Research in International Business and Finance 68 (2024) 102185

Contents lists available at ScienceDirect

Research in International Business and Finance

journal homepage: www.elsevier.com/locate/ribaf

Lending activity efficiency. A comparison between fintech firms and the banking sector

Grazia Onorato [a], Francesca Pampurini [b,*], Anna Grazia Quaranta [c]

[a] *Department of Economics, University of Foggia, Via Romolo Caggese, 1, 71121 Foggia, Italy*

[b] *Department of Economics and Business Management Sciences, Catholic University of the Sacred Heart of Milan, Largo Gemelli 1, 20123 Milan, Italy*

[c] *Department of Economics and Law, University of Macerata, Via Crescimbeni, 14, Macerata 62100, Italy*

ARTICLE INFO

JEL classification:
C58
G14
G21
G23

Keywords:
Fintech
Banks
Lending
Efficiency
Stochastic Data Envelopment Analysis

ABSTRACT

The FinTech phenomenon is undoubtedly increasingly changing the morphology of the global financial system, as well as the existing competitive levers in particular sectors, including lending. The aim of this study is to offer a comparative analysis of the level of efficiency exhibited by FinTech firms operating in this sector with that of banks, which have traditionally carried out this activity. We measure efficiency levels by implementing the Stochastic Data Envelopment Analysis (SDEA). The study, referred to 2021, analyses a data set composed of all the Italian FinTech firms engaged in the lending business and all the Italian banks. We find higher efficiency levels for banks compared to FinTech firms. The results are certainly interesting both at corporate level and for regulatory purposes.

1. Introduction

For a long time, the banking system has had to reconsider its structure, organisation and role due to the increasing use of more and more technologically advanced solutions, as well as the contextual parallel development of the FinTech sector. At the same time, the FinTech world is also affected by great turmoil shown by the increasing tech solutions being offered in the financial markets, including those related to lending, equity and crowdfunding.

The FinTech phenomenon has also affected Italy, a country historically anchored to important pillars, such as household savings, bank credit and the heavy presence of small and medium-sized enterprises (SMEs). Moreover, some particular characteristics of FinTech and InsurTech services were decisive at critical moments during the health emergency and the subsequent lockdown (Najaf et al., 2022; Fu and Mishra, 2022).

Over the last years, the number of FinTech start-ups has increased, as along with the number of Italian consumers who interact with their banks through digital channels. This is a reflection of how digital technology is beginning to change the habits of Italian consumers and firms in the financial and insurance markets (Campanella et al., 2022; Stefanelli and Manta, 2023).

Given this scenario, this paper compares the efficiency of Italian FinTech firms engaged in lending with that of traditional banks since, it is a topic which, to the best of our knowledge, has not been yet analysed in depth.

We decided to focus only on lending activity for two main reasons. First, as it is notoriously difficult to pinpoint a universally agreed

* Corresponding author.
E-mail address: francesca.pampurini@unicatt.it (F. Pampurini).

https://doi.org/10.1016/j.ribaf.2023.102185
Received 29 June 2023; Received in revised form 20 September 2023; Accepted 14 November 2023
Available online 19 November 2023
0275-5319/

definition of FinTech (Financial Stability Board, 2017a), we decided to start analysing the FinTech firms engaged in lending since it is certainly among the activities that traditionally characterise the business of financial intermediaries. Second, this choice is also supported by the fact that, in recent years, FinTech lending has been growing rapidly all over the world (although its magnitude varies from economy to economy; Claessens, 2018).

We will measure efficiency with an approach known as Stochastic Data Envelopment Analysis (SDEA – Khodabakhshi et al., 2010; Wanke et al., 2018; Olesen and, Petersen, 2016) since, in our case, it struck us as being the most suitable to solve the well-known problems that characterise the two methodologies that are still widespread for measuring efficiency, namely the Stochastic Frontier Approach (SFA – Quaranta et al., 2018) and the (deterministic) Data Envelopment Analysis (DEA – Charnes et al., 1978; Thanassoulis et al., 2004; Ray, 2004).

In more detail, first of all, having to analyse FinTech firms, a DEA approach is, in any case, more suitable since it overcomes the SFA problem related to the identification of the production function structure that, in the case of FinTech firms, is particularly difficult.

Moreover, in relation to our study, among the different DEA approaches, it is surely preferable to employ a Stochastic DEA model, as it is able to solve the only deterministic DEA limit that may adversely affect our results. Such a limit occurs if we assume the input and output values without noise and without proposing any assumption on the distributional structure of deviations from a best-fit frontier. In fact, in our case, it is not appropriate to consider the input and output values as deterministic because, apart from all the possible reasons for measurement errors related to data collection, another cause is that financial statements data are observations referred to a particular day of the year and, therefore, can change from day to day. This implies that to obtain a fair efficiency quantification it should be better to employ observations of a stochastic nature (Kao and Liu, 2009). If this aspect were not taken into account when measuring efficiency, it would certainly have a negative impact on its measurement and thus could lead to an improper assessment of phenomena, directly or indirectly, connected to it.

We analyse all the Italian FinTech firms engaged in the lending business in 2021 (latest available data) as per the PWC report, and all the Italian banks for which the same data were available in relation to 2021. We pay particular attention to the identification of the different possible efficiency drivers to be able to deduce indications on the aspects which could positively influence the results.

We find higher efficiency levels for banks compared to FinTech firms. The information obtained is certainly interesting at corporate level and can also provide important guidelines for regulatory purposes, given that the coexistence of FinTech firms dedicated to lending and more traditional intermediaries deserves to be constantly and carefully monitored, in order to maintain an adequate level of financial system stability (Vučinić, 2020).

The remainder of the paper is organised as follows: Section 2 introduces the FinTech context and offers a literature review, while Section 3 describes the methodology we apply with the aim of comparing the efficiency of FinTech firms and banks. In Section 4 (Empirical Analysis) we present the data description and the results with their discussion. Section 5 concludes.

2. Literature review

2.1. An analysis of the general context

In recent years, financial services developed thanks to disruptive technological innovation that saw technological firms which did not belong to the traditional financial system emerge as main players (Chen et al., 2019).

