



ELSEVIER

Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Research in International Business and Finance

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

Does efficiency matter in M&A of FinTech firms?

Francesca Pampurini^{a,*}, Anna Grazia Quaranta^b, Grazia Onorato^c

^a Department of Economics and Business Management Sciences, Catholic University of the Sacred Heart of Milan, Largo Gemelli 1, Milan 20123, Italy

^b Department of Economics and Law, University of Macerata, Via Crescimbeni, 14, Macerata 62100, Italy

^c Department of Economics, University of Foggia, Via Romolo Caggese, 1, Foggia 71121, Italy

ARTICLE INFO

Keywords:

FinTech
Efficiency
Stochastic Data Envelopment Analysis
M&A

ABSTRACT

The increasing presence of FinTech firms is reshaping the structure, behaviour and business models of the different players operating within the financial sector. The aim of this study is to understand whether there is any relationship between the achievement of specific efficiency levels by FinTech firms and their greater/minor involvement in M&A transactions. Since such a relationship could be in the opposite direction, the topic is important for a wide range of financial stakeholders, from individual investors to key market players and regulators. We measured efficiency via two different Stochastic Data Envelopment Analysis (SDEA) models. The results, obtained starting from a hand-collected data set made up of Italian FinTechs operating in the period 2021–2023, show that M&A transactions essentially involved firms characterised by both quite high or quite low levels of efficiency.

1. Introduction

The recent emergence and rise of FinTech firms are progressively and significantly reshaping the structure, behaviour and business models of the different players operating within the financial sector to keep them in line with the ongoing progress of new technologies (Pandey et al., 2024).

There are three main approaches available to both financial intermediaries and other players to engage with FinTechs in order to react effectively to the growing demand for innovation in the products and services offered to the public, precisely because of the substantial competition exerted by the latter in areas that have traditionally been the domain of the former. Indeed, they can make new investments in increasingly advanced technologies themselves, implement *ad hoc* partnerships, or directly merge or acquire existing FinTech firms.

This contribute focuses on the latter strategy for a number of reasons. First, recent studies have shown that mergers and acquisitions (M&A) of FinTechs are increasing, particularly in the financial sector, and it seems that they will also tend to overtake the number of partnerships in the near future (KPMG, 2018). Secondly, in spite of the undoubted and well-known challenges involved in the valuation of a FinTech, the preference for strategic acquisitions is probably a direct consequence of many factors; among them, the lower costs involved in such transactions as compared to autonomously seeking in-house adaptation of the digital technologies already in place, as well as some key advantages in terms of exclusivity, rapid access to new customers/markets and data security (Kwon et al., 2024).

* Corresponding author.

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

<https://doi.org/10.1016/j.ribaf.2025.103027>

Received 24 January 2025; Received in revised form 16 June 2025; Accepted 18 June 2025

Available online 20 June 2025

0275-5319/© 2025 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

In particular, the aim of this study is to understand whether there is any relationship between the achievement of specific efficiency levels by FinTech firms and their greater/minor involvement in M&A transactions. As it will be better outlined in [Section 2](#), this topic can be interesting for a wide range of stakeholders in the financial sector, from individual investors, like customers/end users of FinTech platforms, to key market players, such as FinTech firms themselves, market analysts and financial advisors, and regulators ([Zhao and Ma, 2025](#)). Indeed, it is very important for all of them to understand if M&A deals are focused only on the most efficient FinTechs or, on the contrary, on the less efficient ones to benefit, respectively, from their particular managerial ability or from low acquisition prices ([Calipha et al., 2010](#); [Nguyen et al., 2012](#); [Harjoto et al., 2012](#); [Zheng and Mao, 2024](#); [Wang et al., 2024](#)).

With more detail, it should first be noted that the reason why one acquires or merges with a target may be twofold. In fact, it may happen either (i) because the latter appears somehow *ideal* (and then, among the requirements to be so, inevitably, there is also to be efficient, given that this factor can be immediately linked to the search for appropriate operational synergies able to determine increases in revenues and/or reductions in costs), or (ii) because the target has a *convenient* price considering its status ([Malik et al., 2014](#); [Fidrmuc and Xia, 2019](#), [Collecchio et al., 2024](#)).

