources of funds, etc., which ultimately lead to growth in the productivity performance of MFIs in India.

5.3 Productivity variations across organizational forms of MFIs

This section explains the variations in the TFP change and its sources across the different legal types of MFIs in India. As discussed earlier, we classify our sampled MFIs into two groups: (1) NBFC MFIs and (2) non-NBFC MFIs, which consist of NGOs, trusts and societies. An empirical investigation of productivity differences across NBFCs and non-NBFCs is important because these MFIs fall under distinct regulatory structures and follow distinct business strategies. We believe that there may exist differences in productivity levels and technical advances across distinct legal forms of MFIs. The bootstrapped estimates of TFP change and its decompositions corresponding to these two forms of MFIs are reported in Table 4 and displayed in Figure 2. We note NBFCs and non-NBFCs experienced productivity gains at the rate of 7.6 and 5.6%, respectively, during the entire study period. This finding signifies that NBFC MFIs reportedly observed higher productivity growth as compared with non-NBFC MFIs (see Panel B of Table 4). The notable TFP gains in NBFCs are largely attributed to the efficient catch-up process. In the case of non-NBFCs MFIs, the productivity improvements are more or less equally driven by efficiency increase and technical progress.

In order to assess the effect of regulatory changes on the TFP levels of NBFC and non-NBFC MFIs, we again compared the bootstrap estimates of MPI indices across distinct sub-periods. From the geometric means of the estimates, as reported in Panel B of Table 4, we find both NBFCs and non-NBFCs have shown productivity growth of around 7% per annum in the first sub-period. It is interesting to note that, for NBFCs, this TFP gain was entirely driven by efficiency improvement with a meager innovation effect of 0.08% before the inception of regulatory reforms in 2011. Nevertheless, in the case of non-NBFCs, the productivity is driven partially by the technical progress at the rate of 2.1% per annum along with catching up at the rate of 5.3% per annum in the first sub-period. However, in the second sub-period, the productivity gaps between the NBFC and non-NBFC MFIs got widened to 3% per annum (7.3% versus 4.3%). Despite the technical progress, the efficiency decline attributed to lower TFP growth by 3.3% in the second sub-period (i.e. 7% in the first sub-period versus 4.3% per annum in the second sub-period).

Although the technology innovations enabled the MFIs to assess borrowers' creditworthiness, the collection rate has been boosted. Recently, technology advancement, mobile penetration, entry of financial technology (FinTech) firms lowered the transaction cost, expanded the outreach to a new market, increased competition with small finance bank and payment bank and universal banks have enabled the MFIs to raise their performance levels (the World Bank, 2017). Yet, innovations have not fully been transmitted to reap higher productivity gains especially due to low catching-up in the second sub-period in the Indian MFI industry. Overall, the slower pace in TFP growth and catching up effect in the second sub-period might reflect the adverse impact of the unfortunate event Andhra Pradesh crisis on both types of MFIs. However, efficiency deterioration was statistically significant only for the *EFFCH* component (see Panel C of Table 4). Based on statistical testing, we also find that variations in the technical change component are statistically significant for both NBFCs and non-NBFCs. However, the slower pace in EFFCH is observed to be significant only for non-NBFCs in the second sub-period.

5.4 Productivity variations across MFIs by size groups

Next, we move to examine the productivity variations across the various sizes of MFIs. For size classification, we relied on the MIX Market criterion and categorized the MFIs as small, medium and large based on the total assets. The estimates of *TPFCH, EFFCH* and *TECH* across the different scale sizes of MFIs are reported in Table 4 and graphically displayed in Figure 3. Astonishingly, the small MFIs show higher TFP growth at the rate of 12.6% per annum, followed by the large MFIs (i.e. 4.80% per annum) and medium MFIs (i.e. 4.1% per annum). In all the cases, *EFFCH* remains the major contributing element for productivity progress. This might be because debt-based funding was easily available to small MFIs for lending purposes. Moreover, the favorable regulatory environment, technological advancement and the increased competitiveness with small finance banks and universal banks and FinTech firms might have enabled MFIs belonging to this size group to bring operating costs down and maximize operating efficiency and productivity. Variations in