They create effects within the financial system that affect the efficiency of new business processes through blockchain technology and other innovative products that streamline financial constraints, especially for SMEs, and circumvent regulatory system restrictions.

Some research (Wu et al., 2023; Tseng and Guo, 2022) states that non-financial firms offering such solutions can have negative effects both on the sector and on the level of competition for traditional financial intermediaries who, unlike FinTech firms characterised by a high degree of technological innovation, invested less in research and technical development and implemented less in their business processes.

Studies (Stulz, 2019; Sheng, 2021) show that, in addition to having effects on the cost of services, these FinTech firms are able to process applications for financing much more quickly by increasing their use of financing without simultaneously affecting the default rate.

High regulatory standards make the cost of financing through traditional channels higher; this is why crowdfunding and other types of lenders captured all those firms, mainly small, that had been excluded from the traditional evaluation processes (Stulz, 2019; Buchak et al., 2018).

Actually, there is still no shared definition of *FinTech*. The most widespread definition is certainly the one given by the Financial Stability Board (Financial Stability Board, 2017b – page 7) which defines it as “technological innovation in financial services that could result in new business models, applications, processes or products with a material effect associated with the provision of financial services”.

FinTech has greatly reshaped the way in which financial institutions provide financial services; it generated such an important impact on the financial sector that new share challenges need to be faced in order to react effectively to the growing competition generated by the presence of new players that have more advanced and more efficient technologies. The introduction of new technologies, therefore, gave birth to business models that are able to provide a wide range of more efficient remote financial services (Thakor, 2020).

The ability of FinTech (and BigTech) to offer cheaper and more tailored products in retail banking, investments, as well as the use of cryptocurrencies and blockchains, turned into a threat for traditional banks (Gai et al., 2018; Gomber et al., 2018; Ozili, 2018), i.e., banks that engage in classic credit intermediation (thus excluding investment banks). As a result, the risk of losing market share and customers encouraged the latter to reconsider their strategies.

For this reason, there is no doubt that such technological advances provided cost benefits for financial intermediaries through the economies of scale exploitation, data collection and use, and information dissemination (Thakor, 2020). In some cases, this dynamic could generate higher efficiency levels for the whole financial system (Lee and Shin, 2018; Dhar and Stein, 2017; Nakashima, 2018; Romanova et al., 2018).

In fact, FinTech firms are specialising in products and services formerly exclusive to banks, such as payment services, which were later joined by lending and investment facilities (Stulz, 2019).

Among the most popular services offered in the FinTech context is lending, i.e. platforms that, in the absence of bank intermediation, provide a source of financing for small businesses and individuals, complementing the services provided by traditional banks (Claessens et al., 2018; Cornelli et al., 2020). Lending platforms interact with users almost exclusively online: they perform preliminary credit and loan risk analysis through counterparty screening, using their own algorithms that combine lenders' offers with demand (Thakor, 2020).

Whilst banks have been able to respond by offering online methods for payment services (Navaretti et al., 2018), the same flexibility has not been found for lending services. In fact, FinTechs are even faster in loan processing and are a complementary form of small loan servicing than more traditional channels (Cornelli et al., 2020).

Although it is possible to say that the services provided by these firms are complementary to some banking processes, such as greater efficiency at the customer screening stage (Thakor, 2020), it is not possible to fully understand what decision-making process they use, that, moreover, is often difficult to verify.

Several authors (Boot, 2017; Navaretti et al., 2018; Panetta, 2018; Stulz, 2019; Vives, 2019; Thakor, 2020; Murinde et al., 2022) argue that these alternative forms of financing aimed at those who generally cannot access bank loans will not be able to replace the role of the big banks. However, in times of crisis or in a context characterised by a regulatory gap – as happened after the 2007 financial crisis or in China where there is very little regulation – FinTech firms are certainly able to gain a competitive advantage (Suryono et al., 2020; Vives, 2019).

2.2. Efficiency of the financial system and FinTech-banks comparison

FinTech innovation could also lead to greater efficiency in the financial system. Indeed, some studies seem to suggest that the development of FinTech enables a fairer capital allocation and, thus, greater efficiency. Using Chinese-listed companies from 2011 to 2018, Song et al. (2021) found that FinTech improves firm productivity through decreased credit constraints. Therefore, they may be able to allocate capital more efficiently and, using credit scoring, can identify the most productive and least risky firms and channel external financing to these companies (Wurgler, 2000; Bena and Ondko, 2012; Song et al., 2021; Ntwiga, 2020).

Berg et al. (2022) in their work through a careful review of the literature, point out how often some of the typical advantages of FinTech firms do not necessarily translate into advances in efficiency for the financial market. They assert that automation processes characterised by greater elasticity of credit supply and simplicity in the way in which the interested party applies for credit, may in fact lead them to situations of moral hazard. This evidence is in line with Di Maggio and Yao's (2021) research showing how FinTech borrowers use additional credit not to consolidate their debts, but for further purchases, finding higher default rates for unsecured FinTech loans. Thus, unlike traditional banks, due to the lack of soft information that machine learning models cannot detect, FinTech lenders may find themselves more exposed to criminal behaviour by their customers. It is worth noting that the paper by Suryono et al. (2020) identifies other efficiency limitations of P2P lending compared to banking, such as information asymmetry. In fact, in the risk assessment process, the data collected by P2P lending comes from third parties and it emerges how the credibility of the data does not have the same validity compared to the credit score available from a bank. These two phenomena, compounded by the lack of a mature regulatory architecture, event failures, and fraud on the part of both FinTech firms and their customers.

There are additional contributions that discuss competition between FinTech and banks as one of the causes of the latter's increased efficiency (Vives, 2017; Saksonova and Kuzmina-Merlino, 2017; Jakšič and Marinč, 2019; Kwon et al., 2023). However, as stated by Xie (Xie and Zhu, 2022), FinTech can also intensify competition in the loan market through competition between FinTech lenders and lead to a growth of loans from unqualified borrowers. However, if the effect of competition is not accompanied by the development of appropriate regulations, it could lead to delicate inefficiency problems.

As a consequence of all the above, FinTech growth is something that may be able to strengthen the financial system, potentially making it more efficient and flexible through the adoption of technological innovations in order to meet the needs of customers and businesses (Carney, 2017; Demir et al., 2020). This especially if the new FinTech players prove to be highly efficient competitors for more traditional intermediaries.