Then, as regards the direction of the relationship, in the first case it would be positive – and thus greater efficiency would tend to lead to greater involvement in M&A transactions. In the second, on the other hand, given that the evaluation of takeover/merger would inevitably be driven by the expected value of the takeover premium rather than by the level of efficiency achieved by the target (which could thus be, indifferently, either high or medium or, even, low or very low), the relationship between efficiency and involvement in M&A transactions could either not exist or possibly show a link with low levels of efficiency.

As far as we know, no research has yet directly examined how the achievement of efficiency is related to the level of involvement of firms, including FinTech, in M&A. This paper, therefore, aims to begin such an investigation, with the aim of filling a relevant gap in the existing literature. Then, this study will try to understand what actually happens and, to this end, it will analyse what emerges from the M&A deals involving Italian FinTechs in 2021–2023.

Actually, the choice of the observed period was strongly constrained by data availability.

As far as the measurement of efficiency is concerned, given the well-known drawbacks of the Stochastic Frontier Approach (SFA) and of the (deterministic) Data Envelopment Analysis (DEA) ([Onorato et al., 2024](#)) – i.e. of the best-known methodologies used for this purpose – FinTechs' efficiency will be measured via Stochastic Data Envelopment Analysis (SDEA), this representing another cue of originality in the paper.

In particular, two models will be employed belonging to the SDEA approach that uses inputs and outputs values distributions referred to each statistical unit (in this study, each FinTech) to replace data on which the standard DEA is based. With more detail, a model in a more general form (that is the one that includes slack variables – [Khodabakhshi et al., 2010](#)) will be used, as well as a model within the family of the Stochastic Input-Oriented Data Envelopment Analysis (SIODEA – [Demerdash et al., 2013](#); [Balak et al., 2021](#); [Mourad, 2022](#)).

The paper is organised as follows. In [Section 2](#) a literature review. [Section 3](#) describes the methodology adopted. [Section 4](#) presents the dataset used, while in [Section 5](#) there are the results and their discussion. [Section 6](#) concludes.

2. Literature Review

M&A involving FinTech firms have garnered significant attention in both academic research and industry practice, reflecting the dynamic evolution of the financial services sector. As a consequence, there is a very wide range of literature on this topic which is considered from different points of view.

In a nutshell, literature underscores that M&A activities involving FinTech firms, driven by the necessity for innovation and technological advancement in the financial sector, offer potential benefits, including enhanced profitability and competitive positioning, but can also present challenges that require careful consideration.

In more detail, traditional financial institutions pursue M&A with FinTech firms to enhance technological capabilities, innovate service offerings, and maintain competitive advantage ([Akhtar, and Nosheen, 2022](#); [Chiu et al., 2022](#); [Zheng and Mao, 2024](#); [Li, 2024](#)). [Kwon et al. \(2024\)](#) investigated the drivers behind such deals, highlighting that banks with greater capital strength and liquidity and lower IT spending are more likely to be acquirors. Also [Klus et al. \(2019\)](#) examined the strategic motivations for banks to acquire or merge with FinTechs, emphasizing that banks are particularly interested in benefiting from rapid innovation without necessarily being involved in its development, while FinTechs require resources and know-how to grow in the highly regulated financial sector.

[Bellardini et al. \(2022\)](#) assessed that the characteristics of a target are influenced significantly, though not entirely, by the risk-return profile of the bank. Additionally, the regulatory framework plays a limited yet meaningful role, particularly in shaping the selection of financing methods. This influence often drives banks to opt for equity financing, especially when they encounter increased competition from unregulated lenders.

[Hornuf et al. \(2021\)](#) examined which banks typically collaborate with FinTech firms, how intensely they do so, and which form of alliance they prefer.

The integration of FinTechs through M&A can significantly influence the profitability and operational efficiency of traditional banks ([Alhenawi and Stilwell, 2017](#); [Bianconi and Tan, 2019](#)). A systematic review by [Suryono et al. \(2020\)](#) analyzed the challenges and trends of FinTechs, noting that such integrations often lead to improved customer experience and streamlined processes. Other recent studies ([Wang and Nor, 2022](#); [Dasilas and Karanović, 2023](#); [Tarawneh et al., 2024](#)) provided evidence of the impact of FinTech M&A on banks' profitability, suggesting that these transactions can enhance financial performance when effectively managed.

