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## Article

# Microfinance's digital transformation for sustainable inclusion

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# Microfinance's digital transformation for sustainable inclusion

Microfinance's  
digital  
transformation

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## Abstract

**Purpose** – The purpose of this paper is to evaluate the performance of Microfinance Institutions (MFIs) offering FinTech services. This study contributes to the existing literature on microfinance digitalization, financial inclusion and sustainable development. The study also takes into consideration a behavioral perspective through the efficiency evaluation process of MFIs offering FinTech services.

**Design/methodology/approach** – The following study employs the Stochastic Frontier Analysis approach to estimate the operational and social efficiency scores of the 387 MFIs over the period 2005–2019. Then, it tries to consider factors influencing MFIs' efficiency and assess their effects. Hence, two separate models for operation and social efficiency introducing a set of factors, including FinTech proxies and overconfidence proxies, are tested. The first model for operational efficiency uses a random-effects estimator while the second one for social efficiency uses a fixed-effects estimator.

**Findings** – The results show that innovative MFIs have weaker averages of operational efficiency than non-innovative ones but higher averages of social efficiency. This was justified by the fact that innovative MFIs are more socially oriented. Further, findings of this study depict that the proxies of FinTech affect negatively the level of operational efficiency of MFIs. They also depict a negative relationship between FinTech proxies and the level of social efficiency. These results hold through robustness tests.

**Originality/value** – The highlight of this study is that it takes heed of the indirect effect of technological innovation on the efficiency of MFIs. It has been proved that it moderates the impact of managerial overconfidence (manifested by excessive risk-taking, viz., high levels of PAR30, LGR and NIM) on the level of both operational and social efficiencies.

**Keywords** Digital transformation, Financial performance, Social performance, Microfinance institutions, FinTech services

**Paper type** Research paper

## 1. Introduction

It has remained evident today that microfinance plays an important role in financial and social inclusion within the ecosystem of many developing countries (Dang and Quynh Vu, 2020). Many efforts have been maintained to guarantee the financial and consequently the social sustainability of the microfinance sector. Efforts or rather objectives such as penetrating financial markets, obtaining regulatory legitimacy and being open to institutional transformation. Far from the spotlight, microfinance institutions (MFIs) have continued to grow, serving millions of people without changing their methods (Benami and Carter, 2021). Financial services play a central role in the functioning of an economy, whether it is a country like the USA or a simple village in Africa.

However, things have started to change and the digital revolution has changed the world so profoundly that it cannot be ignored. The focus and support of the international financial



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inclusion industry have shifted sharply from credit for the poor to innovation in payment methods and delivery channels. Today, we are talking about digital finance (or financial technology, also, inclusive finance or impact finance) and its potential to reach the vulnerable and the unbanked. Many excluded people from the conventional banking system are not excluded from mobile networks and are connected to the digital world. Financial Technology (FinTech) field in the broad sense includes all companies implementing innovative solutions aimed at improving or rethinking the financial sector. The FinTech raises a real enchantment, from insurance technology; to machine learning; to payments; reverse factoring platforms; blockchain-based digital identity solutions; digital micro-pensions; credit market platforms; dematerialized loans; commerce online; artificial intelligence; etc. . . . It is a field that has three golden criteria such as energy, creativity and money trying to bring mass financial services to emerging markets. The poor are at the heart of the equation.

Digital technology could be perceived as a threat to traditional financial markets, especially for MFIs. Since these FinTech startups are creating and offering new financial services that are more cost-efficient and it has the ability to reach more poor and unbanked population. At this stage, a question arises: can this technology alone accomplish this mission? Since digital services are supposed to facilitate access for the poor, how does the dematerialized world communicate with the other world, that of cash, in which most of the poor still live? Technology is obviously part of the solution, but it is only a means. Many have anticipated that FinTech startups will destabilize traditional financial institutions, such as MFIs, but they have faced two fundamental problems: acquiring customers and raising capital. The operators of this new technology must have solid economic models and a perfect understanding of the development conditions in which we evolve, to make a real difference and change the game (Benami and Carter, 2021).

Banks and MFIs retain an essential place in the new landscape of financial services. The needs of the poor are not limited to dematerialized payments and short-term credit. They must be able to save, invest and insure their property. In many respects, MFIs are particularly well-equipped to meet these expectations. However, in our era, being all technological, they must rethink their operating methods. The profile of microfinance clients will change significantly in the coming decades: young people, perfectly mastering new technologies, increasingly educated, and living in urban areas with more defined expectations. As an example, according to the African Development Bank (AfDB), nearly 40% of Africa's population will be between 10 and 29 by 2030, and the literacy rate will have reached 80%. In total, 50% of the African population will live in cities and migratory flows, mostly intercontinental, will be increased. Therefore, better knowledge of the needs of low-income populations and a more competitive microfinance sector are already encouraging operators to innovate. They should continue to expand their product line to meet the needs of their customers and diversify their customer base. There is a real challenge for microfinance operators to place new technologies at the heart of their strategy and their operations.

Many networks, such as Microcred; international FINCA; ACTION; Opportunity international and Procredit are reinforcing their growth by relying on new technological means. ACCION, for example, has become one of the world's leading finTech investors for financial inclusion with products such as payment networks; remittances; loans to Small and Medium Enterprises, etc. . . . MFIs as well are more and more embracing financial technologies in order to enlarge their social outreach and reach more unbanked people. Microfinance banks have already implemented technologies to develop alternative distribution channels such as biometric automated teller machines (ATMs). There are MFIs that have invested in remote and digital distribution channels. In Jordan, microfinance for women moved more than 30% of its loan disbursements to client e-wallets in September 2020, and its clients made 22% of their repayments through remote payment points.

Bancamia had equipped its mobile sales agents in Colombia with a mobile application. These agents used the mobile app to enroll 270,000 clients for government grant payments and process 82% of MFI loan applications since 2019. In Peru, Caja Municipal de Ahorro y Crédito used digital channels to coordinate with clients and reschedule more than 60% of its loan portfolio (Microfinance Barometer, 2019).

Embracing this technology contributes to reducing operational costs and, therefore, allows MFIs to offer low-cost financing for their clients (Dang and Quynh Vu, 2020). According to the Consultive Group to Assist the Poor (Ignacio and Kumar, 2008), digital banking manages to lower costs for banks and financial institutions by over half by reducing operating costs. By reducing operational costs, MFIs can reduce the high-interest rates that they used to charge in order to cover micro-loans administration costs (Benami and Carter, 2021). Furthermore, the lack of reliable data about the financial and transaction history of the poor rural population is a challenge for MFIs. FinTech's embracing will provide MFIs the information about the credit worthiness of borrowers (Ye *et al.*, 2020). Finally, yet importantly, digital transformation and technology adoption will provide MFIs the opportunity to reach more unbanked population and the underserved low-income markets (Dang and Quynh Vu, 2020). Besides, and according to the Microfinance Barometer (2021), MFIs that have invested in remote and digital distribution channels were able to rely on these solutions to reach customers and continue their activities, even when the branches closed in the context of lockdown because of the Covid-19 pandemic crisis.

Academic and research studies regarding MFIs digitalization are very scarce and it is mostly due to the lack of sufficient data. There is a limited empirical regard to the intervention of financial technology in the microfinance mission of financial and social inclusion. This research aims to fill this gap and contribute to the existing literature on microfinance digitalization, financial inclusion and sustainable development. Toward the limited empirical studies on the financial and social efficiency evaluation of MFIs offering digital banking services. Thus, in our study, we evaluate and compare financial and social efficiency scores of FinTech offering and non-FinTech offering MFIs using the Stochastic Frontier Analysis (SFA) approach. Therefore, our research contributes to the existing literature on microfinance and digitalization and being, as far as our knowledge, the first study to evaluate the operational and social efficiency of MFIs offering mobile banking services using accounting indicators. In addition, the results of our investigation have brought some implications for practitioners, policymakers and FinTech start-ups. Our findings provide evidence for practitioners (MFI management) to improve their efficiency and expand their outreach capacity and, therefore, contribute to the development of the IMF sector. Our revealed results show MFIs have the opportunity to use digital tools to pursue their missions in an increasingly digitalized world. Digitalization offers MFIs the opportunity to reduce operational and administration charges, provide low-cost loans and reach more unbanked populations. Furthermore, our study presents a useful tool for policymakers and confirms that the existing regulation models should incorporate new particularities of digital transformation. It is necessary to review, even define the regulatory scope; license and monitor the digital transition. It is essential to give regulatory bodies the necessary means to face the challenges ahead. As for FinTech start-ups, our findings show some practical implications in the context of the opportunities for fusion projects with MFIs. In order to deal with two fundamental problems, namely, customer acquisition and capital raising and eventually paving the way for many MFIs and helping them to transform from traditional to digital. The remainder of the paper is organized into three parts. Section 2 describes the conceptual framework of the research and presents a brief review of previously published related works. Section 3 introduces the studied data and the pursued methodology. Finally, Section 4 exposes and discusses in detail the revealed results.

## 2. Literature review

The purpose of the present literature review is to evaluate and synthesize existing research (as provided in [Table 1](#)) and eventually conclude with a summary of the key findings and insights.

The new technological financing models have been developed outside the conventional financial system and are seen as a powerful alternative for better financial inclusion. [Buchak et al. \(2018\)](#) combined data from Home Mortgage Disclosure Act (HMDA), Fannie Mae and Freddie Mac's single-family loan performance, the Federal Housing Administration 88 (FHA) and US Census between 2007 and 2015. They found that the market share of FinTechs has passed from 3% in 2007 to 12% in 2015, providing loans to less credit-worthy borrowers. [Jagtiani and Lemieux \(2018\)](#) used data from both Lending Club's consumer platform and Y-14 M data reported by US banks during the period 2010–2016 to examine the impact of FinTech lending on credit accessibility of unsecured consumers. The results substantiated that FinTech lenders had a higher market share in areas that are underserved by traditional banks and where the local economy is not performing well. Likewise, [Rau \(2018\)](#), exploring over 3000 crowdfunding platforms, demonstrated that crowdfunding ensured borrowers had greater ease of access to the financial system.

The digital revolution has changed the world so profoundly that it cannot be ignored. The focus and support of the international financial inclusion industry have shifted from credit for the poor to innovation in payment methods and delivery channels. For MFIs to successfully turn these challenges into opportunities, they must be ready for digital transformation. MFIs have the opportunity to use digital tools to pursue their missions in an increasingly digital world. Studies on digital finance and microfinance are still very rare and often fragmented. In this context, [Budampati and Raghunath \(2018\)](#) study the impact of the intervention of information technology in increasing the efficiency and outreach of the microfinance industry in India. Their review shows the opportunities that IT can bring to MFIs; however, the only barrier is the resistance of the Indian rural population to embrace technological change. These conclusions are in accordance with the investigation research conducted by [Saon et al. \(2018\)](#) on the Indian MF context as well. However, the authors mention other kinds of barriers, such as inequality compared to big firms in terms of fast and efficient integration of new technologies and digitalization, pointing fingers at three important factors, i.e. regulatory framework, country-specific business climate and skills level of labor force.

A more recent research by [Dang and Quynh Vu \(2020\)](#), studied FinTech services and activities in the microfinance sector and recommend FinTech adoption of MFIs in Vietnam. The authors follow qualitative designed research to evaluate the microfinance sector in Vietnam and suggest instructions and recommendations for the digital transformation of the Vietnamese MFIs. In this sense of digital transformation as well, [Mia \(2020\)](#) empirically conducts a non-parametric investigation where she studies the determinant factors of the introduction of technological change and innovation in Bangladeshi MFIs. The author estimates the Malmquist Productivity Index to distinguish the technical change among the studied MFIs over the 2009–2014 period. The estimation results of the factors determining the technical change index highlight the importance of peer borrowing among MFIs, decentralized branches as well as the geographical location to improve the introduction of the technical innovation.