Therefore, it is of fundamental importance to measure the efficiency level achieved by FinTech firms and then to compare it with the level reached by other more traditional intermediaries like banks.

While the topic of the comparison of efficiency achieved by FinTech firms and banks in relation to lending activities has been little explored, there are some studies that analyse the efficiency levels of credit intermediaries due to their investments (large or small) in FinTech or, more generally, high-tech. It emerges that the development of FinTech innovations, on the one hand, improves efficiency and reduces costs in the lending process of banks and, on the other, leads to advances in the technology adopted by banks (Berger, 2003; Houston et al., 2010; FSB, 2017; Lee et al., 2021; Borello et al., 2022).

As anticipated, the comparison between the efficiency of FinTechs and banks in the context of lending activity has not yet been thoroughly analysed. An interesting contribution that, in some way, recently approached this topic is that of Hughes (Hughes et al., 2022). This work shows that, in general, large players – both FinTechs and banks – have a very bad NPL ratio, which is probably because they also go out of their way to finance excessively risky entities, despite the fact that this has been clearly highlighted by the creditworthiness assessment process. Moreover, in agreement with Bernanke (Bernanke, 2011), the authors find that small intermediaries are more effective at credit assessment and loan management than large lenders.

In any case, given the importance that FinTech firms have now assumed in the financial system and particularly in the lending market, it is critically important to understand and compare the efficiency of FinTech firms and traditional banks. Indeed, it is not yet clear whether the presence of FinTech firms will disrupt traditional banking or, on the contrary, strengthen the financial system over time.

Given this background, our aim is to fill the gap in the academic literature by providing a comparison of the actual efficiency levels achieved in the banking and FinTech sectors, as well as to assess possible further research developments in this field. In particular, in order further substantiate what we have discussed thus far, we would like to verify whether the entry of these new players, which are known to be characterised by a very lean structure and the use of the most advanced technologies, into the lending market can contribute to increasing the level of efficiency of the market itself.

3. Methodology

The aim of this paper – to compare the level of efficiency of Italian FinTech firms engaged in lending with the level of efficiency of traditional banks in supplying credit – derives directly from remarks made in the previous literature review.

As underlined in Section 1, our analysis focuses on lending by FinTech firms and banks as it constitutes a well-known traditional business that, in particular in the FinTech context, has grown rapidly in recent times.

Of course, we addressed the question of how to measure FinTech firm and bank efficiency as correctively as possible, given that in the literature there are supporters of both approaches currently considered most suitable for the purpose, namely the Stochastic Frontier Approach (SFA) and the deterministic Data Envelopment Analysis (DEA). This support exists despite the limits of both approaches.

All in all, the main limits of the SFA lie in the identification of the correct functional form, as well as in the statistical difficulties related to the assumptions about the distribution of the two error components (Quaranta et al., 2018).

On the other hand, even though the deterministic DEA (Charnes et al., 1978; Thanassoulis et al., 2004; Ray, 2004) – a non-parametric method that, starting from observed data, estimates efficiency without specifying any functional form – can overcome the aforementioned problems, its limits are equally well known. In fact, in its 'basic' form, it (i) is sensitive to outliers, (ii) considers inputs and outputs as homogeneous entities, suggesting misleading results when they are not homogeneous, (iii) shows a large percentage of efficient DMUs when the number of observations is low compared to the number of inputs and outputs, and (iv) does not take into account the widespread randomness in evaluation processes that mainly stems from all possible types of errors in data collection (Olesen and Petersen, 2016).

Having made these observations, we realised that the SFA could not be the right choice in our context of analysis since, if we were to measure the efficiency of FinTech firms, we would be faced with many difficulties in identifying a realistic functional form suitable for describing their production process.

This is why we turned our attention to DEA.

Actually, the first of the four aforementioned DEA limits can be easily bypassed after identifying the presence of possible outliers (applying the usual, well-known univariate and multivariate statistical analyses) and then proceeding to their exclusion from the data set. The second DEA problem can also be easily overcome by standardising the input and output values. The third DEA problem would not concern our data set in any way because the number of observations would certainly be high compared to that of inputs and outputs.

On the contrary, the fourth problem needed to be solved as it is not possible, even in our case, to consider the input and output values as deterministic, although they come from financial statements. Indeed, in any case, they could be affected by different kinds of errors during the data collection process, but, much more important, they are snapshot observations of dynamic phenomena that actually change from day to day. So, if we observed the same variable few days earlier or later, we would probably get different values for them; as a consequence, we have to assume that our data is stochastic in nature (Kao and Liu, 2009).

Recent literature suggested overcoming the fourth DEA limit by employing the so-called Stochastic Data Envelopment Analysis (SDEA; Khodabakhshi et al., 2010; Wanke *et al.*, 2018; Olesen and, Petersen, 2016).

In fact, this new approach can be applied in two different ways. The first (the one we adopted, since it is faster to implement) makes use of inputs and outputs value distributions referred to each single unit (that we called DMU, in our case, a specific bank or a specific FinTech firm) to replace the data on which the standard DEA analysis is based. The second, on the contrary, makes use of particular statistical assumptions to obtain a modified DEA approach, essentially based on a statistical model, and on a sampling process that allows for a consistent estimator of the true frontier (Olesen and Petersen, 2016). In any case, both these strategies are suitable for reducing the distance between SFA and deterministic DEA, resulting in hybrid models that are almost free of the original methodological limits.

Armed with more detail, in order to overcome the fourth DEA problem according to the first approach we have just described, Huang and Li (Huang and Li, 2001) proposed to incorporate random noises in the input and output data.

Consider n DMUs $(1 < j < n)$; for DMU_j, $\widetilde{x}_j = (\widetilde{x}_{1j}, ..., \widetilde{x}_{mj})^T$ and $\widetilde{y}_j = (\widetilde{y}_{1j}, ..., \widetilde{y}_{kj})^T$ are, respectively, the input and output random vectors of dimension $(m \times 1)$ and $(k \times 1)$, while $\overline{x}_j = (\overline{x}_{1j}, ..., \overline{x}_{mj})^T$ and $\overline{y}_j = (\overline{y}_{1j}, ..., \overline{y}_{kj})^T$ are the expected input and output vectors.