Table 4. Productivity change and its components by organizational forms of Indian MFIs

MFIs type	NBFC				Non-NBFC			
Year	N_{NBFC}	*TFPCH*	*EFFCH*	*TECH*	$N_{Non\text{-}NBFC}$	*TFPCH*	*EFFCH*	*TECH*
Panel A: Year-wise geometric means								
2005–2006	16	0.996	0.967	1.036	28	1.076	1.024	1.051
2006–2007	24	1.230	1.220	1.003	43	1.182	1.118	1.068
2007–2008	27	1.172	1.036	1.123	26	1.167	1.024	1.145
2008–2009	30	1.031	1.023	1.011	27	1.054	1.071	0.986
2009–2010	36	0.960	1.015	0.947	30	0.925	0.998	0.929
2010–2011	37	1.085	1.164	0.927	35	1.019	1.084	0.950
2011–2012	45	1.081	1.059	1.019	44	1.075	1.052	1.023
2012–2013	43	1.021	0.986	1.037	40	0.939	0.977	0.966
2013–2014	42	1.057	1.043	1.020	35	1.092	1.057	1.036
2014–2015	41	1.058	1.006	1.055	32	1.058	1.015	1.048
2015–2016	44	1.181	1.043	1.123	33	1.081	0.940	1.168
2016–2017	43	1.020	1.122	0.915	33	1.044	1.087	0.971
2017–2018	38	1.095	1.068	1.029	28	1.015	1.028	0.993
Panel B: Geometric mean								
Entire period (2006–2018)		1.076	1.058	1.019	–	1.056	1.036	1.026
First sub-period (2006–2011)		1.079	1.071	1.008	–	1.070	1.053	1.021
Second sub-period (2012–2018)		1.073	1.047	1.028	–	1.043	1.022	1.029
Panel C: Hypothesis testing								
H_0: $FSP_{distriution} = SSP_{distribution}$								
Kruskal–Wallis test		0.050 (0.822)	1.614 (0.203)	5.115 (0.024)**	–	0.062 (0.803)	0.209 (0.647)	1.725 (0.189)
Jonckheere–Terpstra test		248 (0.822)	233 (0.203)	283 (0.024)**	–	234 (0.804)	225 (0.647)	248 (0.189)
Li Test		19.696 (0.498)	1.123 (0.863)	0.195 (0.000)***	–	37.586 (0.158)	1.863 (0.034)**	63.686 (0.000)***

Note(s): (1) N = number of MFIs, (2) *TFPCH* = total factor productivity change, *EFFCH* = efficiency change, *TECH* = technological change, (3) *FSP* = first sub-period, *SSP* = second sub-period and (4) ***, ** and * indicate coefficients are significant at 1, 5 and 10% levels, respectively