By analogy with the surveys related to the operational efficiency of banks mentioned above, we assume that the integration of FinTech services will have the same effect on the operational efficiency of MFIs. Thus, the first hypothesis will be as follows:

- H1.* The integration of FinTech services has a positive effect on the operational efficiency of MFIs

| Author and year  | Sample and period of study  | Key findings   |
|--|---|--|
| <i>Panel A FinTechs as standalone institutions and technological change within FIs: Impact on operational efficiency</i> |   |  |
| Budampati and Raghunath (2018)   | They studied the evolution of the Indian microfinance industry as well as few relevant studies about its technological transformation           | <ul style="list-style-type: none"> <li>- IT improves the processes of MFIs and ensures enhanced outreach more cost-efficiently</li> <li>- The only barrier is the resistance of the Indian rural population to embrace the technological change</li> </ul>   |
| Dang and Quynh Vu (2020)   | The authors followed qualitative designed research to evaluate the microfinance sector in Vietnam and to study its technological transformation | <ul style="list-style-type: none"> <li>- The introduction of FinTech to the microfinance industry leads to better and fast-delivered services, safer and easier access, and most importantly, lower costs. Thus, it enhances the operational efficiency of Vietnamese MFIs</li> <li>- Authors suggest instructions and recommendations for the digital transformation of the Vietnamese microfinance institutions</li> </ul>   |
| Fuster <i>et al.</i> (2019)  | They analyzed FHA Neighborhood Watch Early Warning System (FHA NW) data over the period from 2015 until 2017                                    | <ul style="list-style-type: none"> <li>- Technological innovation enhanced the financial intermediation's efficiency in the US mortgage market with faster processing (nearly 20% faster than traditional lenders)</li> <li>- This speed does not come at the expense of higher default rates (their default rates are about 25% lower compared to those of traditional lenders)</li> <li>- There is no evidence about the prioritization of marginalized populations</li> </ul>   |
| Mia (2020)   | The author selected a sample of 169 MFIs from Bangladesh over 2009–2014   | The estimation results of the factors determining the technical change index highlight the importance of peer borrowing among MFIs, decentralized branches, as well as the geographical location to improve the introduction of technical innovation   |
| Onay and Ozsoz (2012)  | The sample of the survey consists of 18 Turkish banks for the period 1990–2008  | The adoption of Internet banking results in important operational efficiency gains   |
| Saon <i>et al.</i> (2018)  | The paper provides theoretical assumptions  | Technology integration is capable of promoting development through innovation, efficiency, and inclusion, however, the process ahead for the sector may face some challenges such as country-specific business climate and skills level of labor force   |
| Wijesiri <i>et al.</i> (2017)  | They looked at a sample of 420 MFIs operating in different geographic regions around the world for the year 2013                                | <ul style="list-style-type: none"> <li>- Age certainly matters: older MFIs, thanks to their experience, tend to outperform younger MFIs. Thus, they are more financially efficient than younger ones, but they are relatively socially inefficient</li> <li>- MFIs with more assets, staff and clients are able to better achieve their financial and social goals. That is to say, larger MFIs, are more likely to have higher financial and social efficiencies</li> <li>- Regardless of age and size, the average efficiency scores for MFIs are low</li> </ul> |

(continued)

**Table 1.**  
Referenced literature  
and hypotheses

| Author and year  | Sample and period of study   | Key findings  |
|--|--|---|
| <b>Hypothesis 1:</b> The integration of FinTech services has a positive effect on the operational efficiency of MFIs |  |   |
| <i>Panel B Technological change for better financial inclusion</i>   |  |   |
| Buchak <i>et al.</i> (2018)  | They combined data from Home Mortgage Disclosure Act (HMDA), Fannie Mae and Freddie Mac's single-family loan performance, the Federal Housing Administration 88 (FHA), and US Census between 2007 and 2015 | The market share of FinTechs has passed from 3% in 2007 to 12% in 2015, providing loans to less credit-worthy borrowers   |
| Cull <i>et al.</i> (2007)  | They surveyed a sample of 124 MFIs in 49 developing countries for the 1999–2002 period   | Both social and financial goals could come together except for the MFIs targeting extremely poor clients  |
| Dorfleitner <i>et al.</i> (2019)   | They conducted their research for 999 worldwide MFIs over 2012–2017  | <ul style="list-style-type: none"><li>- Larger commercial MFIs are more likely to adopt mobile technology</li><li>- Their social mission (depth of outreach) is weakly positively related to the provision of MFS</li></ul>   |
| Ejigu (2009)   | They looked at a relatively small sample of 16 Ethiopian MFIs between 2001 and 2007  | There is a trade-off between social efficiency in terms of depth of outreach and financial sustainability, more precisely, operational self-sufficiency   |
| Hermes and Lensink (2011)  | They relied on a sample of 435 MFIs over the period 1997–2007, giving 1,318 total observations   | MFIs with a greater depth of outreach and those with more percentage of women borrowers are less cost-efficient   |
| Jagtiani and Lemieux (2018)  | They used data from both Lending Club's consumer platform and Y-14 M data reported by US banks during the period 2010–2016   | FinTech lenders had a higher market share in areas that are underserved by traditional banks and where the local economy is not performing well   |
| Kumar and Sensarma (2017)  | They examined the efficiency-outreach relation for 75 Indian MFIs over 2004–2014   | <ul style="list-style-type: none"><li>- They confirmed the trade-off between cost efficiency and reaching the poorer</li><li>- When it comes to empowering women, there is no such trade-off. MFIs are thereby willing to lend to women as it concomitantly helps to fulfill part of their social mission without damaging their financial sustainability</li></ul> |
| Rau (2018)   | They explored over 3,000 crowdfunding platforms over the period 2005–2015  | Crowdfunding ensured borrowers having greater ease of access to the financial system  |
| Serrano-Cinca and Gutierrez-Nieto (2014)   | They based their survey on a large sample of around 1,000 worldwide MFIs between 2006 and 2010   | Targeting very poor populations causes severe financial problems for MFIs   |
| Vogeley and Lonbani (2017)   | They examined 6 Indonesian MFIs over the two years 2014–2015   | Employing mixed qualitative and quantitative methods, findings indicate clearly the positive impact of digital technology growth (particularly mobile money products) on social efficiency growth   |
| <b>Hypothesis 2:</b> The integration of FinTech services improves the scope and scale of the outreach of MFI         |  |   |
| <i>Panel C Overconfidence bias</i>   |  |   |

Table 1.

(continued)



| Author and year   | Sample and period of study   | Key findings  |
|---|--|---|
| Baker <i>et al.</i> (2007)  | They provided a brief review of the behavioral corporate finance literature limited to the link between corporate financing decisions and profit management                            | <ul style="list-style-type: none"> <li>- Overconfident managers are risk-seeker</li> <li>- They (overconfident managers) tend to engage in more low-quality mergers and serious overinvestments</li> <li>- They are prone to more illusion of the control of technologies owned even if they have no knowledge about</li> </ul> |
| Ben-David <i>et al.</i> (2007)  | They examined the relationship between managerial overconfidence and corporate decision for a large number of US managers who provided 6901 S&P500 forecasts over the period 2001–2007 | Overconfident managers tend to engage intensively in risky investments, which may result in a considerable loss of efficiency   |
| Chen and Chen (2012)  | They studied a sample composed of 64 banks with overconfident managers, 2 with neutral managers and 70 with non-overconfident managers from 2005 to 2012                               | Overconfident managers are more likely to take higher credit and insolvency risks   |
| Dietzmann and Alt (2019)  | They considered the 100 largest US banks between 2005 and 2015   | Technological innovation moderates the risk-bearing for 95% of these banks. This is mainly thanks to novel risk management processes and improved algorithms of risk calculation  |
| Galasso and Simcoe (2011)   | They analyzed a panel of 450 large US firms between 1980 and 1994  | Overconfident CEOs are more likely to opt for technological changes and to invest significant amounts for the firm's innovation strategy  |
| Hirshleifer <i>et al.</i> (2012)  | They considered a large sample of 2,577 CEOs from 1771 firms and total firm-year observations of 9,807 during the period between 1993 and 2003   | Firms led by overconfident CEOs invest more in innovation   |
| Huang <i>et al.</i> (2016)  | They based their study on a sample of 4309 US firms over the 6 years between 2006 and 2012   | Firms driven by overconfident managers carry a greater level of liquidity risk, which is due to the preference of overconfident managers for short-term debts   |
| Mahdi and Boujelbène (2018)   | The focused on 133 FIs (96 conventional and 37 Islamic) of the MENA region for the period 2005–2016  | There is a positive relationship between managerial overconfidence and excessive risk-taking as well as cost inefficiency   |
| Skala (2010)  | They used a sample of 311 European FIs over 1997–H12008  | Overconfidence brings about more risk tolerance   |
| <b>Hypothesis 3:</b> The integration of FinTech services moderates the impact of managerial overconfidence on the operational efficiency of MFIs          |  |   |
| <b>Hypothesis 4:</b> The integration of FinTech services moderates the impact of managerial overconfidence on the scope and scale of the outreach of MFIs |  |   |
| <b>Source(s):</b> Authors' own elaboration  |  |   |

Table 1.

Hermes and Lensink (2011) relied on a sample of 435 MFIs during the period over the period 1997–2007, giving 1,318 total observations. They found convincing evidence that MFIs with a greater depth of outreach and those with more percentage of women borrowers are less cost-efficient. A conclusion that Ejign (2009) has already found for a smaller sample of MFIs in Ethiopia between 2001 and 2007. This negative relation led researchers to further investigate this topic. By the same logic, Cull *et al.* (2007) surveyed a sample of 124 MFIs in 49 countries and proved that both social and financial goals could come together except for the MFIs



targeting extremely poor clients. Later on, [Kumar and Sensarma \(2017\)](#) examined the efficiency-outreach relation for 75 Indian MFIs over 2004–2014. They confirmed the trade-off between cost efficiency and reaching the poorer. However, when it comes to empowering women, there is no such trade-off. MFIs are thereby willing to lend to women as it concomitantly helps to fulfill part of their social mission without damaging their financial sustainability. [Serrano-Cinca and Gutierréz-Nieto \(2014\)](#), based on a large sample of worldwide MFIs between 2006 and 2010, proved that targeting very poor populations causes severe financial problems for the MFIs. In such cases, the solution is to focus on gaining more operational efficiency while maintaining their commitment to achieve social goals through the appropriate use of innovative communication technologies. Going further in the MFIs' efficiency debate, [Vogeley and Lonbani \(2017\)](#) examined the impact of digital technologies on the social efficiency of Indonesian MFIs over the two years 2014–2015 and employing mixed qualitative and quantitative methods. Findings indicate clearly the positive impact of digital technology growth (particularly mobile money products) on the social efficiency growth of almost all the MFIs in the sample. [Dorfleitner et al. \(2019\)](#) conducted their research for 999 worldwide MFIs to provide a shred of initial empirical evidence about the factors driving the introduction of Mobile Financial Services (MFS [1]). Two key findings interest us: That larger commercial MFIs are more likely to adopt mobile technology and that their social mission (depth of outreach) is weakly positively related to the provision of MFS.

*H2. The integration of FinTech services improves the scope and scale of the outreach of MFI*

According to [Baker et al. \(2007\)](#), the review of the behavioral corporate finance literature highlights that overconfident managers are risk-seeker and that they tend to engage in more low-quality mergers, more serious overinvestments and that they are prone to more illusion of control of technologies owned even if they have no knowledge about. [Hirshleifer et al. \(2012\)](#) found that during the period between 1993 and 2003, firms led by overconfident CEOs invest more in innovation. [Galasso and Simcoe \(2011\)](#) analyzed a panel of 450 large US firms between 1980 and 1994. The results showed strong empirical evidence that overconfident CEOs are more likely to opt for technological changes and to invest significant amounts in the firm's innovation strategy. [Ravichandran and Zhao \(2018\)](#) examined a sample of 477 firms from 1999 to 2006. They found that long-term compensations of CEOs incentivize overconfidence and risk-taking behaviors. Obviously, there is a strong interrelation between overconfidence, risk-taking, and efficiency. The starting point is to look into the credit risk in the microfinance industry. [Lassoued \(2017\)](#) found that the credit risk has been significantly reduced with the methodology of group lending and with a higher percentage of women served, i.e. MFIs adopting the welfarist approach (social MFIs) have lower credit risks. This conclusion confirming the creditworthiness of poor customers and efficacy of solidarity credit was based on a sample of 638 MFIs across 87 countries over the period 2005–2015. Overall, the survey proved that social orientation ensures better financial performance thanks to a lower default rate. From a behavioral perspective, the overconfidence cognitive bias of managers has been amply documented in the literature on behavioral corporate finance. [Ben-David et al. \(2007\)](#) argued that overconfidence needs to be explicitly reflected when studying managerial decision-making. They examined the relationship between managerial overconfidence and corporate decision for a large number of US managers over the period 2001–2007. The major finding of the survey is that overconfident managers tend to engage intensively in risky investments, which may result in a considerable loss of efficiency. [Chen and Chen \(2012\)](#) studied the effect of managerial overconfidence on banks' risk-taking for a sample composed of 64 banks with overconfident managers, 2 with neutral managers and 70 with non-overconfident managers from 2005 to 2012. They showed that overconfident managers are more likely to take higher credit and

insolvency risks. [Mahdi and Boujelbène \(2018\)](#) proved a positive relationship between managerial overconfidence and excessive risk-taking as well as cost inefficiency of FIs (conventional and Islamic) of the MENA region for the period 2005–2016. Same results are concluded in the study conducted by [Fersi and Boujelbène \(2021\)](#) on MFIs. [Huang et al. \(2016\)](#) revealed that over the 6 years between 2006 and 2012, firms driven by overconfident managers carry a greater level of liquidity risk is due to the preference of overconfident managers for short-term debts. This empirical evidence was developed based on a sample of 4,309 US firms. Based on a sample of 311 European FIs over 1997–H12008, the survey of [Skala \(2010\)](#) showed that overconfidence brings about more risk tolerance. [Dietzmann and Alt \(2019\)](#) proved that technological innovation for the 100 largest US banks between 2005 and 2015 moderates the risk-bearing for 95% of these banks. This is mainly thanks to novel risk management processes and improved algorithms of risk calculation.