Moreover, for each DMU_j we assume to know the conjunct probability distribution of $(\widetilde{x}_j, \widetilde{y}_j)$ obtained from the input and output historical data.

Stating the above, we can write the SDEA model in its more general form that includes slack variables (i.e. variables able to change a disequality in an equality) as follows (Khodabakhshi et al., 2010):

$$\text{minimize}\theta_0 + \epsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{k} s_r^+\right)$$

$$\text{subject to} P\left\{\sum_{j=1}^{n} \lambda_j \widetilde{x}_{ij} + s_i^- \le \theta_0 \widetilde{x}_{i0}\right\} = (1-\alpha), i = 1, \ldots, m$$

$$P\left\{\sum_{j=1}^{n} \lambda_j \widetilde{y}_{rj} - \widetilde{y}_{r0} \ge s_r^+\right\} = (1-\alpha), r = 1, \ldots, k$$

$$s_i^-, s_r^+, \lambda_j \ge 0$$

(1).

where θ_0 represents the efficiency, ϵ is a not Archimedean (i.e. that every positive hyperreal is greater than $1/n$ for some standard natural number n) positive infinitesimal, λ_j measures the rate of input utilisation, s_i^- and s_r^+ are the slack variables and α is a (pre-determined) fixed value that indicates the fit level (meaning that, the smaller its value, the greater the accuracy of the results).

Since a solution with $\theta_0 = 1$, $\lambda_0 = 1$, $\lambda_j = 0 (j \neq 0)$ always exists, then the optimal value of the objective function is less than or equal to 1. Stochastic efficiency, therefore, can be defined as:

Definition 1. DMU_0 is efficient in a stochastic sense if and only if the following conditions are met:

- $\theta_0^* = 1$,
- the slack variables are zero in all alternative solutions to the optimal one.

Therefore, we have a constrained linear optimisation problem with stochastic variables that can allow for the proper handling of any possible errors in data collection as well as of the possible variability of the values extracted from financial statements.

Following the well-known intermediation approach (Berger and Humphrey, 1997; Hughes et al., 1996), after defining the proper outputs and inputs of lending activity (as well as their proxies), we will proceed by identifying, as underlined via Stochastic DEA, the efficiency levels of each of the entities considered within the two subsets (banks and FinTech firms). With more detail, as a proxy for the output (O), we will consider gross loans and we will also refer to the following four inputs: Human Capital (I1), Financial Capital (I2), Fixed Capital (I3) and Equity (I4). They will be respectively proxied by Staff Expenses to Total Assets, (Interest Expense + Commission Expense) to Total Liabilities, Other Administrative and Operating Expenses to (Fixed Assets + Intangible Assets) and, finally, Total Equity.

All of the above will allow us to obtain some interesting information regarding (i) identification of the most efficient FinTech firms and the most efficient banks; (ii) the prevailing characteristics (i.e., a particular size and/or a particular level of profitability, liquidity, capitalisation and overall efficiency etc.) of the most efficient units among FinTech firms and banks. We will consider these prevailing characteristics as possible high efficiency determinants; (iii) checking whether the previous prevailing characteristics are the same in the two different sets.

Next, the average level of efficiency achieved by FinTech firms will be compared with that obtained by all the banks considered, and, as a robustness check, also with the level reached by a stratified sample (McCombes, 2023) of banks (extracted from the set of all the analysed banks) of the same size as the group of FinTech firms. In this way, we will be able to verify if the conclusions drawn in relation to the average efficiency level reached by the set composed of FinTech firms and the other set comprising the banks would not have been invalidated by the different size of the two groups considered.

In relation to the stratification criteria, we will consider the size, the specialisation and the cost to income ratio, since the latter is generally considered a good indicator of overall efficiency.

4. Empirical analysis

4.1. Data

To achieve the aim of this paper, our empirical analysis comprises a data set composed of all the Italian FinTech firms engaged in lending in 2021, and all the Italian banks with the equivalent available data in the same year. As a consequence, in relation to the latter, we considered the whole population of Italian banks that, in 2021, comprised commercial banks (19%), cooperative banks (78%), and savings banks (%).

The list of the Italian FinTech firms comes from the PWC FinTech Observatory (PWC, 2021), while that of banks from Bank Focus. We extracted all the data needed for the analysis, for the FinTech firms, from AIDA and, for the banks, from Bank Focus.

We applied the usual well-known univariate and multivariate statistical approaches (respectively, each statistical unit input and output plot analysis together with the variance level analysis of the same values as for the first case, and the Malhanobis distance analysis (Malhanobis, 1936) – at a significance level of 99% – for the second) to handle the problem of possible outliers. As a result, we obtained a set of 44 FinTech firms and another set of 297 banks.

Tables 1 and 2 summarise, respectively, some general information about the two sets considered.

In both sets, the high variability of the variable values considered is clearly visible. This is because these two groups comprise units that are extremely heterogeneous in size.

4.2. Results and discussion

Having already removed the outliers, and thus solved the first of the problems that can negatively impact the results of a DEA approach, before using the specifically arranged Matlab code for the implementation of the SDEA model in [1], we also solved the problem (ii) of a generic DEA approach by standardising output and input values. On the other hand, as already mentioned, our data set did not encounter any trouble with regard to the problem (iii) of a DEA approach.

The SDEA model was then applied separately to the sets of FinTech firms and banks in order to obtain the efficiency level reached by each unit,[1] and thus to identify, among them, the most efficient FinTech firms and banks, as illustrated in item (i) in Section 3.

In more detail, during the implementation of the optimization model in [1], α – which is the only model parameter to be fixed – was set to 0.01. As far as the distributions of input and output values are concerned, we used the values of the five years from 2017 to 2021 for banks, while for FinTech firms, as this data was not available, a normal distribution centred on the values of 2021 was assumed.

After studying the efficiency value skewness in each of the two sets, the FinTech firms and the banks were divided into three groups, in order to be able to identify the prevailing characteristics (i.e., a particular size – small, medium or large – and/or a particular level of profitability, liquidity, capitalisation and overall efficiency) of the most and least efficient units.