Source(s): Authors' calculations

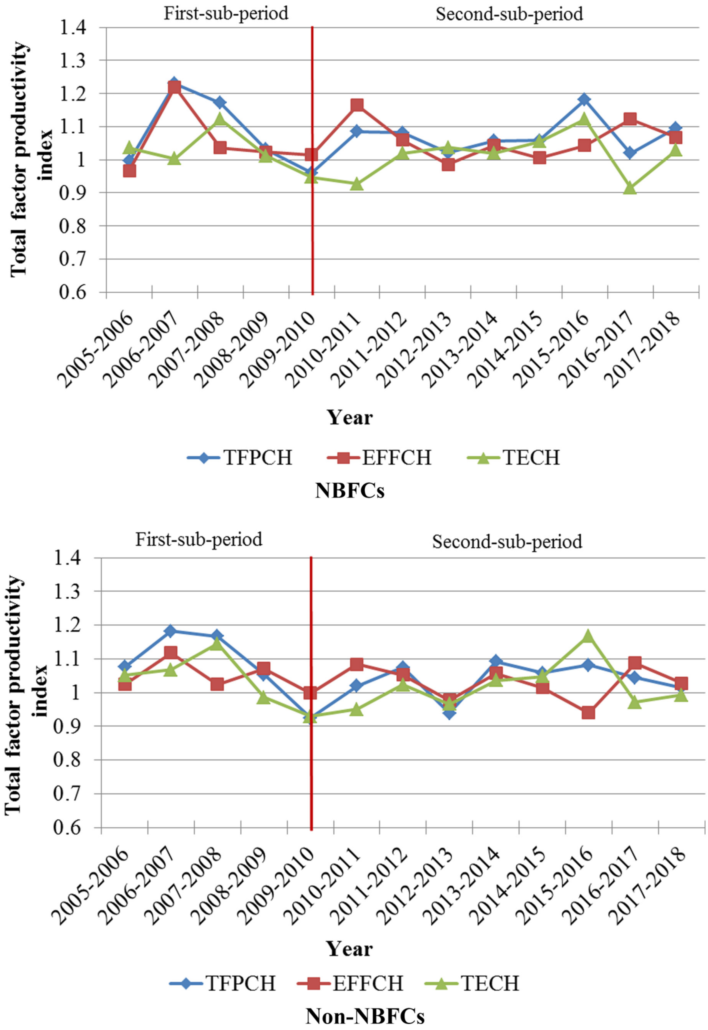

Figure 2.
Trends in TFP change and its components by the organizational form

productivity changes during the sub-periods reveal that TFP growth was higher during the first sub-period, especially for small MFIs, which stood at the rate of 16.80% per annum. While examining the sources of productivity gain, we note the efficiency change has contributed mainly to this change.

The productivity trend was observed to be really interesting in the second sub-period. The medium and large MFIs experienced a significant TFP improvement while, for small MFIs, the TFP rate was slowed by one-half. The perceived gains in productivity levels in medium MFIs were primarily attributable to technological advancement in the second sub-period, wherein efficiency improvement led to productivity enhancement for large MFIs. This is clearly indicated from the fact that small and medium MFIs adopted the new business model to deliver microfinancial services to the poor (PwC, 2019). Even though TFP improved for large and medium MFIs in the later period, the rate of TFP growth remained higher for small MFIs. Further, the decline in the productivity during the year 2009–2010 in the case of small