[Li et al. \(2023\)](#) showed that banks' outperformance is primarily linked to investments in fin-native FinTech startups and those whose operations align closely with the banks' core business areas. This is completely consistent with corporate venture capital

literature and supports the idea that banks leverage their specialized industry expertise to identify promising FinTech startups. Furthermore, they demonstrated that banks are more actively involved on the boards of FinTech startups compared to other types of ventures, suggesting that their stronger investment outcomes are not solely due to selection but also to their active participation and oversight.

The FinTech M&A landscape is characterized by rapid growth and evolving regulatory frameworks. A content analysis by [Gomber et al. \(2018\)](#) identified key trends, including the diversification of services and the emergence of new business models within the FinTech sector.

However, challenges persist, such as cultural integration between traditional banks and FinTech startups, regulatory compliance, and the need for robust risk management practices. [Suryono et al. \(2020\)](#) highlighted these obstacles, emphasizing the importance of strategic alignment and due diligence in M&A processes. Moreover, also [Collevecchio et al. \(2024\)](#) offer managers and policymakers preliminary guidance on the impact of FinTech M&As on traditional banks, highlighting that these deals can be advantageous only when specific conditions are met (for example, among them, a highly sustainable bank can achieve a strong anticipated performance by acquiring a minority stake in a FinTech firm operating within a significantly different institutional environment).

As already underlined in [Section 1](#), understanding the relationship's nature between the achievement of specific efficiency levels by FinTech firms and their greater/minor involvement in M&A transactions can be interesting for a wide range of stakeholders in the financial sector.

First of all, FinTech firms themselves are obviously interested in appreciating whether achieving a high level of operational and overall efficiency can really make them more competitive and attractive in the market, thereby determining and influencing real M&A opportunities ([Hay and Guy, 1997](#); [Herbert and Reimann, 2005](#); [Appadu et al., 2016](#)). Then, it can be useful for market analysts and financial advisors to assess potential investment opportunities in this industry, to exploit directly or to suggest to other kinds of investors ([Oberholzer, 2010](#); [Santosuosso, 2014](#)).

The topic may also be of interest to customers/end users of FinTech platforms to understand whether the firm they have approached may possibly become even more efficient after the merger or acquisition process ([Eisenmann et al., 2009](#); [Ryu, 2018](#)); this, moreover, could further increase their trust in the brand and support their decision to continue using the services offered ([Nangin et al., 2020](#); [Pramaswari et al., 2021](#); [Kini et al., 2024](#)).

Finally, assessing how efficiency influences the consolidation of the financial sector via M&A with FinTechs could influence regulatory policies by guiding adjustments to competition policy, licensing processes, risk management standards, data privacy regulations, and client protection measures with the consequence to foster innovation, maintain market integrity, and safeguard the interests of consumers and investors in an evolving financial landscape ([Cummins and Xiaoying, 2008](#); [Rezaee, 2011](#); [Restoy, 2019](#)).

Despite all this, to the best of our knowledge, there are still no studies that specifically analyse the nature of the relationship between the achievement of efficiency and greater/minor involvement of firms, FinTech or otherwise, in M&As. It is for this reason that this paper aims to begin to explore the topic, thus attempting to fill a gap on an issue that needs to be attended to.

3. Methodology

As underlined several times, the aim of the paper is to understand whether there is any relationship between the achievement of specific efficiency levels by FinTechs and their involvement in M&A transactions. In particular, as stated in [Section 1](#), there are two main reasons for acquiring or merging with a target company. First, the target may be considered *ideal*, often due to its efficiency, which supports potential synergies leading to increased revenues or reduced costs. Second, the target may be attractive due to its low price relative to its condition. In the first scenario, the link between efficiency and M&A involvement should be positive (*Hypothesis 1*). In the second, decisions are driven by the takeover premium, not efficiency, meaning targets can be efficient or not. Thus, the relationship between efficiency and M&A activity might not exist or be related to low levels of efficiency (*Hypothesis 2*).

Inevitably, the analysis will have to start with measuring the level of efficiency reached by the FinTechs. The first problem to be solved will then be how to quantify efficiency, given that the literature has extensively highlighted the weaknesses of both the best-known methodologies used in this regard, namely the Stochastic Frontier Approach (SFA – [Aigner et al., 1977](#); [Battese and Coelli, 1995](#); [Coelli et al., 2005](#); [Pampurini and Quaranta, 2018](#); [Pagano, 2021](#)) and Data Envelopment Analysis (DEA – [Charnes et al., 1978](#); [Ray, 2004](#); [Thanassoulis et al., 2004](#); [Feng et al., 2024](#)).