In more detail, we used three sets to group, separately, the FinTech firms and banks with the highest, medium and lowest efficiency values. Due to a clear skewness of the efficiency values distribution in both sets, the cut-off values used to separate the three groups were the median plus the standard deviation of the values – to establish the threshold above which the units with the highest efficiency could be identified – and the median minus the standard deviation of the values – to identify the units with the lowest efficiency.

Table 3 illustrates how we proxied the variables (size, profitability, liquidity, capitalisation and overall efficiency) analysed in relation to efficiency.[2] Then, Tables 4 and 5, according to item (ii) in Section 3, show the results obtained in relation to the prevailing characteristics of the most and least efficient units.

These last two tables help us to check whether the prevailing characteristics are the same in the two different groups, as we wrote in item (iii) in Section 3.

The distribution of FinTech firms and banks within the high, medium and low efficiency groups is broadly similar (30%, 59% and 11% for FinTech firms and 31%, 61% and 8% for banks).

In the FinTech sector, there seems to be no relationship between firm size and efficiency level. On the contrary, as far as the other issues investigated are concerned, there is clear evidence in terms of prevailing characteristics: the most efficient FinTech firms are in fact those that show the highest values for profitability, liquidity and capitalisation and, consistent with being the most efficient, also the lowest value of the cost-to-income ratio.

As far as banks are concerned, the situation is practically the same, with the only difference being that in this context the units with both high and medium efficiency are characterised by being those of medium-small size, with a prevalence of the medium size for the most efficient (Pampurini and Quaranta, and, 2018, 2022). In confirmation of this last result, the group of the least efficient banks is entirely composed of large-sized units.[3]

Following the analysis process described at the end of Section 3, the next step was to compare the average level of efficiency achieved by FinTech firms with that obtained by all the banks considered, and – as a robustness check – also with that referring to a stratified sample of banks (extracted from the set of all the analysed banks) of the same size as the group of FinTech firms.

With regard to the stratified sample of banks design, given the small number of units it would have to contain (i.e., 44 firms), in order to provide results comparable with the set of FinTech firms, we performed the only possible stratification by referring to the only three variables that could be used, namely size, specialisation and overall efficiency. The proxies described in relation to size and overall efficiency (see Table 3) are the same as those adopted for stratification purposes, while for specialisation the item considered was that of being a commercial or cooperative or savings bank. Despite the intrinsic robustness of this sample deriving from the stratification procedure, its robustness is also greatly strengthened since, even if one wanted to change within the same '*layer*' (and therefore within the same stratification structure, that, as we said above, cannot be changed) the composition of the current stratified sample by modifying the specific banks that are part of it (by using those homologous by stratification criterion – e.g. large banks with other large banks and so on), the essence would not change, since the variability of the considered variables for the banks of the same layer is very low.[4]

Table 6 shows the composition of the stratified sample obtained by reproducing the distribution of the patterns assumed by the

[1] Data available upon request.
[2] In relation to Size, Liquidity and Capitalization we referred to different proxies since Fintech firms and banks have different balance sheets.
[3] Data available upon request.
[4] Data available upon request.

Table 1
Some information about Italian FinTech firms engaged in the lending business (thousands of Euro).

	Gross Loans	Fixed Assets	Total Assets	Total Equity	Total Liabilities
mean	1.714,17	6.059,06	11.630,12	1.804,02	9.432,26
st.deviation	5.779,74	35.151,45	61.093,54	6.277,44	55.050,77
max	31.547,00	236.416,00	410.978,00	39.869,00	370.056,00
min	1,05	1,10	4,25	-997,10	0,01
cv	3,37	5,80	5,25	3,48	5,84

Table 2
Some information about Italian banks (thousands of Euro).

	Gross Loans	Fixed Assets	Total Assets	Total Equity	Total Liabilities
mean	7.716.353,51	189.091,59	12.914.255,64	825.175,53	12.089.080,12
st.deviation	43.593.982,59	1.307.381,41	83.939.782,37	5.321.152,83	78.646.951,05
max	502.468.000,00	19.336.000,00	1.069.003.000,00	64.066.000,00	1.004.937.000,00
min	4.317,00	393,00	13.853,00	4.467,00	831,00
cv	5,65	6,91	6,50	6,45	6,51

Table 3
Variable analysed in relation to efficiency.

	Proxy used
Size	Total Assets (for banks) Total Assets Number of employees (for FinTech firms)
Profitability	$ROA = \frac{\text{Profit(Loss)}}{\text{Total Assets}}$ $ROE = \frac{\text{Profit(Loss)}}{\text{Total Equity}}$
Liquidity	$\frac{\text{Liquid Assets}}{\text{Deposits and Short Term Funding}}$ (for banks) Liquidity Index[a](for FinTech firms)
Capitalization	Total Capital Ratio (for banks) $\frac{\text{Total Equity}}{\text{Total Assets}}$ (for FinTech firms)
Overall Efficiency	$\frac{\text{Cost}}{\text{Income}}$

[a]We considered the Liquidity Index directly provided by AIDA

Table 4
FinTech firms: Prevailing Characteristics in relation to efficiency.

Efficiency Level	Prevailing Characteristics	
High	Size	Not significant
(13 FinTech firms	Profitability ROA	4.17
i.e. 30% out of total)	Profitability ROE	11.84
	Liquidity	1.32
	Capitalization	41.59
	Overall Efficiency	0.98
Medium	Size	Not significant
(26 FinTech firms	Profitability ROA	-10.88
i.e. 59% out of total)	Profitability ROE	-8.6
	Liquidity	1.1
	Capitalization	31.62
	Overall Efficiency	1.59
Low	Size	Not significant
(5 FinTech firms	Profitability ROA	-30.34
i.e. 11% out of total)	Profitability ROE	-11.76
	Liquidity	0.72
	Capitalization	3.10
	Overall Efficiency	1.62

Table 5
Banks: Prevailing Characteristics analysed in relation to efficiency.