*H3.* The integration of FinTech services moderates the impact of managerial overconfidence on the operational efficiency of MFIs.

*H4.* The integration of FinTech services moderates the impact of managerial overconfidence on the scope and scale of the outreach of MFIs.

To close our review, we are going to take the survey of [Wijesiri et al. \(2017\)](#) that is meaningful for our study. It investigates the impact of age and size on both financial and social efficiency for a sample of 420 MFIs operating in different geographic regions around the world. The findings confirmed that age certainly matters: older MFIs, thanks to their experience, tend to outperform younger MFIs. Thus, they are more financially efficient than younger ones, but they are relatively socially inefficient. Additionally, results also revealed that MFIs with more assets, staff and more clients are able to better achieve their financial and social goals. These revealed results are in accordance with those concluded by [Fersi and Boujelbène \(2021\)](#), who empirically showed that larger MFIs, are more likely to have higher financial and social efficiencies. Moreover, regardless of age and size, the average efficiency scores for MFIs are low.

### 3. Sample, data and methodology

This section will be devoted to an exhaustive presentation of the empirical analysis framework. It details the survey's sample and data as well as models that enable the test of research hypotheses.

#### 3.1 Sample selection

The sample taken for our study consists of 387 MFIs from various parts of the globe and with different characteristics (size, age, etc.), of which only 80 MFIs provide FinTech services. Actually, the diversity of our sample reflects the heterogeneity of MFIs and ensures better representativeness and reliability. The MFIs we consider come from 69 underdeveloped countries in South Asia, Eastern Europe and Central Asia (EECA), East Asia and Pacific (EAP), Latin America and the Caribbean (LAC), Middle East and North Africa (MENA) and Sub-Saharan Africa (SSA).

Further, to avoid small-sample associated biases, we focus our analysis on a large period between 2005 and 2019, giving total institutional yearly observations up to 5,805.

#### 3.2 Data description

The full numerical dataset has been collected from the Mix Market portal, which is currently the largest and most reliable database collecting information on MFIs (contains more than 2000 institutions). Almost every research study related to the microfinance sector refers to the Mix Market for the collection of numerical data.

For the current survey, we are using unbalanced panel data combining both social (about outreach and impact) and financial information. From the data extracted and using FinTech proxies, we will be able to test our hypotheses. In fact, the panel or longitudinal data is a combination of cross-sectional [2] and time-series [3] data. It is simply about cross-sectional observations over several periods at regular intervals. A panel is said to be unbalanced if the subjects of the study (individuals, firms, countries, etc.) are not observed over the entire period, which is the case here.

### 3.3 Models and variables description

The SFA and DEA methods are the most commonly used among researchers aiming to assess the efficiency of FIs. What has been obvious in the existing literature is the absolute majority of surveys about MFIs' efficiency (to the best of our knowledge) have chosen the DEA method. Nevertheless, its weaknesses (namely, its constraint ability to discriminate inefficient DMUs as well as its great sensitivity inherent to the nature of data, the sample size and to the presence of outliers) that can be avoided with SFA have led us to opt for the latter method. The choice of the best-suited method depends on the nature of the data we have as well as the purpose of our study. According to Coelli *et al.* (2005), unlike DEA, the SFA method is appropriate for bigger samples. Further, Hjalmarsson *et al.* (1996) indicated that SFA has an undeniable advantage by ensuring accurate analysis of panel data. Hence, SFA seems to be relevant to the issue and data we had chosen.

#### (1) Model specification

In this context, specification is about a particular combination of inputs and outputs. In practice, the choice between varieties of possible specifications for all forms of modeling is determined by practical constraints on the data and their analysis. The SFA is no exception; however, the underlying theory is not restrictive in the view of the selection of variables nor the number of variables to be included. Thus, the existing literature, as well as rules of common sense, can serve as a reference for the specification of the model. Obviously, the higher the number of variables included; the less the model is discriminant (a greater number of DMUs are likely to be declared efficient). Therefore, it is appropriate to specify the model with a certain number of variables; so that it would be more discriminant while still allowing for a number of efficient DMUs for making comparisons between pairs. For operational efficiency, we adopted an output-oriented model with multiple inputs and a single output, which is consistent with the characteristics of SFA and in compliance with previous surveys. Namely, we will adopt exactly the same input-output selection of Khan and Shireen (2020). A rigorous selection that includes net operating income as a proxy of operational performance. According to Khan and Shireen (2020), with reference to the definition proposed by the Mix Market, it is the amount an MFI earns from its loan portfolio after the deduction of all operational expenditures. Also, it includes three inputs: total assets, operating expenses and interest expense on borrowings.

- (1) Inputs: Total assets, operating expenses and interest expense on borrowings
- (2) Output: Net operating income

For social efficiency, we adopted an output-oriented model but with multiple inputs and outputs. We referred to the paper of Efendic and Hadziahmetovic (2017) and that of Lebovics *et al.* (2016) for our inputs-outputs selection.

- (1) Inputs: Total assets, number of employees, and financial costs
- (2) Outputs: Average loan balance per borrower, number of active borrowers and percentage of female borrowers

At this stage, to complete our estimation models, we are once again facing a choice between different functional forms models: Cobb–Douglas, Translog, CES, etc. The Cobb–Douglas is usually more applied in the literature due to its accuracy and ease of use. Ideally, all the same, it should be chosen for our survey because it accommodates CRS (which is our case) and because it is better adapted for our multi-inputs and multi-outputs selection.

The selection set of factors that could substantially influence the efficiency of MFIs (with reference to the papers of [Abdur Rahman and Mazlan \(2014\)](#) and [Khan and Shireen \(2020\)](#)) as well as the underlying logic to them are well explained in [Table 2](#).

**3.3.1 Determinants of operational and social efficiencies.** In order to acquire a full understanding of MFIs' operational and social efficiency, we estimate the following regression models that measure the effect of each determinant factor.

#### MFI specific determinants

|                             |   |   |
|-----------------------------|---|---|
| Portfolio At Risk (30 days) | The PAR is a universal proxy for the quality of the loan portfolio. It refers to overdue loans, and it is usually expressed as a percentage of the total loan portfolio   | $PAR_{30days} = \frac{\text{Loan Portfolio with 30 days arrears or more}}{\text{Total outstanding loan portfolio}}$ |
| Size                        | The size of an MFI is determined by the logarithm of its total assets. According to <a href="#">Khan and Shireen (2020)</a> , larger MFIs are more able to achieve significant economies of scale and better efficiency |   |
| Return On Assets (ROAs)     | It is an important financial indicator as it informs about the efficacy of using the available assets to generate profits   | $ROA = \frac{\text{Net operating profit after taxes}}{\text{Total assets}}$   |
| Capital-to-asset ratio      | Usually expressed as a percentage, this ratio talks about whether the company's assets are totally financed by its capital  | $CAR = \frac{\text{Capital}}{\text{Total assets}}$  |

#### Macroeconomic determinants

|  |  |   |
|--|--|---|
| Gross Domestic Products  | A country-specific macroeconomic variable that counts only for production. The GDP of a country indicates the market value of all finished products and services produced within this country in a year  | $GDPG = \frac{GDP_n - GDP_{n-1}}{GDP_{n-1}}$  |
| Overconfidence proxies (referring to <a href="#">Mahdi and Boujelbène (2018)</a> ) |  |   |
| Loan growth  | It is simply the increase in total loans of the institution, which can be generated by raising their lending (amounts and number of loans) to new customers or existing ones. In fact, loan growth has been broadly studied in the banking literature. It has been mostly associated with heightened credit risk and proved to positively affect the level of inflation  | $LGR = \frac{\text{Net Loan Portfolio}_n - \text{Net Loan Portfolio}_{n-1}}{\text{Net Loan Portfolio}_{n-1}}$ |
| Net Interest Margin (NIM)  | This ratio is specific to FIs, and it shows how successful the institution is at investing its funds in comparison to the expenses incurred during a given period. It determines the difference between the amounts of interest received on loans granted and the amount of interest paid out to lenders and/or depositors relative to the assets involved to generate these earnings (also called earning assets) | $NIM = \frac{\text{Interests earned} - \text{interests paid}}{\text{average invested assets}}$                |

**Source(s):** Authors' own elaboration

**Table 2.**  
Determinants of MFIs  
efficiency

$$\begin{aligned} \text{Operational efficiency}_{ikt} = & \alpha_0 + \alpha_1 \text{OFS DUMMY}_i + \alpha_2 \text{PAR30}_{ikt} + \alpha_3 \text{LGR}_{ikt} + \alpha_4 \text{NIM}_{ikt} \\ & + \alpha_5 \text{SIZE}_{ikt} + \alpha_6 \text{ROA}_{ikt} + \alpha_7 \text{CAR}_{ikt} + \alpha_8 \text{GDPG}_{kt} + \varepsilon_{ikt} \end{aligned} \quad (1)$$

$$\begin{aligned} \text{Social efficiency}_{ikt} = & \alpha'_0 + \alpha'_1 \text{OFS DUMMY}_i + \alpha'_2 \text{PAR30}_{ikt} + \alpha'_3 \text{LGR}_{ikt} + \alpha'_4 \text{NIM}_{ikt} \\ & + \alpha'_5 \text{SIZE}_{ikt} + \alpha'_6 \text{ROA}_{ikt} + \alpha'_7 \text{CAR}_{ikt} + \alpha'_8 \text{GDPG}_{kt} + \varepsilon'_{ikt} \end{aligned} \quad (2)$$

To capture the effect of FinTech, we have to extend our models by including the FinTech proxies.

$$(1) \quad \text{VTMBNOI} = \frac{\text{Value of Transactions via Mobile Phones}}{\text{NOI}}$$

$$(2) \quad \text{VTINOI} = \frac{\text{Value of Transactions by Internet}}{\text{NOI}}$$

The resulting models are as follows:

$$\begin{aligned} \text{Operational efficiency}_{ikt} = & \alpha_0 + \alpha_1 \text{OFS DUMMY}_i + \alpha_2 \text{PAR30}_{ikt} + \alpha_3 \text{LGR}_{ikt} + \alpha_4 \text{NIM}_{ikt} \\ & + \alpha_5 \text{VTMBNOI}_{ikt} + \alpha_6 \text{VTINOI}_{ikt} + \alpha_7 \text{SIZE}_{ikt} + \alpha_8 \text{ROA}_{ikt} \\ & + \alpha_9 \text{CAR}_{ikt} + \alpha_{10} \text{GDPG}_{kt} + \varepsilon_{ikt} \end{aligned} \quad (3)$$

$$\begin{aligned} \text{Social efficiency}_{ikt} = & \alpha'_0 + \alpha'_1 \text{OFS DUMMY}_i + \alpha'_2 \text{PAR30}_{ikt} + \alpha'_3 \text{LGR}_{ikt} + \alpha'_4 \text{NIM}_{ikt} \\ & + \alpha'_5 \text{VTMBNOI}_{ikt} + \alpha'_6 \text{VTINOI}_{ikt} + \alpha'_7 \text{SIZE}_{ikt} + \alpha'_8 \text{ROA}_{ikt} \\ & + \alpha'_9 \text{CAR}_{ikt} + \alpha'_{10} \text{GDPG}_{kt} + \varepsilon'_{ikt} \end{aligned} \quad (4)$$

where  $i$  indexes MFIs ( $i = 1, \dots, 389$ ),  $t$  indexes time periods ( $t = 1, \dots, 15$ ) and  $k$  indexes countries ( $k = 1, \dots, 69$ )

Operational efficiency<sub>ikt</sub>: operational efficiency score of the  $i$ -th MFI from the  $k$ -th country and at the time period  $t$  (equation 5)

Social efficiency<sub>ikt</sub>: social efficiency score of the  $i$ -th MFI from the  $k$ -th region and at the time period  $t$  (equation 6)

OFS-DUMMY <sub>$i$</sub> : set to 1 if the MFI Offers FinTech Services and to 0 otherwise

PAR30<sub>ikt</sub>: Portfolio At Risk of the  $i$ -th MFI at the time period  $t$

LGR<sub>ikt</sub>: Loan growth rate of the  $i$ -th MFI at the time period  $t$

NIM<sub>ikt</sub>: Net Interest Margin of the  $i$ -th MFI at the time period  $t$

VTMBNOI<sub>ikt</sub>: Value of Transactions via Mobile phone to the Net Operating Income of the  $i$ -th MFI at the time period  $t$

VTINOI<sub>ikt</sub>: Value of Transactions by the internet to the Net Operating Income of the  $i$ -th MFI at the time period  $t$

SIZE<sub>ikt</sub>: total assets of the  $i$ -th MFI at the time period  $t$

ROA<sub>ikt</sub>: Return On Assets of the  $i$ -th MFI at the time period  $t$

CAR<sub>ikt</sub>: Capital-to-Asset ratio of the  $i$ -th MFI at the time period  $t$

GDPG<sub>ikt</sub>: Gross Domestic Products Growth of the k-th country at the time period t

$\alpha_n$  and  $\alpha'_n$ : Vectors of k unknown parameters to be estimated (*with*  $n = 1, \dots, 10$ )

$\varepsilon_{ikt}$  and  $\varepsilon'_{ikt}$ : Random errors that are deemed to be out of the MFT's control

Since we seek to propose a holistic understanding of the impact of FinTech on MFIs efficiency, we have to look at its moderating effect on managerial overconfidence as it could improve the level of efficiency.