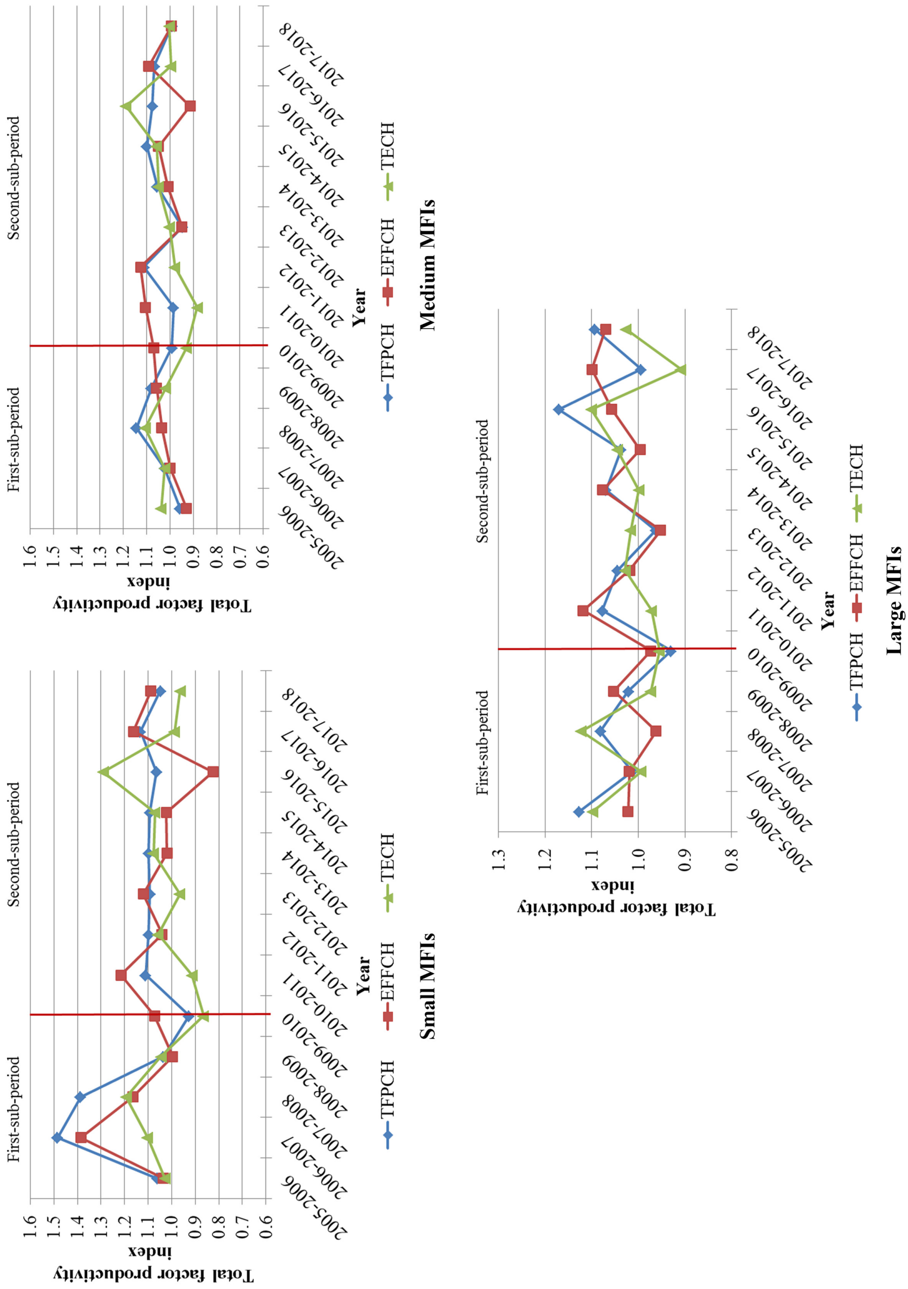

Figure 3.
Trends in TFP change and its components by size groups

(i.e. (−)7.4%) and large (i.e. (−)7%) MFIs clearly reflects the adverse impact of the Andhra Pradesh crisis on Indian MFI industry. However, the immediate action of the RBI with a new policy framework brought the MFI industry on the right track. The Kruskal–Wallis test, Jonckheere–Terpstra and Li tests confirm the significant variations in the technological change component for medium and large MFIs during the first and second sub-periods. The Li test confirms significant changes in TFP levels of medium MFIs at a 1% level of significance (see Table 5).

5.5 Second-stage bootstrap truncated regression results

We extend the analysis to identify the factors determining the productivity change and its components in the Indian MFI industry. The study employs the bootstrap truncated regression algorithm of Simar and Wilson (2007) for the second-stage analysis to provide reliable second-stage estimates. Simar and Wilson (1999, 2007) point that traditional DEA-based MPI may produce inconsistent and biased estimators, which can mislead the economic interpretation. We overcome this situation by utilizing Simar and Wilson's double bootstrap procedure that yields statistically valid estimates and accounts for the biasness and serial correlation among the estimates in the second stage, i.e. in post-DEA analysis. Interested readers are directed to Simar and Wilson (2007) for more details about the double bootstrap procedure. In this study, we regressed the bootstrap MPI estimates and its components obtained in the first stage on the predefined explanatory variables as specified in equation (14) below:

$$TFPCH_{i,t}(\text{or } EFFCH_{i,t} \text{ or } TECH_{i,t}) = \beta_0 + \beta_1 SIZE_{i,t} + \beta_2 REFORMS_{i,t} + \beta_3 PAR30_{i,t} + \beta_4 ORGFORM_{i,t} + \beta_5 AGE_{i,t} + \beta_6 SUSTAINABILITY_{i,t} + \varepsilon_{i,t} \tag{14}$$