In a nutshell, in the first case the main difficulties concern the identification, on the one hand, of the relationship that analytically links exhaustively the output and the inputs characterising the production process of the units considered and, on the other, the definition of the assumptions underlying the two regression error components distribution ([Quaranta et al., 2018](#); [Onorato et al., 2024](#)).

As for the DEA's drawbacks ([Olesen and Petersen, 2016](#)), they clearly emerge considering inputs and outputs with different measurement units or few observations (especially if fewer in number than inputs and outputs, given that this may result in the over-identification of very efficient units), or in the case of a high presence of outliers, as well as of the consideration of data as if they were deterministic when in fact, for different reasons, they are not (e.g., because they are trivially affected by errors in the collection of the same or precisely because they cannot be considered as such).

In the peculiar case of FinTechs, the first problem of SFA is practically unsolvable, given that their production process is even more difficult to capture through a production function than is already the case for other firms. DEA, as a nonparametric method that, therefore, does not require an *a priori* definition of the link between outputs and inputs of the production process, thus stands as the only feasible way forward. As for the first three aforementioned limits attributable to this approach, they can in fact be overcome by resorting, respectively, to the standardisation of the variables' values used as proxies of inputs and outputs, an adequate number of

observations and the removal of outliers (via the more traditional statistical/econometrical approaches).

Instead, in relation to the fourth DEA limit, the data available to us should certainly be attributed a stochastic nature, despite being extracted from financial statements (Kao and Liu, 2004, 2009; Wong et al., 2014). This is both because for them it is not possible to exclude *a priori* the presence of recognition errors, and since they are values that quantify management traits that take on different values over time and of which we instead have only snapshots at a specific date (i.e., the end of the accounting period).

A robust way to consider the randomness of the variables' values is Stochastic Data Envelopment Analysis (SDEA; Khodabakhshi et al., 2010; Wanke, Kalam Azad, 2018), which is an extension of (deterministic) DEA that is supplemented by considering for the input and output variables a random variability. Actually, it is possible to follow two different strategies in applying this new methodology. The first approach, with the aim to obtain a consistent estimator of the true frontier, adopts specific statistical assumptions to set up a modified DEA based on both a statistical model and a sampling process (Olesen and Petersen, 2016). Otherwise, the second one uses inputs and outputs values distributions referred to each statistical unit (called Decision Making Unit – DMU – and that, in our case, will be a specific FinTech firm) to replace the data on which the standard DEA is based (Huang and Li, 2001), thus incorporating random noises in their values' vectors. Both these ways lead to hybrid models substantially characterised by the absence of the original drawbacks of SFA and DEA and able to exploit their advantages.

In particular, in this study two models belonging to the aforementioned second approach will be applied, since, both a SDEA general model, that is the one that includes slack variables (Khodabakhshi et al., 2010), and a model within the family of the Stochastic Input-Oriented Data Envelopment Analysis (SIODEA – Demerdash et al., 2013; Balak et al., 2021; Mourad, 2022) will be implemented. More details on the structure of the models related to the above two approaches can be found in the Appendix.

Another problem that needed to be solved concerned the definition and subsequent measurement of inputs and outputs referable to the production process of FinTech firms. This problem derived from the fact that the FinTechs that will be analysed exhibit very different production processes; then, it was necessary to find variables able to, at the same time, overcome these differences and represent in a correct way each FinTech's production process, so that the efficiency values obtained can be immediately compared. The in-depth analysis of the financial statements of the different FinTech firms to be considered revealed an extremely varied situation, so much so that the choice of a suitable proxy for all of them in relation to each input/output variable proved particularly difficult. A solution able to be adequately representative of each real situation turned out to be the one that, coherently with the well-known and widely implemented intermediation approach (Berger and Humphrey, 1997; Fethi and Pasiouras, 2010), defined the following output and inputs for the FinTechs' production process: total assets to measure the output (O), staff expenses to total assets to quantify human capital (F1), interest and commission expenses to total liabilities to measure financial capital (F2), other administrative and operating expenses to the sum of tangible and intangible assets to proxy fixed capital (F3), and total equity to quantify the netput (F4). Thus, the two SDEA Models implementation will refer to them.