Efficiency Level	Prevailing Characteristics	
High	Size	Medium-Small
(92 banks	Profitability ROA	0.45
i.e. 31% out of total)	Profitability ROE	4.70
	Liquidity	36.80
	Capitalization	31.49
	Overall Efficiency	66.57
Medium	Size	Medium-Small
(182 banks	Profitability ROA	0.25
i.e. 61% out of total)	Profitability ROE	2.60
	Liquidity	23.80
	Capitalization	20.73
	Overall Efficiency	70.96
Low	Size	Large
(23 banks	Profitability ROA	0.26
i.e. 8% out of total)	Profitability ROE	4.11
	Liquidity	21.44
	Capitalization	18.76
	Overall Efficiency	71.18

three aforementioned variables across all 297 banks considered.

The average efficiency values, both the first calculated on all 297 banks considered and the second, obtained on the sample of 44, show higher efficiency levels of banks compared to FinTech firms concerning lending activity (average value of 0.965 and 0.957, respectively, for all banks and for the sample versus 0.889 for FinTech firms).

There now follows an explanation for the results we have just outlined.

First, in order to assign a meaning, which is as correct as possible, to the previous statements, it is important to always keep in mind that the higher efficiency of banks with respect to that of FinTech firms was established via a comparison of average values. Although the efficiency values variability obtained within the banks and in the FinTechs group is low – thus allowing adequate information power to be assigned to the mean values of the two groups – it is also true that it is higher in the set of FinTechs (banks' variation coefficient 5% vs FinTech variation coefficient 13%). Thus, it is not possible to generalise by saying that all FinTech firms are not efficient, since within that group there are also successful units that operate highly efficiently (Takeda and Ito, 2021).

As such, some of the reasons for why FinTech firms might be less efficient than banks could be traced back to the following: their more limited experience, rapid growth, high use of emerging technologies, difficulties in adapting to regulations in the financial sector and high dependence on third parties.

Regarding the first reason, most FinTech firms are in fact start-ups and therefore, as new entities operating within the financial sector, it is natural that they have not yet gained the same experience and expertise as traditional financial institutions (Chemmanur et al., 2020). It is therefore plausible that it may affect their ability to optimize the lending process and thus achieve higher levels of efficiency.

Another distinctive feature of FinTech firms is their aptitude for very rapid growth. As is well known, the management of a fast-growing firm is generally complex and needs suitable systems and processes to be implemented to maintain efficiency, with consequent cost implications (Basdekis et al., 2022).

FinTech firms are often at the forefront of adopting new technologies, such as artificial intelligence, machine learning and blockchain. Of course, integrating such approaches can take time and is subject to technical challenges, affecting, perhaps just temporarily, their operational efficiency (Irimia-Diéguez et al., 2023).

The financial sector is subject to strict regulations and compliance requirements and, as a consequence, FinTech firms that want to join this sector have to make a considerable effort to meet these requirements and be compliant with existing regulations. This may require the use of additional resources and thus negatively affect the level of operational efficiency (Cumming and Schwienbacher, 2018).

Another aspect that should not be underestimated is the fact that FinTech firms, by necessity, have a large number of relationships with external service providers for some specific activities, such as payment processing or customer identity authentication. Dependence on third parties could therefore affect not only the speed of processes but also operational efficiency (Carbó-Valverde et al., 2021).

Thus, the efficiency of a FinTech firm depends on many factors, both internal and external (Balyuk, 2022), which, if properly managed, can enable it to offer, on a par with banks, innovative solutions and cheap services for its customers.

5. Conclusions

For several years now, we have been witnessing a continuous change in the financial system structure due to the increasing presence of FinTech firms operating in different sectors and to the resulting competitive pressures they exert on other intermediaries. This paper has sought to analyse a topic that has yet not been studied in depth, namely, the comparison of the efficiency level exhibited by all Italian FinTech firms engaged in lending and by all traditional banks. To this aim, we adopted an approach known as Stochastic

Table 6
Stratified Sample's Composition.

		Overall Efficiency		
		High	Medium	Low
Commercial	Large	2	2	2
Commercial	Medium	0	1	0
Commercial	Small	1	0	1
Cooperative	Large	4	3	1
Cooperative	Medium	5	5	4
Cooperative	Small	2	4	6
Savings	Large	0	0	0
Savings	Medium	0	1	0
Savings	Small	0	0	0

Data Envelopment Analysis (SDEA) to measure the efficiency, in 2021, of FinTech firms and banks. We found higher efficiency levels for banks compared to FinTech firms.

The results obtained in the analyses are of great importance at corporate level. First of all, they are very useful to establish the positioning, in terms of efficiency, of each unit with respect to competitors. Secondly, they are also helpful to understand which drivers have the greatest impact in obtaining the highest levels of efficiency and, consequently, to define the most suitable strategies for improving performance.

However, the evaluation of the actual degree of lending activity efficiency also gives important information for those units potentially interested in acquisition processes or in the development of new partnerships. In fact, this phenomenon is particularly noteworthy since it is increasingly widespread in the financial sector, due to the growing interest that traditional intermediaries are showing in FinTech firms.

The results obtained may also interest supervisory and regulatory authorities, since they have to constantly and carefully monitor the financial system in order to ensure stability in an environment populated both by FinTech firms dedicated to lending and by more traditional intermediaries. Indeed, as is well known, FinTech lending offers an alternative source of financing to firms and consumers, thereby facilitating access to credit also for those who are underserved for various reasons. Furthermore, some studies (Claessens et al., 2018) have already shown that FinTech credit reaches higher volumes in countries with less severe banking regulation and that this phenomenon raises several issues for supervisory authorities. Many of these problems relate to the need to ensure adequate protection for consumers and investors.

Challenges and benefits for financial stability could therefore emerge if the FinTech lending sector were to expand further, or if banks start making greater use of similar technological innovations in their credit supply.

This analysis must necessarily be considered as preliminary since it is heavily constrained by the limited availability of data. As a consequence, the results will have to be further confirmed by extending both the time window analysed and the data set composition as soon as new data becomes available.

Given the above, could the inclusiveness of FinTech lead to inefficiency? It is possible to hypothesise that the answer might depend on which of the following two circumstances will occur. Indeed, it could be that the inclusion of FinTech firms, which, at the moment, would appear to be less efficient than banks, will lead to a general reduction in the overall system efficiency, or that the presence of these new players in the lending sector will lead banks to greater levels of efficiency as a result of improvements in their production process.

With future research development, we also aim to answer that question.

Data Availability

The data that has been used is confidential.