*3.3.2 FinTech moderating effect on managerial overconfidence.* It has long been demonstrated that overconfidence leads managers to excessive risk-taking decisions, which deteriorates the company's efficiency. Hence, if we can prove a moderating effect of FinTech solutions on the overconfidence bias, it will be hugely beneficial.

$$\begin{aligned} \text{Operational efficiency}_{ikt} = & \gamma_0 + \gamma_1 \text{PAR30}_{ikt} + \gamma_2 \text{NIM}_{ikt} + \gamma_3 \text{LGR}_{ikt} + \gamma_4 \text{VTINOI}_{ikt} \\ & + \gamma_5 \text{VTMBNOI}_{ikt} + \gamma_6 \text{SIZE}_{ikt} + \gamma_7 \text{ROA}_{ikt} + \gamma_8 \text{CAR}_{ikt} \\ & + \gamma_9 \text{GDPG}_{kt} + \beta_1 (\text{PAR}_{ikt} * \text{VTINOI}_{ikt}) \\ & + \beta_2 (\text{PAR}_{ikt} * \text{VTMBNOI}_{ikt}) + \beta_3 (\text{LGR}_{ikt} * \text{VTINOI}_{ikt}) \\ & + \beta_4 (\text{LGR}_{ikt} * \text{VTMBNOI}_{ikt}) + \beta_5 (\text{NIM}_{ikt} * \text{VTINOI}_{ikt}) \\ & + \beta_6 (\text{NIM}_{ikt} * \text{VTMBNOI}_{ikt}) + \varepsilon_{ikt} \end{aligned} \quad (5)$$

With  $\varepsilon_{ikt} = \mu_{ik} + \nu_{ikt}$

$$\begin{aligned} \text{Social efficiency}_{ikt} = & \gamma'_0 + \gamma'_1 \text{PAR30}_{ikt} + \gamma'_2 \text{NIM}_{ikt} + \gamma'_3 \text{LGR}_{ikt} + \gamma'_4 \text{VTINOI}_{ikt} \\ & + \gamma'_5 \text{VTMBNOI}_{ikt} + \gamma'_6 \text{SIZE}_{ikt} + \gamma'_7 \text{ROA}_{ikt} + \gamma'_8 \text{CAR}_{ikt} \\ & + \gamma'_9 \text{GDPG}_{kt} + \beta'_1 (\text{PAR}_{ikt} * \text{VTINOI}_{ikt}) \\ & + \beta'_2 (\text{PAR}_{ikt} * \text{VTMBNOI}_{ikt}) + \beta'_3 (\text{LGR}_{ikt} * \text{VTINOI}_{ikt}) \\ & + \beta'_4 (\text{LGR}_{ikt} * \text{VTMBNOI}_{ikt}) + \beta'_5 (\text{NIM}_{ikt} * \text{VTINOI}_{ikt}) \\ & + \beta'_6 (\text{NIM}_{ikt} * \text{VTMBNOI}_{ikt}) + \varepsilon'_{ikt} \end{aligned} \quad (6)$$

where i indexes' MFIs ( $i = 1, \dots, 389$ ), t indexes time periods ( $t = 1, \dots, 15$ ) and k indexes countries ( $k = 1, \dots, 69$ )

Operational efficiency<sub>ikt</sub>: operational efficiency score of the i-th MFI from the k-th country and at the time period t (equation 5).

Social efficiency<sub>ikt</sub>: social efficiency score of the i-th MFI at the time period t (equation 6).

$\gamma_n$  and  $\gamma'_n$ : Vectors of n unknown parameters to be estimated (*with*  $n = 1, \dots, 9$ )

$\beta_m$  and  $\beta'_m$ : Vectors of m unknown parameters that measure the moderating effect of FinTech on the managerial overconfidence bias and the level of risk-taking within an institution (*with*  $m = 1, \dots, 6$ )

$\varepsilon_{ikt}$  and  $\varepsilon'_{ikt}$ : Random errors that are deemed to be out of the MFT's control

Now that we have developed our empirical methodology, and before delving deep into the analyses and interpretations of the estimation findings, we must start with the overall statistical descriptions.

4. Descriptive analysis

Descriptive analysis and specification tests are the primary steps for all empirical studies. Indeed, they are crucial to extract useful information from data and prepare it for further analyses. The following will provide more information and details.

The first result to underline in the summary results table is that our dependent variables have low averages with not too high volatilities (lower than 30%), as measured by standard deviations. In fact, given that the efficiency scores are always between 0 and 1 and that the averages of operational and social efficiencies are about (0.4995) and (0.5140), respectively, they are considered low.

The FinTech proxies have the lowest averages (3.0651% for VTINOI and 6.4582% for VTMBNOI); hence, we can conclude the low adoption of FinTech services. Furthermore, the extreme values indicate a broad dispersion, which suggests that these overall averages are driven by only a few institutions. Whereas the growth of MFIs in terms of outreach measured by loan growth rates is increasing with an average of (17.308%), but also with relatively high volatility (36.0851%).

From a sustainability standpoint, the MFIs maintain an average CAR of (24.9222%); namely, three times the minimum required for all FIs, fixed at 8% in accordance with Basel principles. Besides, as it could be expected, MFIs have small sizes with a mean of log assets of (6.3947%).

Concerning their profitability, Table 3 shows an average interest income of (13.602%), as measured by the NIM, whose drawback is that it does not measure the overall profitability of an institution. It neglects the non-interest income, operating expenses and non-performing assets. To gain a more holistic vision, the ROA is satisfactory. The descriptive statistics prove that MFIs in our sample have an average ROA of (1.893%), which implies that they have good profitability. In addition, they have a tolerable risk of default with an average PAR (4.6217%).

From another standpoint, the positive high averages of NIM and LGR, which is about 17.31%, demonstrate the lack of prudence of the MFIs' managers. Finally, the table of descriptive statistics shows a GDPG average of (4.7351%) ranging between a minimum of (−27.9944%) and a maximum of (34.4662%) with a standard deviation of (3.4569%).

This analysis still with no great significance, but rather we need to assess the relationship between the different variables in our models, notably, the correlation coefficients taken in pairs. Generally, ranging between −1 and 1, a coefficient close to 1 implies a strong positive correlation; by contrast, a value close to −1 indicates a strong negative correlation. Briefly and by reference to Table A2, all correlation coefficients are low with few negative ones. Viz., for example, the operational efficiency with the social efficiency and with the FinTech

**Table 3.**  
Summary of  
descriptive statistics

| Variable               | Observations | Mean      | Standard deviation | Min        | Max       |
|------------------------|--------------|-----------|--------------------|------------|-----------|
| Operational efficiency | 5,805        | 0.4994736 | 0.2794661          | 0.0000571  | 0.999532  |
| Social efficiency      | 5,805        | 0.5140177 | 0.2154528          | 0.0004613  | 0.999531  |
| VTINOI                 | 5,805        | 0.0306507 | 1.788659           | −39.42664  | 120.8413  |
| VTMBNOI                | 5,805        | 0.0645823 | 3.050232           | −44.8433   | 196.5598  |
| LGR (%)                | 5,805        | 17.307974 | 36.08507           | −148.10836 | 560.9784  |
| NIM (%)                | 5,805        | 13.602005 | 12.771874          | −130.82594 | 114.9199  |
| PAR30 (%)              | 5,805        | 4.62175   | 9.714166           | 0          | 373.18    |
| CAR (%)                | 5,805        | 24.922218 | 23.8403631         | −149.79616 | 147.55436 |
| ROA (%)                | 5,805        | 1.8929612 | 8.621921           | −123.11    | 158.9435  |
| SIZE                   | 5,805        | 6.394725  | 2.636033           | 0          | 9.908261  |
| GDPG (%)               | 5,805        | 4.735132  | 3.456964           | −27.99444  | 34.46621  |

**Source(s):** Authors' own elaboration



proxies. As these coefficients highly depend on the sample size, we can use correlation tests that allow measuring the significance of the correlation [4].

Evidently, the impacts of all control and explanatory variables on the operational and social efficiencies will be fully considered hereafter, but before, it is quite important to analyze the correlation between these variables (explanatory and control). This correlation analysis will help us better understand the relevance of the selected attributes and make sure whether moderation really exists.

At first glance, we notice a positive significant correlation between VTINOI and VTMBNOI. It is as if they come as a package. Further, the directions of correlation to all control variables (captured by the signs of coefficients) are the same for both FinTech proxies. That is to say, the two proxies move in the same direction for each control variable.

The positive correlations to LGR indicate that the more MFIs offer financial services via technological channels, the more they enhance their outreach to new and current customers. However, the correlation is only significant for VTINOI, which leads us to conclude that the Internet channel is better suited and preferred for loan application processes.

Positive, weak and insignificant correlations to NIM prove that opting for a technological change slightly improves the level of NIM for MFIs. Referring to the previous statement, we can say that FinTech channels could really help to reach new customers, but maybe not at lower costs.

Similarly, the correlations to PAR30 are also positive, weak and insignificant, which means that relying more on FinTech services causes a weak deterioration of the quality of the loan portfolios. If we will presume that FinTech channels increase the ease of access to financial services (including loans) for marginalized populations, then these positive correlations could be fully explained.

For the SIZE variable, the correlations are positive and insignificant, too. They indicate that MFIs are able to benefit from technological changes to expand their activity, reach more clients and grow.

Finally, there are negative, weak and insignificant correlations to both; CAR and ROA, suggesting that MFIs offering FinTech services have lower profitability and that they rely more on current liabilities to finance their operations.

It is really worth mentioning that correlation does not mean necessarily causation especially when it is not significant.

## 5. Results and interpretations

This section provides the analysis and interpretation of the econometric results obtained from our models allowing us to respond to the problem posed in this thesis, which is mainly to know the impact of the integration of FinTech services within MFIs on their operational and social efficiency.

### 5.1 Operational and social efficiency scores

Referring to [Table 4](#), the averages per year show that non-innovative MFIs have greater operational efficiency than those offering FinTech services for almost the whole period (12 years out of 15), which does not comply with our expectations. It is noteworthy to mention that even for the three years (2012, 2014 and 2019) when the operational efficiency of innovative MFIs exceeds that of non-innovative ones, the differences are too weak. By contrast, the differentials are sufficiently high when they are in favor of non-innovative MFIs especially, for the years 2009, 2010 and 2015. During these years, the operational efficiency of MFIs offering FinTech services dropped to its lowest levels.