Then, for each year in the observed period, the FinTechs' efficiency values will be used to cluster all the DMUs into three homogeneous groups; in particular, cluster 1 will group FinTechs that will show the lowest efficiency levels, cluster 2 will comprise the medium efficiency DMUs, while cluster 3 will refer to the most efficient ones. In order to properly divide FinTechs into groups, the skewness level of the efficiency values distributions for each year will be assessed.

Thus, in the case of skewed distributions, the following three ranges will be defined (as it is statistical practice):

[minimum value; (median – standard deviation)]

[(median – standard deviation); (median + standard deviation)]

[(median + standard deviation); maximum value]

(1)

and, obviously, in the case of symmetrical distribution, the median value will be equal to the mean.

At this point, it will be necessary to describe, for each year, the profile of the DMUs included in each cluster in order to understand the traits that FinTechs belonging to each group have in common. To this end, together with the FinTechs' qualitative characteristics 'geographic area' and 'core business' (Crowdfunding, Crypto and DeFi – Decentralised Finance, InsurTech, Invoice and Tax Management, Lending, Neo banks, Payments, PFM, Real Estate FinTech, RegTech, TechFin, WealthTech¹), the following quantitative variables will be used, whose data come from the respective balance sheets²: financial assets, receivables, financial fixed assets, tangible assets, intangibles and total fixed assets, sales, number of employees, liquid assets, leverage (debt/equity), ROA, and ROE. To avoid distortions due to the different size of the firms, each variable (excluding Leverage, ROA and ROE) was divided by total assets.

The last step will be to verify whether there is any relationship between the achievement of specific efficiency levels by FinTech firms and their greater/minor involvement in M&A transactions. This will be done via the implementation of a traditional statistical connection analysis (chi-square and Cramer's V).

¹ The classification used is the one proposed by Fintech District.

² Accounting and balance sheet data were obtained from AIDA (Bureau Van Dijk). The choice of the aforementioned variables depended not only on the specific descriptive capacity of each one, but also on the actual availability of an adequate number of information and thus the absence of missing values in their data vectors.

4. Data

Before proceeding with the description of the hand-collected dataset used in this study, it is necessary to underline the initial difficulty found in identifying the list of FinTech firms that have been operating for at least the last three years. This problem stems from at least two reasons; firstly, it is difficult to objectively identify which firms can actually be defined as a FinTech (Giglio, 2021) and, as a consequence, there is no universally consensual list that joins them all. Therefore, special thanks are due to FinTech District,³ which provided the list of their member firms updated to early 2024, also pointing out which of them have been involved in M&A transactions in the last three years.

In order to obtain the balance sheet data necessary for the analysis – which, as we know, are currently only available up to the year 2023 – AIDA (Bureau Van Dijk) was used and therefore, from the 295 firms initially on the aforementioned list, it was necessary to eliminate those not operating in Italy. This resulted in 214 units. From these, it was then necessary to remove, for each year, all the firms that either had not yet been established in that year or had gradually ceased their activities, thus arriving at being able to consider, in the 2021–2023 period, the FinTechs shown in Table 1, also split according to their core business.

The narrowing of the analysis to the Italian context has undoubtedly made it possible to overcome the problem of the different possible impacts on the efficiency levels achieved by each FinTech deriving from specific circumstances (e.g. environmental characteristics, socio-political events, adoption of particular accounting standards, etc.) that during the period may have affected some countries instead of others. This certainly made the values assumed by the variables used to quantify the efficiency of the different firms more comparable.

As shown in Table 1, in the different years, the number of firms specialised in the different core businesses is low and therefore not adequate for the implementation of a robust sector-by-sector analysis. Hence, as discussed in Section 3, the choice of the proxies listed there for the variables representing the output and inputs of the FinTech production process.

5. Empirical results

From the efficiency values obtained for each FinTech via the two described SDEA models, it was possible to derive, for each of the three years considered, substantially overlapping rankings of DMUs.⁴ Starting from these efficiency values, each DMU was attributed to a specific cluster on the basis of the criteria outlined in Section 3. For each year, Tables 2 and 3 show, respectively, the cluster composition and the average values of the variables that describe the profile of the DMUs belonging to each efficiency group. As anticipated in Section 3, throughout the observation period, FinTechs have been classified annually into three distinct clusters based on their efficiency levels. Specifically (Table 2), Cluster 1 includes the number of the least efficient decision-making units (DMUs), Cluster 2 comprises the number of those with intermediate efficiency, and Cluster 3 consists of the number of the most efficient FinTechs. To ensure the appropriate classification, the skewness of the annual efficiency values distributions has been analysed for each year.