References

Balyuk, T., Berger, A.N., & Hackney, J., 2022. What is Fueling FinTech Lending? The Role of Banking Market Structure. Available at SSRN: https://ssrn.com/abstract=3633907 or https://doi.org/10.2139/ssrn.3633907.

Basdekis, C., Christopoulos, A., Katsampoxakis, I., Vlachou, A., 2022. FinTech's rapid growth and its effect on the banking sector. J. Bank. Financ. Technol. 6 (2), 159–176.

Bena, J., Ondko, P., 2012. Financial development and the allocation of external finance. J. Empir. Financ. 19 (1), 1–25.

Berg, T., Fuster, A., Puri, M., 2022. Fintech lending. Annu. Rev. Financ. Econ. 14, 187–207.

Berger, A.N., 2003. The economic effects of technological progress: evidence from the banking industry. J. Money, Credit Bank. 141–176.

Berger, A.N., Humphrey, D.B., 1997. Efficiency of financial institutions: international survey and directions for future research. Eur. J. Oper. Res. 98, 175–212.

Bernanke, B., 2011. Speech at the independent community bankers of America national convention. San. Diego, Calif., March 23.

Boot, A.W., 2017. The future of banking: from scale & scope economies to fintech 29. Eur. Econ. 2, 77–95.

Borello, G., Pampurini, F., Quaranta, A.G., 2022. Can High-tech investments improve banking efficiency? J. Financ. Manag., Mark. Inst. 10 (01), 2250003.

Buchak, G., Matvos, G., Piskorski, T., Seru, A., 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. J. Financ. Econ. 130 (3), 453–483.

Campanella, F., Serino, L., & Crisci, A. 2022. Governing Fintech for sustainable development: evidence from Italian banking system. *Qualitative Research in Financial Markets*, (ahead-of-print).

Carbó-Valverde, S., Cuadros-Solas, P.J., Rodríguez-Fernández, F., 2021. FinTech and banking: an evolving relationship. In: King, T., Stentella Lopes, F.S., Srivastav, A., Williams, J. (Eds.), Disruptive Technology in Banking and Finance. Palgrave Studies in Financial Services Technology. Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-030-81835-7_6.

Carney, M., 2017. Building the Infrastructure to Realise FinTech's Promise, Speech given by Mark Carney, Governor of the Bank of England International FinTech Conference 2017, Old Billingsgate, 12 April.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision-making units. Eur. J. Oper. Res. 2 (6), 429–444.

Chemmanur, T.J., Imerman, M.B., Rajaiya, H., Yu, Q., 2020. Recent developments in the fintech industry. J. Financ. Manag., Mark. Inst. 8 (01), 2040002.

Chen, M.A., Wu, Q., Yang, B., 2019. How valuable is FinTech innovation? Rev. Financ. Stud. 32 (5), 2062–2106.

Claessens, S., Frost, J., Turner, G., & Zhu, F., 2018. Fintech credit markets around the world: size, drivers and policy issues, BIS Quarterly Review, September 2018.

Cornelli, G., Frost, J., Gambacorta, L., Rau, P.R., Wardrop, R., Ziegler, T., 2020. Fintech and big tech credit: a new database. BIS Work. Pap. 887 (No).

Cumming, D.J., Schwienbacher, A., 2018. Fintech venture capital. Corp. Gov.: Int. Rev. 26 (5), 374–389. https://doi.org/10.1111/corg.12256.

Demir, A., Pesqué-Cela, V., Altunbas, Y., Murinde, V., 2020. Fintech, financial inclusion and income inequality: a quantile regression approach. The European. J. Financ. 28 (1), 86–107.

Dhar, V., Stein, R.M., 2017. Economic and business dimensions: FinTech platforms and strategy. Commun. ACM Vol. 60 (No. 10), 32–35.

Di Maggio, M., Yao, V., 2021. FinTech borrowers: lax screening or cream-skimming? The. Rev. Financ. Stud. 34 (10), 4565–4618.

Financial Stability Board, 2017a. FinTech credit. Market structure, business models and financial stability implications, Financial Stability Board and Committee on the Global Financial System.

Financial Stability Board, 2017b. Financial Stability Implications from FinTech. Supervisory and Regulatory Issues that Merit Authorities' Attention, Financial Stability Board and Committee on the Global Financial System.

Fu, J., Mishra, M., 2022. Fintech in the time of COVID− 19: technological adoption during crises. J. Financ. Inter. 50, 100945.

Gai, K., Qiu, M., Sun, X., 2018. A survey on FinTech. J. Netw. Comput. Appl. 103, 262–273.

Gomber, P., Kauffman, R.J., Parker, C., Weber, B.W., 2018. On the fintech revolution: interpreting the forces of innovation, disruption, and transformation in financial services. J. Manag. Inf. Syst. 35 (1), 220–265.

Houston, J.F., Lin, C., Lin, P., Ma, Y., 2010. Creditor rights, information sharing, and bank risk taking. J. Financ. Econ. 96 (3), 485–512.

Huang, Z., Li, S.X., 2001. Stochastic DEA models with different types of input-output disturbances. J. Product. Anal. 15, 95–113.

Hughes, J.P., Lang, W., Mester, L., Moon, C., 1996. Efficient banking under interstate branching. J. Money Credit Bank. 28, 1045–1071.

Hughes, J.P., Jagtiani, J., Moon, C.G., 2022. Consumer lending efficiency: commercial banks versus a fintech lender. Financ. Innov. 8 (38), 1–39.

Irimia-Diéguez, A., Velicia-Martín, F., Aguayo-Camacho, M., 2023. Predicting FinTech innovation adoption: the mediator role of social norms and attitudes. Financ. Innov. 9 (1), 1–23.

Jakšič, M., Marinč, M., 2019. Relationship banking and information technology: the role of artificial intelligence and FinTech. Risk Manag. 21, 1–18.

Kao, C., Liu, S.T., 2009. Stochastic Data Envelopment Analysis in measuring the efficiency of Taiwan commercial banks. Eur. J. Oper. Res. Volume 196 (Issue 1), 312–322.