**Table 4.**  
Operational efficiency  
scores

|              | Africa | MFIs offering FinTech services |      |      |      | SA   | Av per year  | Africa | MFIs non-offering FinTech services |      |      |      | SA   | Av per year |
|--------------|--------|--------------------------------|------|------|------|------|--------------|--------|------------------------------------|------|------|------|------|-------------|
|              |        | EAP                            | ECCA | LAC  | MENA |      |              |        | EAP                                | ECCA | LAC  | MENA |      |             |
| 2005         | 0.41   | 0.37                           | 0.59 | 0.52 | 0.23 | 0.70 | 0.47         | 0.50   | 0.46                               | 0.51 | 0.52 | 0.51 | 0.54 | 0.51        |
| 2006         | 0.51   | 0.46                           | 0.52 | 0.49 | 0.28 | 0.46 | 0.45         | 0.53   | 0.42                               | 0.52 | 0.52 | 0.53 | 0.45 | 0.50        |
| 2007         | 0.59   | 0.49                           | 0.53 | 0.47 | 0.20 | 0.50 | 0.46         | 0.64   | 0.44                               | 0.40 | 0.55 | 0.52 | 0.55 | 0.52        |
| 2008         | 0.52   | 0.35                           | 0.54 | 0.47 | 0.19 | 0.29 | 0.40         | 0.44   | 0.51                               | 0.48 | 0.48 | 0.46 | 0.50 | 0.48        |
| 2009         | 0.42   | 0.30                           | 0.50 | 0.46 | 0.16 | 0.49 | 0.39         | 0.54   | 0.50                               | 0.45 | 0.51 | 0.59 | 0.46 | 0.51        |
| 2010         | 0.55   | 0.36                           | 0.15 | 0.41 | 0.31 | 0.52 | 0.38         | 0.52   | 0.40                               | 0.55 | 0.47 | 0.65 | 0.55 | 0.52        |
| 2011         | 0.51   | 0.44                           | 0.56 | 0.41 | 0.49 | 0.49 | 0.48         | 0.51   | 0.38                               | 0.49 | 0.49 | 0.60 | 0.46 | 0.49        |
| 2012         | 0.61   | 0.41                           | 0.64 | 0.43 | 0.83 | 0.42 | 0.56         | 0.48   | 0.45                               | 0.41 | 0.51 | 0.53 | 0.49 | 0.48        |
| 2013         | 0.40   | 0.39                           | 0.44 | 0.42 | 0.45 | 0.53 | 0.44         | 0.55   | 0.46                               | 0.46 | 0.53 | 0.60 | 0.50 | 0.52        |
| 2014         | 0.59   | 0.34                           | 0.69 | 0.47 | 0.59 | 0.42 | 0.52         | 0.42   | 0.53                               | 0.42 | 0.49 | 0.59 | 0.49 | 0.49        |
| 2015         | 0.42   | 0.38                           | 0.46 | 0.42 | 0.36 | 0.52 | 0.43         | 0.52   | 0.52                               | 0.50 | 0.43 | 0.61 | 0.45 | 0.51        |
| 2016         | 0.49   | 0.63                           | 0.40 | 0.52 | 0.50 | 0.56 | 0.52         | 0.60   | 0.55                               | 0.54 | 0.46 | 0.63 | 0.51 | 0.55        |
| 2017         | 0.44   | 0.38                           | 0.43 | 0.44 | 0.31 | 0.60 | 0.43         | 0.56   | 0.41                               | 0.49 | 0.47 | 0.58 | 0.45 | 0.49        |
| 2018         | 0.45   | 0.36                           | 0.55 | 0.46 | 0.48 | 0.65 | 0.49         | 0.56   | 0.47                               | 0.41 | 0.52 | 0.63 | 0.50 | 0.52        |
| 2019         | 0.60   | 0.60                           | 0.59 | 0.60 | 0.59 | 0.59 | 0.60         | 0.59   | 0.59                               | 0.59 | 0.60 | 0.60 | 0.57 | 0.59        |
| Av by region | 0.50   | 0.42                           | 0.51 | 0.46 | 0.40 | 0.52 | Av by region | 0.53   | 0.47                               | 0.48 | 0.50 | 0.57 | 0.50 |             |

**Source(s):** Authors' own elaboration

It must be emphasized that the geographical distribution of our sample matters and that the significant deterioration of innovative MFIs' operational efficiency may coincide with times of disruption for the regions where the majority of innovative institutions in our sample come from. Thus, in such cases, the interpretation of the above observations must take account of the financial and economic context of these regions. For that reason, please note that the scores of efficiency by country proving the relevance of the regional distribution of MFIs are displayed and detailed in [Table A1](#).

We know that more than 50% of innovative MFIs in our sample are from the LAC region, a very unstable region with successive wars, crises (political, diplomatic, economic, etc.) and very bad relationships between its countries having serious repercussions on all sectors. Moreover, we found that more than 30% of these institutions are in Ecuador, which is the most vulnerable and the less stable country within the region. It went through very rough times during our study period:

- (1) 2008–2010, characterized by the famous global crisis of subprime added to the Andean crisis.
- (2) 2015 was a year of severe recession and uncertainty.

Looking at the averages by region, we noticed that only the innovative MFIs in South Asia and the EECA regions have greater operational efficiency compared to non-innovative MFIs (not too high differentials). This can be due to the fact that both regions have great expertise in FinTech. In Asia, digital financial systems are highly developed and deeply penetrated, while Europe has a robust, innovative market with very supportive regulations.

[Table 5](#) shows that the scores of efficiencies of both innovative and non-innovative MFIs are so close (nearly the same) with very little lead in favor of MFIs offering FinTech services, except for the year 2016. That year was marked by a superiority of traditional MFIs with a score fairly above that of innovative ones for this same year (0.55 against 0.48), which is the highest level of social efficiency for our sample throughout the entire period. Actually, the distribution of non-innovative MFIs in our sample is too geographically scattered, but still, there is a certain dominance for a few countries in terms of the number of institutions therein. Namely, Peru, Bangladesh and India. They are in the lead of the microfinance industry for the year 2016 (according to the Microfinance Barometer of 2017), and they are among the top social performers. Their mutual specificity is that they all have very high levels of poverty but also a socially engaged microfinance sector.

More importantly, the table above shows that the social efficiency of MFIs has reached significant levels (on average, 0.5) and that it has not fluctuated greatly until 2018. However, during the year 2019, the social efficiency of both innovative and non-innovative MFIs has plummeted sharply, to the lowest level since 2005. Besides, the comparison between operational and social efficiencies of both innovative and non-innovative MFIs indicates that 2019 is a key year. During that year, they both achieved their highest level of operational efficiency and their lowest level of social efficiency. As is reasonably logic to expect, the massive rise that has been known to the microfinance industry during the last years could be at the expense of its social mission if it translates into over-indebtedness or abusive recovery. In that respect, only poor people bear the adverse consequences of this growth.

The averages by region of social efficiency of innovative and non-innovative MFIs across the six regions considered in our sample prove that MFIs offering FinTech services in Africa, EAP and LAC have better social efficiency than non-innovative MFIs in these regions. In fact, this observation is not surprising at all, as we know that they have a priority shift toward social issues and that they were always able to develop or introduce novelty solutions suited to their specificities. In this case, they knew how to take advantage of the deep digital penetration, the high affordability of mobile phones and the great acceptance of technology among their populations for better social performances.

**Table 5.**  
Social efficiency scores

|                                     | Africa | MFIs offering FinTech services |      |      |      | SA   | Av per year  | Africa | MFIs non-offering FinTech services |      |      |      | SA   | Av per year |
|-------------------------------------|--------|--------------------------------|------|------|------|------|--------------|--------|------------------------------------|------|------|------|------|-------------|
|                                     |        | EAP                            | EECA | LAC  | MENA |      |              |        | EAP                                | EECA | LAC  | MENA |      |             |
| 2005                                | 0.42   | 0.40                           | 0.63 | 0.59 | 0.35 | 0.54 | 0.49         | 0.52   | 0.38                               | 0.58 | 0.54 | 0.44 | 0.38 | 0.47        |
| 2006                                | 0.40   | 0.45                           | 0.71 | 0.62 | 0.34 | 0.31 | 0.47         | 0.45   | 0.40                               | 0.56 | 0.56 | 0.44 | 0.36 | 0.46        |
| 2007                                | 0.48   | 0.43                           | 0.80 | 0.63 | 0.36 | 0.22 | 0.49         | 0.51   | 0.40                               | 0.60 | 0.56 | 0.46 | 0.39 | 0.49        |
| 2008                                | 0.50   | 0.42                           | 0.75 | 0.64 | 0.37 | 0.40 | 0.51         | 0.51   | 0.39                               | 0.55 | 0.59 | 0.42 | 0.39 | 0.48        |
| 2009                                | 0.53   | 0.42                           | 0.73 | 0.62 | 0.38 | 0.33 | 0.50         | 0.51   | 0.40                               | 0.61 | 0.58 | 0.45 | 0.42 | 0.50        |
| 2010                                | 0.49   | 0.42                           | 0.71 | 0.67 | 0.38 | 0.39 | 0.51         | 0.51   | 0.42                               | 0.64 | 0.58 | 0.42 | 0.42 | 0.50        |
| 2011                                | 0.53   | 0.50                           | 0.73 | 0.67 | 0.40 | 0.34 | 0.53         | 0.50   | 0.44                               | 0.68 | 0.59 | 0.52 | 0.43 | 0.53        |
| 2012                                | 0.58   | 0.46                           | 0.72 | 0.63 | 0.44 | 0.33 | 0.53         | 0.50   | 0.41                               | 0.69 | 0.55 | 0.58 | 0.39 | 0.52        |
| 2013                                | 0.56   | 0.55                           | 0.71 | 0.63 | 0.43 | 0.34 | 0.54         | 0.50   | 0.38                               | 0.69 | 0.56 | 0.60 | 0.40 | 0.52        |
| 2014                                | 0.52   | 0.59                           | 0.46 | 0.65 | 0.42 | 0.33 | 0.50         | 0.47   | 0.42                               | 0.66 | 0.55 | 0.61 | 0.41 | 0.52        |
| 2015                                | 0.52   | 0.60                           | 0.48 | 0.62 | 0.43 | 0.33 | 0.50         | 0.51   | 0.47                               | 0.63 | 0.56 | 0.56 | 0.42 | 0.53        |
| 2016                                | 0.56   | 0.60                           | 0.33 | 0.64 | 0.44 | 0.31 | 0.48         | 0.51   | 0.48                               | 0.69 | 0.51 | 0.66 | 0.42 | 0.55        |
| 2017                                | 0.65   | 0.60                           | 0.48 | 0.68 | 0.46 | 0.24 | 0.48         | 0.48   | 0.46                               | 0.61 | 0.57 | 0.64 | 0.42 | 0.53        |
| 2018                                | 0.60   | 0.45                           | 0.50 | 0.65 | 0.47 | 0.32 | 0.50         | 0.48   | 0.46                               | 0.63 | 0.56 | 0.58 | 0.42 | 0.52        |
| 2019                                | 0.42   | 0.42                           | 0.42 | 0.42 | 0.42 | 0.38 | 0.45         | 0.42   | 0.42                               | 0.42 | 0.41 | 0.42 | 0.42 | 0.42        |
| Av by region                        | 0.52   | 0.49                           | 0.61 | 0.63 | 0.41 | 0.34 | Av by region | 0.50   | 0.42                               | 0.62 | 0.55 | 0.52 | 0.41 |             |
| Source(s): Authors' own elaboration |        |                                |      |      |      |      |              |        |                                    |      |      |      |      |             |

It can be clearly noticed that FinTech services offering does not ensure better social and operational efficiency at once. It is as if they are mutually exclusive. For each region, where MFIs offering FinTech services have greater social efficiency compared to those that do not offer FinTech services, they have lower operational efficiency and vice versa. The only exception to that is MENA since it has very low averages of operational and social efficiency for MFIs offering FinTech services. This can be due to its lack of expertise in FinTech.

### 5.2 Determinants of operational and social efficiency

The specific impact of each of the explanatory variables on the operational and social efficiency of MFIs will be observed on the various regressions (Models 5 and 6), the key results of which are summarized in the following tables.

Looking at the results summed up in [Table 6](#), the first feature to note is the insignificant impact of the NIM and the VTMBNOI variables on the operational efficiency of MFIs in our sample. Hence, we cannot consider their impact

The PAR30, SIZE, ROA, CAR and the OFS-DUMMY have a highly significant negative impact on the operational efficiency of MFIs (they are all significant at 1%). The negative coefficient for PAR30 is congruent with our expectations and with several anterior studies ([Bassem \(2012\)](#), [Kulkarni \(2017\)](#) and [Navin and Sinha \(2020\)](#)), proving that it poses a serious obstacle to the profitability and operational efficiency of MFIs. Concerning the sign of coefficient capturing the relationship between the MFIs' size and their operational efficiency, there have been mixed results. The coefficient displayed by our regression is consistent with the surveys of, e.g. [Bassem \(2008\)](#), [Efendic and Hadziahmetovic \(2017\)](#) and [Johan \(2019\)](#). Actually, it can be explained by the fact that larger MFIs have a vast number of clients, which makes the due diligence mission harder and, thus, a higher level of risk taken. Further, it is too hard to satisfy the specific needs of each of them individually. For the ROA and the CAR, our results contradict the majority of researchers that have proved a positive correlation of these variables with the operational efficiency of FIs. In fact, according to the results in [Table 6](#), they have weak impacts in terms of the absolute value of coefficients but, still statistically significant for our model. An acceptable explanation for these negative relationships is that internally generated funds, as well as equity financing, can lead to more agency problems, as managers, in such instances, are willing to invest more in inefficient projects (in compliance with the agency theory).

The LGR has a positive impact on the operational efficiency of MFIs, significant at 5%. This is compliant with the results of [Kwan and Eisbens \(1997\)](#), indicating that moderate LGRs, up to a certain level [\[5\]](#), are positively related to the operational efficiency of FIs. The GDPG as a macroeconomic determinant is negatively related to the efficiency of MFIs, significant at 10%. This negative relation was confirmed in, e.g. [Bolt et al. \(2012\)](#), [Combey and Togbenou \(2017\)](#) and [Khrawish \(2011\)](#). Concerning the second proxy of FinTech, contrary to our expectations, our results reveal a negative impact, statistically significant at 10%, with an absolute value of the associated coefficient of 0.0081659 (slightly different from zero). This means that an increase of one unit in the VTINOI translates into a decrease of 0.0081659 in the score of operational efficiency of MFIs. Actually, some studies from the banking literature looked at the impact of technology investments on the financial and operational performance of banks and found a negative relationship. [Khrawish and Al-Sa'di \(2011\)](#), [Malhotra and Singh \(2009\)](#) and [Willy and Obinne \(2013\)](#) explained such a negative relationship by the very high expenses and costs associated with the integration and the execution of these services.