where β_0 is the intercept, $\beta_1, \ldots, \beta_6$ are the parameters and ε represents the error. The study considers the impact of MFI *SIZE* (log of total assets), the impact of the credit quality of the loan portfolio by incorporating the PAR30 (portfolio at risk greater than 30 days) as an indicator of credit quality and five dummy variables: *REFORMS, ORGFORM, AGE, AND SUSTAINABILITY* to capture the impact of new regulatory reforms, organizational form, year of experience of MFIs and the impact of sustainability, respectively. This paper uses *OSS*, i.e. operational self-sufficiency, as a proxy for *sustainability*. *OSS* is defined as operating income/(financing cost + operating cost + other loan loss provisions). The *OSS* represents that MFIs can cover all the operating and financing costs of operations. The results of regression analysis are demonstrated in Table 6. The explanatory powers of each model are high since the value of Wald χ^2 statistics for all the regression equations is statistically significant (see Panel B of Table 6).

We observe from the empirical results that *SIZE* is negatively associated with productivity change and its components. However, this association is statistically significant for *TFPCH* and *TECH* only. Similar findings have been observed by Mia and Soltane (2016) in South Asian MFIs that large MFIs tend to have relatively lower productivity levels that reflect the inefficiency of large MFIs in asset utilization. It is worth mentioning here that the larger MFIs are not engaged in significant technological innovations. Only small and medium-sized MFIs are aggressively focusing on technological advancement to further enhance their productivity level. Besides, in line with Wijesiri and Meoli (2015), the coefficient of *AGE* is negatively associated with the TFP level and its components and significant for productivity change and efficiency change. This is evident that younger MFIs are achieving better productivity level relatively. These findings are consistent with the view that mature MFIs cannot manage the latest developments that hamper their productivity level (Barron *et al.*, 1994). Wijesiri and Meoli (2015) also concluded a similar inference for the MFIs operating in Kenya.

Table 5. Productivity change and its components by size categories

Size groups		Small MFIs			Medium MFIs			Large MFIs	
Year	*TFPCH*	*EFFCH*	*TECH*	*TFPCH*	*EFFCH*	*TECH*	*TFPCH*	*EFFCH*	*TECH*
Panel A: Year-wise geometric means									
2005–2006	1.062	1.035	1.029	0.957	0.929	1.038	1.128	1.022	1.098
2006–2007	1.485	1.386	1.102	1.023	0.999	1.022	1.013	1.019	0.994
2007–2008	1.387	1.165	1.194	1.144	1.035	1.107	1.081	0.962	1.123
2008–2009	1.035	0.996	1.045	1.081	1.057	1.019	1.021	1.053	0.973
2009–2010	0.926	1.073	0.865	0.993	1.070	0.930	0.930	0.973	0.955
2010–2011	1.111	1.215	0.914	0.985	1.106	0.883	1.077	1.118	0.971
2011–2012	1.098	1.041	1.057	1.113	1.126	0.980	1.044	1.018	1.028
2012–2013	1.092	1.120	0.966	0.947	0.949	1.002	0.963	0.952	1.016
2013–2014	1.098	1.020	1.077	1.054	1.009	1.050	1.069	1.077	0.999
2014–2015	1.093	1.022	1.072	1.100	1.050	1.057	1.037	0.996	1.045
2015–2016	1.064	0.824	1.290	1.075	0.914	1.188	1.170	1.057	1.100
2016–2017	1.133	1.163	0.988	1.068	1.092	0.996	0.994	1.099	0.909
2017–2018	1.048	1.088	0.963	0.992	0.993	1.003	1.094	1.070	1.027
Panel B: Geometric mean									
Entire period (2006–2018)	1.126	1.088	1.043	1.041	1.025	1.021	1.048	1.032	1.018
First sub-period (2006–2011)	1.168	1.145	1.025	1.030	1.033	1.000	1.042	1.024	1.019
Second sub-period (2012–2018)	1.089	1.040	1.059	1.050	1.019	1.039	1.053	1.038	1.018
Panel C: Hypothesis testing									
H_o: $FSP_{distriution} = SSP_{distribution}$									
Kruskal Wallis test	1.626 (0.202)	3.447 (0.064)*	0.242 (0.622)	0.838 (0.359)	0.021 (0.884)	3.980 (0.046)**	0.229 (0.632)	0.232 (0.629)	5.127 (0.023)**
Jonckheere-Terpstra test	371 (0.202)	351 (0.064)*	434 (0.622)	724 (0.359)	684 (0.884)	780 (0.046)**	257 (632)	271 (0.629)	231 (0.023)**
Li Test	0.938 (0.520)	1.695 (0.738)	1.273 (0.873)	14.111 (0.000)***	3.334 (0.432)	15.629 (0.000)***	2.041 (0.901)	1.133 (0.936)	4.667 (0.000)***