Khodabakhshi, M., Asgharian, M., Gregoriou, G.N., 2010. An input-oriented super-efficiency measure in stochastic data envelopment analysis: evaluating chief executive officers of us public banks and thrifts. Expert Syst. Appl. 37 (3), 2092–2097.

Kwon, K.Y., Molyneux, P., Pancotto, L., Reghezza, A., 2023. Banks and FinTech acquisitions. J. Financ. Serv. Res. 1–35.

Lee, C.C., Li, X., Yu, C.H., Zhao, J., 2021. Does fintech innovation improve bank efficiency? Evidence from China's banking industry. Int. Rev. Econ. Financ. 74, 468–483.

Lee, I., Shin, Y.J., 2018. Fintech: ecosystem, business models, investment decisions, and challenges. Bus. Horiz. 61 (1), 35–46.

Mahalanobis, P.C. (1936). Mahalanobis distance. In *Proceedings National Institute of Science of India*, Vol. 49, No. 2, pp. 234–256. [14:16] annagrazia.quaranta@unimc.it.

McCombes, S. (2023). Sampling Methods. Types, Techniques & Examples. Scribbr. ⟨https://www.scribbr.com/methodology/sampling-methods/⟩.

Murinde, V., Rizopoulos, E., Zachariadis, M., 2022. The impact of the FinTech revolution on the future of banking: opportunities and risks. International Review of Financial. Analysis 81, 102103.

Najaf, K., Subramaniam, R.K., Atayah, O.F., 2022. Understanding the implications of FinTech Peer-to-Peer (P2P) lending during the COVID-19 pandemic. J. Sustain. Financ. Invest. 12 (1), 87–102.

Nakashima, T., 2018. Creating credit by making use of mobility with FinTech and IoT, IATSS Research, Vol. 42, No. 2, pp.61–66.

Navaretti, G.B., Calzolari, G., Mansilla-Fernandez, J.M., Pozzolo, A.F., 2018. Fintech and banking. Friends Or. foes? Eur. Econ. (2)).

Ntwiga, D.B., 2020. Technical efficiency in the Kenyan banking sector: influence of fintech and banks collaboration. J. Financ. Econ. 8 (1), 13–22.

Olesen, O.B., Petersen, N.C., 2016. Stochastic data envelopment analysis. A review. Eur. J. Oper. Res. 251, 2–21.

Ozili, P.K., 2018. Impact of digital finance on financial inclusion and stability. Borsa Istanb. Rev. 18 (4), 329–340.

Pampurini, F., Quaranta, A.G., 2018. Sustainability and efficiency of the European banking market after the global crisis: the impact of some strategic choices. Sustainability Vol. 10, 2237. Nos. 1–16.

Pampurini, F., Quaranta, A.G., 2022. European banking groups' efficiency in a decade: an empirical investigation on the determinants. Int. J. Product. Qual. Manag. Vol. 36 (No. 1), 110–126.

Panetta, F., 2018. Fintech and banking: today and tomorrow. Speech of the Deputy Governor of the Bank of Italy, Rome, 12th May.

PWC, 2021. 2021 Italian FinTech Observatory. PWC FinTech Observatory.

Quaranta, A.G., Raffoni, A., Visani, F., 2018. A multidimensional approach to measuring bank branch efficiency. Eur. J. Oper. Res. Vol. 266 (No. 2), 746–760.

Ray, S.C., 2004. Data envelopment. Analysis: Theory and techniques for economics and opera- tions research. Cambridge University Press.

Romanova, I., Grima, S., Spiteri, J., Kudinska, M., 2018. The payment services directive II and competitiveness: the perspective of European fintech companies. Eur. Res. Stud. J. Vol. 21 (No. 2), 3–22.

Saksonova, S., Kuzmina-Merlino, I., 2017. Fintech as financial innovation–the possibilities and problems of implementation. Eur. Res. Stud. J. 3A, 961–973.

Sheng, T., 2021. The effect of fintech on banks' credit provision to SMEs: Evidence from China. Financ. Res. Lett. 39, 101558.

Song, M., Zhou, P., Si, H.T., 2021. Financial technology and enterprise total factor productivity—perspective of "enabling" and credit rationing. China Ind. Econ. 4, 138–155.

Stefanelli, V., & Manta, F., 2023. The rise of digital finance: Empirical evidence on fintech firms, banks and customers. FrancoAngeli.

Stulz, R.M., 2019. Fintech, bigtech, and the future of banks. J. Appl. Corp. Financ. 31 (4), 86–97.

Suryono, R.R., Budi, I., Purwandari, B., 2020. Challenges and trends of financial technology (Fintech): a systematic literature review. Information 11 (12), 590.

Takeda, A., Ito, Y., 2021. A review of FinTech research. Int. J. Technol. Manag. 86 (1), 67–88.

Thakor, A.V., 2020. Fintech and banking: what do we know? J. Financ. Inter. 41, 100833.

Thanassoulis, E., Portela, M., Allen, R., Cooper, W., Seiford, L., Zhu, J., 2004. Handbook on data envelopment analysis. international series in operations. Res. Manag. Sci. 71, 99–138.

Tseng, P.L., Guo, W.C., 2022. Fintech, credit market competition, and bank asset quality. J. Financ. Serv. Res. 61 (3), 285–318.

Vives, X., 2017. The impact of FinTech on banking. Eur. Econ. 2, 97–105.

Vives, X., 2019. Digital disruption in banking. Annu. Rev. Financ. Econ. 11, 243–272.

Vučinić, M., 2020. Fintech and financial stability potential influence of FinTech on financial stability, risks and benefits. J. Cent. Bank. Theory Pract. 9 (2), 43–66.

Wanke, P., Azad, M. A, Kalam, 2018. Efficiency in Asian railways: a comparison between Data Envelopment Analysis approaches. Transp. Plan. Technol. 41 (6), 573–599.

Wu, Y.H., Bai, L., Chen, X., 2023. How does the development of fintech affect financial efficiency? Evidence from China. *Econ. Res.-Èkon. Istraživanja* 36 (2), 2106278.
Wurgler, J., 2000. Financial markets and the allocation of capital. J. Financ. Econ. 58 (1–2), 187–214.
Xie, X., Zhu, X., 2022. FinTech and capital allocation efficiency: another equity-efficiency dilemma? Global Finance. Journal 53, 100741.