To recapitulate, the findings from [Table 6](#) prove that the integration of mobile phone financial services does not affect the operational efficiency of MFIs. However, the integration of Internet financial services adversely affects the level of operational efficiency, which does not validate our first hypothesis.

**Table 6.**  
Estimation results for  
the determinants of  
operational efficiency

|   | PAR      | LGR                | NIM    | VTMBOI | VTNOI  | SIZE   | ROA                  | CAR                  | GDPC   | OFS-DUMM | Const   |
|---|----------|--------------------|--------|--------|--------|--------|----------------------|----------------------|--------|----------|---------|
| Operational efficiency <sub>ikt</sub> = $\alpha_0 + \alpha_1$ OFSDUMMY <sub>i</sub> + $\alpha_2$ PAR30 <sub>ikt</sub> + $\alpha_3$ LGR <sub>ikt</sub> + $\alpha_4$ NIM <sub>ikt</sub> + $\alpha_5$ VTMBOI <sub>ikt</sub> + $\alpha_6$ VTNOI <sub>ikt</sub> + $\alpha_7$ SIZE <sub>ikt</sub> + $\alpha_8$ ROA <sub>ikt</sub> + $\alpha_9$ CAR <sub>ikt</sub> + $\alpha_{10}$ GDPG <sub>ikt</sub> + $\varepsilon_{ikt}$ (3) |          |                    |        |        |        |        |                      |                      |        |          |         |
| Var   |          |                    |        |        |        |        |                      |                      |        |          |         |
| <i>Coef</i>   | -0.027   | 321e <sup>-7</sup> | 0.0004 | -0.002 | -0.008 | -0.014 | -1.89e <sup>-7</sup> | -2.53e <sup>-8</sup> | -0.002 | -0.036   | 0.524   |
| <i>t-z-Statistic</i>  | -3.65*** | 2.03**             | 0.03   | -1.27  | -1.76* | -9.86  | -5.03***             | -2.83***             | -1.86* | -4.01*** | 3.51*** |
| <i>Prob</i>   | 0.000    | 0.042              | 0.975  | 0.206  | 0.079  | 0.000  | 0.000                | 0.005                | 0.063  | 0.000    | 0.000   |

**Note(s):** The number of stars points to the level of significance (\*\*\*for 1%, \*\*for 5%, and \*for 10%)

**Source(s):** Author's own elaboration

Table 7 shows a negative linkage between the social efficiency of MFIs and the two FinTech proxies, which is inconsistent with our expectations. However, they are statistically insignificant. Thus, these negative relationships mean nothing to our model.

The PAR30 exerts a strong positive impact on the social efficiency of MFIs (significant at 1%). Unlike its unfavorable impact on MFIs' operational efficiency, a greater level of tolerated risk implies a better focus on the poor and results in a higher financial inclusion. The variable SIZE also has a statistically significant positive impact on social efficiency, contrary to that exercised on the operational efficiency. In fact, larger MFIs are more able to keep meeting their social responsibilities, thanks to the combination of their financial expertise with ongoing investment in enhancing their understanding of the poor problems (Copestake (2007).)

Given that the growth in granted loans is a sort of manifestation of a larger scale of outreach, it is favorable for social efficiency. The above results confirm our expectations, as it shows a positive relationship between LGR and the social efficiency of MFIs. Except a weaker magnitude in terms of the absolute value of coefficients, compared to that of operational efficiency. Further, the same as for the operational efficiency, Table 7 shows a negative impact of GDPG on the social efficiency of MFIs, significant at 1%, but with a higher magnitude. Actually, the GDPG reduces the demand for MFIs' financial services, and thus, the relative importance of MFIs for financial inclusion, which harms their social and operational efficiency (Tan and Floros (2012).)

Considering the OFS-DUMMY variable, it reveals a negative significant relationship with operational efficiency and a positive significant one with social efficiency. This suggests that innovative MFIs (offering FinTech services) are more socially oriented with better social efficiency but operationally inefficient.

Briefly, we cannot decide about the impact of the integration of FinTech services within MFIs on their social efficiency due to the insignificance of coefficients associated with the FinTech proxies.

### 5.3 *FinTech moderating effect on managerial overconfidence*

Moderation denotes a change in the magnitude of the impact of an explanatory variable on the explained variable due to a third one, denoted moderator. The existence of moderation can be exhibited by the effect of the product obtained by multiplying the moderating and the independent variables (Zainuddin *et al.* (2020)).

Since the moderating variables selected for our survey are the FinTech proxies, we limit our attention to the institutions offering FinTech services. First, we will estimate our models for operational and social efficiency without neither the FinTech variables nor the moderating variables (OE base model and SE base model). Then, we re-estimate our models with these variables, which are Models (5) and (6).

From the first part of Table 8 (on the left-hand side), the OE's base model shows a positive [6] significant impact of PAR30. This finding is contrary to the result observed in Table 6 for the whole sample with no distinction between innovative and non-innovative MFIs, which leads us to say that maybe the innovative MFIs are better at striking a balance between operational efficiency and risk. Also, this first part of the table shows a positive insignificant impact of the LGR and a negative insignificant impact of the NIM on the operational efficiency of MFIs. Whereas Model (5) indicates a lower and insignificant coefficient of PAR30, a positive insignificant coefficient of LGR with a lower magnitude, and a positive but insignificant coefficient of NIM.

Indeed, the interaction variables included in Model (5) are used to capture the moderating effect of FinTech services on the overconfidence-operational efficiency relationship. The integration of mobile phone and Internet financial services positively moderates the



|   | PAR     | LGR                  | NIM     | VTMBNOI | VTINOI  | SIZE     | ROA                 | CAR                 | GDPG     | OFS-DUMM | Const    |
|---|---------|----------------------|---------|---------|---------|----------|---------------------|---------------------|----------|----------|----------|
| Social efficiency <sub>ikt</sub> = $\alpha'_0 + \alpha'_1$ OFSDUMMY <sub>i</sub> + $\alpha'_2$ PAR30 <sub>ikt</sub> + $\alpha'_3$ LGR <sub>ikt</sub> + $\alpha'_4$ NIM <sub>ikt</sub> + $\alpha'_5$ VTMBNOI <sub>ikt</sub> + $\alpha'_6$ VTINOI <sub>ikt</sub> + $\alpha'_7$ SIZE <sub>ikt</sub> + $\alpha'_8$ ROA <sub>ikt</sub> + $\alpha'_9$ CAR <sub>ikt</sub> + $\alpha'_{10}$ GDPG <sub>ikt</sub> + $\epsilon'_{ikt}$ (4) |         |                      |         |         |         |          |                     |                     |          |          |          |
| Var   |         |                      |         |         |         |          |                     |                     |          |          |          |
| <i>Coef</i>   | 0.002   | 7.68e <sup>-11</sup> | -0.0001 | -0.0003 | -0.0004 | 0.016    | 6.34e <sup>-8</sup> | 4.53e <sup>-9</sup> | -0.003   | 0.0461   | 0.415    |
| <i>t-Statistic</i>  | 3.86*** | 5.61***              | -0.38   | -0.21   | -0.21   | 10.55*** | 1.60                | 0.48                | -3.06*** | 4.86***  | 35.97*** |
| <i>Prob</i>   | 0.000   | 0.000                | 0.705   | 0.837   | 0.835   | 0.000    | 0.109               | 0.630               | 0.002    | 0.000    | 0.000    |

**Source(s):** Authors' own elaboration

|          | OE's base model       |       | Operational efficiency    |       | SE's base model       |       | Social efficiency          |       | Model (6)                  |       |
|----------|-----------------------|-------|---------------------------|-------|-----------------------|-------|----------------------------|-------|----------------------------|-------|
|          | Coef                  | Prob  | Coef                      | Prob  | Coef                  | Prob  | Coef                       | Prob  | Coef                       | Prob  |
| PAR30    | 0.003346**            | 0.049 | 0.000176                  | 0.641 | 0.008336***           | 0.000 | 0.001437***                | 0.000 | 0.001437***                | 0.000 |
| LGR      | 1.75 e <sup>-11</sup> | 0.639 | 2.50 e <sup>-12</sup>     | 0.848 | 5.99 e <sup>-12</sup> | 0.800 | 7.80 e <sup>-11</sup> ***  | 0.000 | 7.80 e <sup>-11</sup> ***  | 0.000 |
| NIM      | -0.000036             | 0.842 | -0.000039                 | 0.813 | 9.20 e <sup>-6</sup>  | 0.942 | -0.000099                  | 0.567 | -0.000099                  | 0.567 |
| SIZE     | -0.0214***            | 0.000 | -0.014012***              | 0.000 | 0.224515              | 0.000 | 0.015872***                | 0.000 | 0.015872***                | 0.000 |
| ROA      | -0.002116             | 0.154 | -1.89 e <sup>-7</sup> *** | 0.000 | 0.002113**            | 0.033 | 5.98 e <sup>-8</sup>       | 0.132 | 5.98 e <sup>-8</sup>       | 0.132 |
| CAR      | 0.000589*             | 0.095 | -2.51 e <sup>-8</sup> *** | 0.005 | -0.000892***          | 0.000 | 3.17 e <sup>-9</sup>       | 0.737 | 3.17 e <sup>-9</sup>       | 0.737 |
| VTMENOI  |                       |       | -0.009650                 | 0.270 |                       |       | 0.005766                   | 0.531 | 0.005766                   | 0.531 |
| VTNOI    |                       |       | 0.009224                  | 0.550 |                       |       | -0.005779                  | 0.722 | -0.005779                  | 0.722 |
| PAR*     |                       |       | 0.003031*                 | 0.054 |                       |       | -0.003795**                | 0.023 | -0.003795**                | 0.023 |
| VTMENOI  |                       |       | 0.0021734*                | 0.051 |                       |       | 0.000639                   | 0.589 | 0.000639                   | 0.589 |
| VTNOI    |                       |       | 2.75 e <sup>-11</sup> *   | 0.060 |                       |       | -4.70 e <sup>-11</sup> *** | 0.002 | -4.70 e <sup>-11</sup> *** | 0.002 |
| LGR*     |                       |       | -2.56 e <sup>-11</sup> *  | 0.065 |                       |       | 8.84 e <sup>-12</sup>      | 0.675 | 8.84 e <sup>-12</sup>      | 0.675 |
| VTMENOI  |                       |       | -0.150671**               | 0.041 |                       |       | 0.140414                   | 0.197 | 0.140414                   | 0.197 |
| VTNOI    |                       |       | -0.142766**               | 0.019 |                       |       | 0.000244                   | 0.998 | 0.000244                   | 0.998 |
| NIM*     |                       |       |                           |       |                       |       |                            |       |                            |       |
| VTMENOI  |                       |       |                           |       |                       |       |                            |       |                            |       |
| VTNOI    |                       |       |                           |       |                       |       |                            |       |                            |       |
| GDPG     | -0.004608*            | 0.085 | -0.001964*                | 0.064 | -0.000135             | 0.941 | -0.003831***               | 0.001 | -0.003831***               | 0.001 |
| Constant | 0.605508***           | 0.000 | 0.498703***               | 0.000 | 0.418121              | 0.000 | 0.425749                   | 0.000 | 0.425749                   | 0.000 |

Source(s): Authors' own elaboration

**Table 8.**  
Estimation results  
capturing the FinTech  
moderating effect

PAR30-OE relationship at level 10%, which means that the level of PAR30 will become more beneficial for MFIs with increased reliance on FinTech services.

The LGR-OE relationship is positively moderated by the integration of mobile phone financial services at 10%. However, it is negatively moderated by the integration of Internet financial services at the same level, which means that the impact of LGR on OE will become less positive. They both having inverse moderating effects, but ultimately the impact of LGR on operational efficiency remained positive and insignificant.

The two FinTech proxies VTMBNOI and VTINOI, negatively moderate the NIM-OE relationship at 5%. This means that the negative effect of NIM on the OE of MFIs with more technological innovations will become more negative. Actually, a very high level of NIM can be due to a twice alternatives. Either high-interest rates charged to clients that damage their repayment abilities and thus, the level of operational efficiency because of excessive default risk, or low-interest rates offered to depositors that prevent them from allocating their funds in such institutions, hence, obliging these institutions to switch to more expensive funding sources. Anyways, these two alternatives lead to the same result (more operational inefficiency), and they are more justified for innovative MFIs as they seek to cover the exceptionally high costs of the integration of FinTech services.

From the second part of Table 8 (on the right-hand side), the SE's base model shows a positive impact of PAR30, LGR and NIM on the social efficiency of innovative MFIs. However, only the PAR30 exercises a significant impact at a 1% level. For the interaction variables, only the PAR\*VTMBNOI and the LGR\*VTMBNOI are significant at 5% and 1%, respectively. They are both negative, which means that the integration of FinTech services within MFIs limited the overconfidence of managers and relegated the focus on depth of outreach to the background.