Note(s): (1) *TFPCH* = total factor productivity change, *EFFCH* = efficiency change, *TECH* = technical change, (2) *FSP* = first sub-period, *SSP* = second sub-period and (3) ***, ** and * indicate coefficients are significant at 1, 5 and 10% levels, respectively
Source(s): Authors' calculations

MFIs' sustainability status also affects the productivity level. A negative and statistically significant coefficient of *SUSTAINABILITY* suggests that nonsustainable MFIs are trying hard to become sustainable. Therefore, adopting more innovative technology in the production function could have improved their productivity level. As far as the organizational form concern, it positively affects productivity growth. The NBFC MFIs report higher efficiency than their non-NBFC MFIs peers. However, these non-NBFC MFIs are better performing relatively in technological innovations and up-gradation of the production process. Babu and Kulshrestha (2014) also observe that the TFP level is relatively higher for NBFC MFIs than its counterparts. Regarding the credit quality of the loan portfolio, we note that PAR30 reflects a negative impact on productivity growth, but the coefficient of *PAR30* is not statistically significant. The coefficient of *REFORMS* appears to have a positive and significant impact on the technical change component, hinting toward the adoption of new technology and innovations with the onset of regulatory reforms in the MFI industry. The findings of the second-stage analysis align with the productivity trends as discussed above.

6. Conclusions and policy implications

This paper examines the productivity behavior of MFIs in India in the light of new regulatory reforms initiated by the RBI in 2011. The unbalanced data of MFIs operating from 2005 to 2018 are used for the analysis. The TFP scores and its two distinct components, namely efficiency change and technical change, for individual MFIs are computed by bootstrapping Malmquist productivity indices in a DEA framework. In addition, a bootstrap truncated regression algorithm of Simar and Wilson (2007) is employed to identify the contextual factors driving MPI. The double bootstrap procedure adopted in this study performs well, both in terms of allowing correct estimation of bias and deriving statistically consistent MPI estimates in the first stage and root mean square error in the second stage of the analysis. Besides, the study also scrutinizes the variations in productivity levels across the distinct organizational forms and size groups of MFIs. In order to perform the analysis, we divided the sampled MFIs into two categories: NBFC and non-NBFC-MFIs, and the variations in the productivity levels of MFIs across distinct scale sizes are captured by categorizing them into small, medium and large MFIs based on Mix Market classification. To examine the impact of