The results prove that the integration of FinTech services moderates the impact of overconfidence on the level of social and operational efficiencies, which is compliant with Hypotheses 3 and 4.

#### 5.4 Robustness check

To prove the robustness of the above results, we need to test our models with more variables that could be correlated with MFIs' operational and social efficiencies. For the current study, we assume it would be appropriate to add two control variables, which are capital structure indicators (debt to equity ratio and deposits to asset ratio) and one macroeconomic variable (inflation).

- (1) Debt to Equity Ratio (DER): It is considered as a leverage ratio, and it tells the proportional relationship of total liabilities to total equity. The DER reveals the accuracy of the long-term financial policy of an institution.

$$DER = \frac{\text{Total liabilities}}{\text{Total equity}} \quad (7)$$

There is no standard rule of decision, but it is about comparing the ratio of an institution to that of others in the same sector. Generally, a high ratio (above 1) may indicate that the institution is more heavily financed through debts, which are expensive funding resources.

- (1) Deposits to Assets Ratio (DAR): *"It measures the relative portion of the MFIs total assets that is funded by deposits and gives an informed analysis of the role of deposits as funding source"*.

$$DAR = \frac{Total\ deposits}{Total\ assets} \quad (8)$$

According to the surveys of [Cull and C-Kunt \(2011\)](#) and [Muriu \(2011\)](#), there is a significant positive impact of the DAR on the MFIs' sustainability, and hence, they are required to broaden their deposit offerings. Nevertheless, contrary to the evidence mentioned above, [Bogan \(2009\)](#) found a negative relation between DAR and operational efficiency. He suggested that this is perhaps due to the limited experience of MFIs in terms of deposit-taking activity.

- (1) Inflation: As for the GDPG mentioned earlier, it is a yearly country-specific macroeconomic variable. It is the general rise in the prices of goods and services (of daily and common use or even industrial goods) leading to the destruction of purchasing power.

The resulting models are as follows:

$$\begin{aligned} \text{Operational efficiency}_{ikt} = & \alpha_0 + \alpha_1 \text{OFSDUMMY}_i + \alpha_2 \text{PAR30}_{ikt} + \alpha_3 \text{LGR}_{ikt} + \alpha_4 \text{NIM}_{ikt} \\ & + \alpha_5 \text{VTMBNOI}_{ikt} + \alpha_6 \text{VTINOI}_{ikt} + \alpha_7 \text{SIZE}_{ikt} + \alpha_8 \text{ROA}_{ikt} \\ & + \alpha_9 \text{CAR}_{ikt} + \alpha_{10} \text{DER}_{ikt} + \alpha_{11} \text{DAR}_{ikt} + \alpha_{12} \text{GDPG}_{kt} \\ & + \alpha_{13} \text{INF}_{kt} + \varepsilon_{ikt} \end{aligned} \quad (9)$$

$$\begin{aligned} \text{Social efficiency}_{ikt} = & \alpha'_0 + \alpha'_1 \text{OFSDUMMY}_i + \alpha'_2 \text{PAR30}_{ikt} + \alpha'_3 \text{LGR}_{ikt} + \alpha'_4 \text{NIM}_{ikt} \\ & + \alpha'_5 \text{VTMBNOI}_{ikt} + \alpha'_6 \text{VTINOI}_{ikt} + \alpha'_7 \text{SIZE}_{ikt} + \alpha'_8 \text{ROA}_{ikt} \\ & + \alpha'_9 \text{CAR}_{ikt} + \alpha'_{10} \text{DER}_{ikt} + \alpha'_{11} \text{DAR}_{ikt} + \alpha'_{12} \text{GDPG}_{kt} + \alpha'_{13} \text{INF}_{kt} \\ & + \varepsilon'_{ikt} \end{aligned} \quad (10)$$

We seek to verify whether the sign and the significance of the independent variables are preserved after extending our models.

Looking at [Table 9](#), the results of Model (9) of operational efficiency indicate that for the PAR30 and VTINOI, both the sign and the significance of associated coefficients changed compared to Model (3). Whereas for the NIM, CAR, GDPG and the DUMMY variable, only the level of significance changed. Thus, we can conclude that our Model (3) is not too significant as a whole, which the low value of  $R^2$  already confirms. But at least the extended model leads to the same conclusion about the negative impact of the integration of FinTech services on the level of operational efficiency of MFIs. The VTINOI became positive but insignificant so we can neglect its effect. The VTMBNOI kept the same negative effect and it remained insignificant. This negative relationship can be attributed to the poor skills of MFIs in FinTech tools or to the very high costs related to the integration of FinTech services.

From Model (10) of social efficiency, all the included variables kept the same  $\pm$  sign and the same level of significance, except the CAR which became insignificant (of course compared to Model (4)). Again, the robustness check confirms our conclusion about the negative impact of the integration of FinTech services on the social efficiency of MFIs.

**Table 9.**  
Results of robustness  
check [7]

|                                     | Operational efficiency (9) |       | Social efficiency (10)    |       |
|-------------------------------------|----------------------------|-------|---------------------------|-------|
|                                     | Coef                       | Prob  | Coef                      | Prob  |
| PAR30                               | 0.000685*                  | 0.072 | 0.001443***               | 0.000 |
| LGR                                 | 2.59 e <sup>-11</sup> *    | 0.052 | 6.50 e <sup>-11</sup> *** | 0.000 |
| NIM                                 | 0.000024                   | 0.881 | -0.000108                 | 0.528 |
| VTMBNOI                             | -0.001175                  | 0.324 | -0.000214                 | 0.865 |
| VTINOI                              | 0.000386                   | 0.849 | -0.000268                 | 0.901 |
| SIZE                                | -0.012349                  | 0.000 | 0.013498***               | 0.000 |
| ROA                                 | -1.86 e <sup>-7</sup> ***  | 0.000 | 5.68 e <sup>-8</sup> *    | 0.052 |
| CAR                                 | -2.51 e <sup>-8</sup> ***  | 0.005 | 4.68 e <sup>-9</sup>      | 0.620 |
| DAR                                 | -0.000395***               | 0.006 | 0.00056***                | 0.000 |
| DER                                 | -0.000019                  | 0.147 | -0.000013                 | 0.349 |
| GDPG                                | -0.002094**                | 0.049 | -0.003644***              | 0.001 |
| INF                                 | 0.000994*                  | 0.066 | -0.000755                 | 0.186 |
| DUMMY                               | -0.804461***               | 0.008 | 0.051059***               | 0.000 |
| Constant                            | 0.586696***                | 0.000 | 0.434119***               | 0.000 |
| Source(s): Authors' own elaboration |                            |       |                           |       |

Indeed, the fact that FinTech services have not proven their promise for enhancing the social efficiency of MFIs in our sample can be due to the reluctance of customers to opt for these services or problems with the network that fails to reach the poorest in rural areas.

**6. Conclusion**

This study focuses on an issue of vital importance about the integration of FinTech services within MFIs. It aimed at assessing its direct impact on the level of operational and social efficiency of MFIs, as well as its moderating impact on the managerial overconfidence-efficiency relationship.

Actually, this work coincides with exceptional circumstances rendering the microfinance and FinTech industries of paramount role to play. Further, we believe that their future together will be even brighter, faster and sooner. This was a strong motivation and a great inspiration for us to choose this topic.

The chosen analysis framework touches six distinct regions with wide disparities; some are leaders of the microfinance industry, others are leaders of the FinTech industry and the majority are characterized by prevailing poverty and overpopulation. The sample we consider consists of 387 institutions coming from 69 countries, with only 80 among them offer FinTech services. Namely, we name by innovative institutions or offering FinTech services, those who provide financial services via mobile phone or via the internet. In order to verify whether the hope raised is justified, we proposed four hypotheses to be tested based on these worldwide collected data. In the first step, we estimated the scores of efficiencies by region, year and type of MFIs using the SFA<sub>CD</sub> method. Our findings show that MFIs offering FinTech services are better in terms of social efficiency, but they are not that good in terms of operational efficiency compared to non-innovative ones. Though, it must be noted that whatever the type of the institution and the region where it is located, the scores of both social and operational efficiencies are weak, with averages of 0.514 and 0.499, respectively. Further, our results reveal that FinTech services' integration does not enhance the social and operational efficiency at once, which is quite clear in the correlation matrix since it displays a negative coefficient of correlation between social and operation efficiency. However, this negative relationship is still insignificant.

In a second step, and in order to have a better understanding of the scores obtained, we estimated two separate models (for operational and social efficiency), with 2 FinTech proxies,

2 overconfidence proxies, 4 control variables and 1 macroeconomic variable. The results do not support the first two hypotheses. Then, we extended them a second time to capture the moderating effect of FinTech on the impact of managerial overconfidence on the level of efficiencies. This time, the results confirm our last two hypotheses (H3 and H4).

The last step of our methodology is the robustness check by adding to the first versions of our models (before interaction variables) three more determinants of efficiency. Again, the results support our conclusion, which means that the integration of FinTech services within MFIs does not enhance either their operational or their social efficiency. Besides, the robustness check proves that MFIs offering FinTech services are socially oriented and that the negative impact of the integration of FinTech services is statistically insignificant for both the operational and social efficiency of MFIs, but of a higher magnitude in terms of the coefficients' absolute value for operational efficiency. Finally, we should mention that the descriptive statistics show that the share of transactions via FinTech services in the profit of MFIs is very weak, with an average of VTMBNOI of about 6% vs. only 3% for VTINOI. This leads us to suggest that the rate of the integration of FinTech services within MFIs in our sample is very weak, that the poor are reluctant to opt for these services or that they are not even accessible to them.

### 6.1 Limitations and perspectives

Although we have tried to conduct a careful study, we note certain limitations, mainly of a methodological nature. First, we encountered a number of problems with data concerning MFIs. In fact, financial and social data are hard to come by, and even the Mix Market provides data with some missing values and some outliers that we tried to eliminate. Second, the choice of the method to use has been revealed to be a daunting task and the SFA with all the advantages it proposes, has its weaknesses. Namely, that it requires the imposition of a specific functional form (production, profit or cost function), and that the inefficiency is assumed to have a half-normal (asymmetric) distribution, which is not only inflexible but also implicitly presumes that most firms are congregated near full efficiency, with a very low probability for high levels of inefficiency. Third, the values of  $R^2$  prove the weak significance of the selected explanatory variables for our models. We should have considered the type of MFIs (whether they are NGOs, Cooperative/credit union, Private Bank, etc.), and we should have segregated between Islamic and conventional MFIs. Finally, this study does not take into consideration of the COVID-19 crisis due to a lack of data, which harms its convenience.

The follow-up to our research work should focus on the inclusion of the COVID-19 crisis period and should distinguish at least between Islamic and conventional MFIs. In addition, it could examine the motivations and perceptions of FinTech services users who are among microfinance customers by using the Technology Acceptance Model (TAM) [8] or Unified Theory of Acceptance and Use of Technology (UTAUT) [9].

### Notes

1. "MFS is broadly defined as the usage of mobile devices with the aim of accessing or utilizing a wide range of transactions, banking activities and information" (Dorfleitner *et al.*, 2019).
2. When many individuals or firms are observed at the same point of time
3. When the same individuals or firms are observed at various points of time
4. For further details, please check [Appendix](#)
5. Depending on the size of the FIs in question
6. [Zamore \(2021\)](#) explained such a result by the fact that the relation between PAR30 and operational efficiency is non-linear, i.e. up to a certain level, an increase in PAR30 (decrease of loan portfolio

quality) improves the operational efficiency of MFIs. In fact, tolerance of an acceptable level of risk reduces the costs of extra efforts of a streamlined selection and monitoring of borrowers as well as costs related to collection activity.

7. To avoid overloading this study and complicating things, we limited our robustness check to only the first part of our work, i.e. the [hypothesis 1](#) and [2](#) that have been initially rejected. Actually, this result was unexpected, and we need to provide further proof.
8. The TAM was first developed by [Davis \(1989\)](#) and is based on behavioral psychology theories (cognitive dissonance and reasoned action). It is mainly for improving the understanding of individual potential users to opt for new technologies. It presumes that the actual or intention to use technologies depends on their Perceived Usefulness (PU) and Perceived Ease Of Use (PEOU). [Venkatesh and Bala \(2008\)](#) propose a new synthesis with great detail of the prior literature and provide a set of prior and post-implementation interventions, which could improve the acceptance of these technologies.
9. The UTAUT was first proposed by [Venkatesh et al. \(2003\)](#) and is based on the TAM and several other theories. It introduced four main variables that are likely to influence the intention to use new technologies. Namely, expected performance, expected efforts, social influence and enabling conditions.

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**Table A1.**  
Summary of  
operational and social  
efficiencies by type of  
MFIs and region

Appendix

| Region | Country          | Full sample            |                   |                        | Sub-sample: Non offering FinTech services |                        |                   | Sub-sample: Offering FinTech services |  |  |
|--------|------------------|------------------------|-------------------|------------------------|---|------------------------|-------------------|---------------------------------------|--|--|
|        |                  | Operational efficiency | Social efficiency | Operational efficiency | Social efficiency                         | Operational efficiency | Social efficiency |                                       |  |  |
| Africa | Benin            | 0.56                   | 0.52              | 0.57                   | 0.56                                      | 0.53                   | 0.35              |                                       |  |  |
|        | Burkina Faso     | 0.56                   | 0.35              | 0.56                   | 0.63                                      | 0.44                   | 0.60              |                                       |  |  |
|        | Cameroon         | 0.54                   | 0.62              | 0.50                   | 0.67                                      |                        |                   |                                       |  |  |
|        | Congo            | 0.50                   | 0.67              | 0.50                   | 0.66                                      |                        |                   |                                       |  |  |
|        | Ethiopia         | 0.45                   | 0.66              | 0.45                   | 0.57                                      | 0.67                   | 0.50              |                                       |  |  |
|        | Ghana            | 0.59                   | 0.43              | 0.57                   | 0.62                                      | 0.46                   | 0.61              |                                       |  |  |
|        | Kenya            | 0.52                   | 0.61              | 0.58                   | 0.64                                      | 0.52                   | 0.53              |                                       |  |  |
|        | Madagascar       | 0.44                   | 0.56              | 0.46                   | 0.31                                      |                        | 0.47              |                                       |  |  |
|        | Malawi           | 0.51                   | 0.42              | 0.50                   | 0.42                                      |                        |                   |                                       |  |  |
|        | Mali             | 0.56                   | 0.42              | 0.56                   | 0.74                                      |                        |                   |                                       |  |  |
|        | Mozambique       | 0.46                   | 0.74              | 0.46                   | 0.39                                      | 0.51                   | 0.51              |                                       |  |  |
|        | Niger            | 0.35                   | 0.39              | 0.35                   | 0.4                                       |                        |                   |                                       |  |  |
|        | Nigeria          | 0.51                   | 0.48              | 0.55                   | 0.44                                      |                        |                   |                                       |  |  |
|        | Rwanda           | 0.46                   | 0.44              | 0.46                   | 0.47                                      |                        |                   |                                       |  |  |
|        | Senegal          | 0.55                   | 0.47              | 0.55                   | 0.38                                      |                        |                   |                                       |  |  |
|        | South Africa     | 0.42                   | 0.38              | 0.42                   | 0.59                                      |                        |                   |                                       |  |  |
| EAP    | Tanzania         | 0.60                   | 0.59              | 0.60                   | 0.43                                      | 0.52                   | 0.52              |                                       |  |  |
|        | Togo             | 0.49                   | 0.43              | 0.49                   | 0.48                                      |                        |                   |                                       |  |  |
|        | Uganda           | 0.52                   | 0.49              | 0.52                   | 0.41                                      | 0.33                   | 0.48              |                                       |  |  |
|        | China            | 0.55                   | 0.41              | 0.55                   | 0.32                                      |                        |                   |                                       |  |  |
|        | Combodia         | 0.45                   | 0.46              | 0.49                   | 0.63                                      |                        |                   |                                       |  |  |
|        | Indonesia        | 0.48                   | 0.32              | 0.48                   | 0.67                                      | 0.55                   | 0.60              |                                       |  |  |
|        | Lao PDR          | 0.43                   | 0.63              | 0.43                   | 0.42                                      | 0.53                   | 0.32              |                                       |  |  |
|        | Papua new guinea | 0.46                   | 0.63              | 0.38                   | 0.32                                      |                        |                   |                                       |  |  |
|        | Philippines      | 0.45                   | 0.41              | 0.45                   | 0.48                                      |                        |                   |                                       |  |  |
|        | Samoa            | 0.48                   | 0.32              | 0.48                   | 0.36                                      |                        |                   |                                       |  |  |
|        | Timor-Leste      | 0.52                   | 0.36              | 0.52                   |   |                        |                   |                                       |  |  |

(continued)

(continued)

Table A1.

|      | Full sample          |      |      | Sub-sample: Non offering FinTech services |      | Sub-sample: Offering FinTech services |      |
|------|----------------------|------|------|---|------|---------------------------------------|------|
|      |                      |      |      |   |      |                                       |      |
| EECA | Armenia              | 0.54 | 0.68 | 0.57                                      | 0.66 | 0.43                                  | 0.76 |
|      | Azerbaijan           | 0.49 | 0.55 | 0.47                                      | 0.55 | 0.58                                  | 0.57 |
|      | Bosnia & Herzegovina | 0.39 | 0.75 | 0.39                                      | 0.75 |                                       |      |
|      | Bulgaria             | 0.57 | 0.53 | 0.57                                      | 0.53 |                                       |      |
|      | Georgia              | 0.38 | 0.73 | 0.34                                      | 0.73 | 0.43                                  | 0.73 |
|      | Kazakhstan           | 0.49 | 0.48 | 0.46                                      | 0.51 | 0.58                                  | 0.39 |
|      | Brazil               | 0.52 | 0.59 | 0.53                                      | 0.63 | 0.51                                  | 0.57 |
|      | Bolivia              | 0.48 | 0.63 | 0.51                                      | 0.57 | 0.45                                  | 0.70 |
|      | Argentina            | 0.53 | 0.57 | 0.56                                      | 0.70 | 0.47                                  | 0.32 |
|      | Chile                | 0.47 | 0.60 | 0.45                                      | 0.70 | 0.50                                  | 0.40 |
|      | Colombia             | 0.47 | 0.61 | 0.49                                      | 0.61 | 0.41                                  | 0.60 |
|      | Costa-Rica           | 0.43 | 0.38 | 0.43                                      | 0.38 |                                       |      |
|      | Dominican            | 0.41 | 0.53 | 0.44                                      | 0.51 | 0.38                                  | 0.57 |
|      | Ecuador              | 0.49 | 0.64 | 0.48                                      | 0.62 | 0.50                                  | 0.68 |
|      | El Salvador          | 0.39 | 0.63 | 0.39                                      | 0.63 |                                       |      |
|      | Guatemala            | 0.49 | 0.49 | 0.49                                      | 0.49 |                                       |      |
|      | Haiti                | 0.55 | 0.53 | 0.61                                      | 0.51 | 0.43                                  | 0.56 |
|      | Honduras             | 0.53 | 0.64 | 0.50                                      | 0.66 | 0.60                                  | 0.58 |
|      | Jamaica              | 0.72 | 0.51 | 0.72                                      | 0.51 |                                       |      |
|      | Mexico               | 0.53 | 0.49 | 0.54                                      | 0.45 | 0.44                                  | 0.43 |
|      | Nicaragua            | 0.53 | 0.56 | 0.53                                      | 0.56 |                                       |      |
|      | Panama               | 0.52 | 0.65 | 0.56                                      | 0.64 | 0.42                                  | 0.68 |
|      | Paraguay             | 0.42 | 0.69 | 0.33                                      | 0.68 | 0.52                                  | 0.70 |
|      | Peru                 | 0.49 | 0.49 | 0.50                                      | 0.48 | 0.38                                  | 0.61 |
|      | Venezuela            | 0.44 | 0.57 | 0.44                                      | 0.57 |                                       |      |

(continued)

Table A1.

| Full sample                         |             | Sub-sample: Non offering FinTech services |      | Sub-sample: Offering FinTech services |      |
|-------------------------------------|-------------|---|------|---------------------------------------|------|
| MENA                                | Egypt       | 0.62                                      | 0.49 | 0.62                                  | 0.49 |
|                                     | Iraq        | 0.59                                      | 0.33 | 0.59                                  | 0.33 |
|                                     | Jordan      | 0.51                                      | 0.43 | 0.66                                  | 0.61 |
|                                     | Lebanon     | 0.58                                      | 0.74 | 0.58                                  | 0.74 |
|                                     | Morocco     | 0.51                                      | 0.66 | 0.51                                  | 0.66 |
|                                     | Palestine   | 0.53                                      | 0.45 | 0.53                                  | 0.45 |
|                                     | Syria       | 0.55                                      | 0.58 | 0.55                                  | 0.58 |
|                                     | Tunisia     | 0.32                                      | 0.54 | 0.32                                  | 0.54 |
|                                     | Yemen       | 0.63                                      | 0.55 | 0.63                                  | 0.55 |
| SA                                  | Afghanistan | 0.49                                      | 0.41 | 0.50                                  | 0.47 |
|                                     | Bangladesh  | 0.49                                      | 0.45 | 0.48                                  | 0.45 |
|                                     | India       | 0.51                                      | 0.46 | 0.51                                  | 0.46 |
|                                     | Nepal       | 0.53                                      | 0.29 | 0.53                                  | 0.29 |
|                                     | Pakistan    | 0.49                                      | 0.46 | 0.49                                  | 0.47 |
| Sri Lanka                           |             | 0.59                                      | 0.48 | 0.59                                  | 0.48 |
| Source(s): Authors' own elaboration |             |   |      |                                       |      |

|                        | O.eff                       | S.eff                       | VTNOI                      | VTMENOI                  | LGR                        | NIM                         | PAR                         | Cap                         | ROA                         | SIZE                    | GDPG |
|------------------------|-----------------------------|-----------------------------|----------------------------|--------------------------|----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-------------------------|------|
| Operational efficiency | 1                           |                             |                            |                          |                            |                             |                             |                             |                             |                         |      |
| Social efficiency      | -0.0026<br><i>0.8438</i>    | 1                           |                            |                          |                            |                             |                             |                             |                             |                         |      |
| VTNOI                  | -0.0006<br><i>0.9663</i>    | 0.0047<br><i>0.7188</i>     | 1                          |                          |                            |                             |                             |                             |                             |                         |      |
| VTMENOI                | -0.0147<br><i>0.2639</i>    | 0.0014<br><i>0.9123</i>     | 0.0690<br><i>0.0000</i> ** | 1                        |                            |                             |                             |                             |                             |                         |      |
| LGR                    | 0.0014<br><i>0.9153</i>     | 0.0910<br><i>0.0000</i> **  | 0.0367<br><i>0.0052</i> ** | 0.0053<br><i>0.6841</i>  | 1                          |                             |                             |                             |                             |                         |      |
| NIM                    | 0.0032<br><i>0.8087</i>     | -0.0056<br><i>0.6671</i>    | 0.0004<br><i>0.9756</i>    | 0.0006<br><i>0.0006</i>  | 0.0075<br><i>0.5699</i>    | 1                           |                             |                             |                             |                         |      |
| PAR                    | 0.0063<br><i>0.6291</i>     | 0.0731<br><i>0.0000</i> **  | 0.0052<br><i>0.6915</i>    | 0.0042<br><i>0.0032</i>  | -0.0063<br><i>0.6294</i>   | 0.0116<br><i>0.3781</i>     | 1                           |                             |                             |                         |      |
| CAP                    | -0.0399<br><i>0.0023</i> ** | 0.0063<br><i>0.6302</i>     | -0.0009<br><i>0.9439</i>   | 0.8076<br><i>-0.0011</i> | -0.0166<br><i>0.2064</i>   | 0.0133<br><i>0.3126</i>     | -0.0042<br><i>0.7499</i>    | 1                           |                             |                         |      |
| ROA                    | -0.0530<br><i>0.0001</i> ** | 0.0059<br><i>0.6532</i>     | -0.0008<br><i>0.9535</i>   | 0.9307<br><i>-0.0009</i> | -0.0137<br><i>0.2967</i>   | 0.0009<br><i>0.9427</i>     | 0.0242<br><i>0.0655</i>     | 0.0653<br><i>0.0000</i> **  | 1                           |                         |      |
| SIZE                   | -0.1206<br><i>0.0000</i> ** | 0.1534<br><i>0.0000</i> **  | 0.0169<br><i>0.1971</i>    | 0.9426<br><i>0.0118</i>  | 0.0127<br><i>0.0000</i> ** | -0.0071<br><i>0.5894</i>    | 0.1446<br><i>0.0000</i> **  | -0.0005<br><i>0.9671</i>    | -0.1083<br><i>0.0000</i> ** | 1                       |      |
| GDPG                   | -0.0283<br><i>0.0312</i> *  | -0.0467<br><i>0.0004</i> ** | -0.0050<br><i>0.7072</i>   | 0.3704<br><i>-0.0068</i> | -0.0011<br><i>0.3953</i>   | -0.0354<br><i>0.0070</i> ** | -0.1240<br><i>0.0000</i> ** | -0.0507<br><i>0.0001</i> ** | -0.0251<br><i>0.0561</i>    | 0.0340<br><i>0.0095</i> | 1    |

**Note(s):** \*\*, indicate values significance at 1 and 5% respectively  
**Source(s):** Authors' own elaboration

**Table A2.**  
Correlation matrix