Table 6. Second-stage bootstrap truncated regression results

Productivity components→ Variables↓	*TFPCH*	*EFFCH*	*TECH*
Panel A: Model coefficients			
Constant	0.193 (0.012)***	0.131 (0.019)***	0.059 (0.022)***
SIZE	−0.006 (0.002)***	−0.003 (0.003)	−0.016 (0.003)***
REFORMS	−0.003 (0.003)	−0.002 (0.004)	0.009 (0.005)*
PAR30	−1.420 (0.001)	−0.001 (0.001)	0.001 (0.001)
ORGFORM	0.001 (0.003)	0.008 (0.004)*	−0.001 (0.005)
AGE	−0.011 (0.003)***	−0.010 (0.004)**	−0.003 (0.005)
SUSTAINABILITY	−0.017 (0.004)***	−0.131 (0.006)**	−0.002 (0.007)
Panel B: Model statistics			
Number of observations	829	829	829
Wald χ^2(p-value)	53.010 (0.000)	16.370 (0.011)	33.290 (0.000)
Number of bootstrap replications	2000	2000	2000
Sigma	0.040 (0.001)***	0.055 (0.002)***	0.069 (0.001)***

Note(s): (1) *TFPCH* = total factor productivity change, *EFFCH* = efficiency change, *TECH* = technical change, (2) Figures in parentheses are bootstrapped standard errors and (3) ***, ** and * indicate coefficients are significant at 1, 5 and 10% levels, respectively
Source: Authors' calculations

regulatory changes on the productivity indices, we divided the entire study period into two distinct sub-periods: the first sub-period (2005–2010) and the second sub-period (2011–2018).

We draw the following observations. First, the Indian MFIs have observed productivity growth at the rate of 6.7%, primarily driven by efficiency increase (or catching-up phenomenon) during the study period. The efficiency improvement from both financial and social perspectives, credit boom and regulatory reforms, coupled with the technological advancements in the MFI sector might have driven the productivity growth. Moreover, mobile penetration, entry of FinTech firms lowered the transaction cost, expanded the outreach to the new market, increased competition with small finance banks and payment banks, and universal banks might have enabled the MFIs to raise their efficiency and productivity levels. Second, the sub-period analysis reveals that although the MFI industry experienced technical progress after the inception of new regulatory reforms, the rate of TFP growth was lower in the second sub-period relative to the level observed in the first sub-period. Third, NBFC MFIs reportedly observed higher productivity growth as compared with non-NBFC MFIs. The notable productivity gains in NBFCs are largely attributed to the catching-up process, while for non-NBFCs MFIs, the TFP improvements are more or less equally driven by efficiency increase and technical progress. Fourth, productivity level has improved across all MFIs operating at different size scales. However, small MFIs are found to have shown higher productivity growth, followed by large and medium-sized MFIs. Fifth, the bootstrap truncated regression analysis suggests that TFP change and its components are negatively associated with the size of MFIs. Our results also reveal that younger MFIs relatively more productive during the sample period. Moreover, the regulatory reforms have accelerated the innovation effect in the Indian MFI industry. However, the reforms and technological developments have only been able to compensate for the shocks of the unfortunate event of the Andhra Pradesh crisis in 2010, and positive spill-over effects of the policy reforms are yet to be realized in the MFI industry in the coming years ahead.

The empirical findings of this study suggest that the regulatory developments of 2011 have effectively contributed toward technological innovation in the Indian microfinance industry. The MFIs could have achieved a high level of productivity growth if they could have effectively implemented the use of technology in their operations. Thus, the study recommends that MFIs need to work in a direction to reap the benefits of new business strategy and up-to-date technology. Innovation in products, better risk assessment, effective credit delivery mechanism and timely repayment system are extremely required to meet clients' actual needs and further enhance the productivity levels of MFIs. The study suggests that MFI management should take the initiative to combine psychometric data and the credit bureau score. This would assist in evaluating the creditworthiness of borrowers before lending. In addition, MFIs must adopt the digital information system along with the physical attributes in order to enhance the credit quality of their portfolio, which would enhance their efficiency level, reduce the cost of operation and cost per transaction for clients and overall productivity levels (MFIN, 2018). Last but not least, the industry must hire and retain competent and professional human capital for deploying the available technology. Future research can be extended to analyze the productivity behavior by explicitly incorporating the role of the nonperforming assets (NPAs) as undesirable or bad output in the MFI production model. In addition, one can also look to adjust the role of subsidies received by MFIs in the financial output while investigating productivity trends.

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