In relation to the geographic area, as clearly evident from the results shown in Table 3, in the three years considered the highest concentration of firms is always in the Lombardy Region, probably due to the fact that the main Italian financial centre is located there. Given this clear evidence, location certainly cannot be considered a factor characterizing the achievement of a particular level of efficiency. Confirming this, the calculated measures of association (Chi-squared and Cramer's V) showed the absence of a link between efficiency and the geographic area where firms are headquartered.

Instead, there would appear to be a very slight relationship between core business and efficiency (Cramer's V = 32 %; p-value of 0.01). It is clear from the results shown in Table 3 that (i) the business carried out in the TechFin⁵ area cannot be considered at all as the discriminating factor within the three clusters in the years considered, but rather just a business that most FinTechs share regardless of the level of efficiency achieved, (ii) the Payments⁶ area would consistently seem to characterize the least efficient firms, and, (iii) although only in 2023, the average efficient firms would seem to be mainly firms devoted to Lending⁷ and InsurTech.⁸

For each year and in the different groups, statistically non-different average values for receivables, financial fixed assets, tangibles, intangibles, and total fixed assets indicate how these variables are not useful in defining a different profile of the efficiency clusters. On the contrary, the average values taken in the three different clusters by financial assets, sales, number of employees, leverage, liquidity ratio, ROA and ROE allow distinctions between the clusters, clearly indicating how the management aspects described by these values are consistently better over the three years for the most efficient firms and generally worse for FinTechs belonging to cluster 1.

Finally, with regard to the main focus of the work, namely whether it is really possible to find a relationship of some kind between

³ <https://www.fintechdistrict.com>.

⁴ Data available upon request.

⁵ This sub-segment contains firms supporting (not only) the Financial Services world with new technologies to optimize processes, increase services efficiency and improve customer experiences, and shows rising contamination between disruptive technologies and the traditional industry. In particular, the activities developed by this kind of firms refer to Chatbot, Cybersecurity, DLT Infrastructure, DnA, ML, AI, Data Management, Open Banking Services/API, Web Services and Solution (Cfr. <https://www.fintechdistrict.com>).

⁶ The Payment sub-segment mainly refers to Mobile Wallets, Smart Payments and Money Transfer (Cfr. <https://www.fintechdistrict.com>).

⁷ The Lending sub-segment mainly refers to Traditional P2P, Invoice Trading and Credit Scoring (Cfr. <https://www.fintechdistrict.com>).

⁸ The insurtech sub-segment mainly refers to Digital Insurers, Digital Brokers, Enablers, Social and P2P Insurance (Cfr. <https://www.fintechdistrict.com>).

Table 1

Distribution of Italian FinTechs in the Fintech District list in the period 2021–2023, according to their core business.

Core business	2021	2022	2023
Crowdfunding	14	14	14
Cripto e DeFi	12	12	16
InsurTech	13	16	15
Invoice e Tax Management	8	8	7
Lending	19	20	20
Neo banks	2	3	3
Payments	22	24	25
PFM	3	5	5
Real Estate FinTech	11	12	12
RegTech	5	6	6
TechFin	49	57	59
WealthTech	14	16	17
Total	172	193	199

Table 2

FinTech groups by year with respect to efficiency.

Cluster	2021	2022	2023
1 – low efficiency	76	88	85
2 – medium efficiency	36	13	40
3 – high efficiency	60	92	74
Total	172	193	199

the level of efficiency achieved by FinTechs and their actual involvement in M&A deals, Table 4 shows the results obtained, broken down by clusters and by individual years. It should be noted that the total number of firms shown in that table for each year is that of the previous year compared to the totals shown in Table 2. This is because it was assumed that the deals were decided and, afterwards, concluded considering the economic-financial and managerial characteristics (and thus, among them, also the level of efficiency) highlighted in the year prior to the deal. Therefore, the connection measures assessed whether or not there was a link between being involved in a deal and the level of efficiency (and thus the cluster to which it belonged) achieved the year prior to the deal.

In the knowledge that the total number of M&As closed in the observed period is small and therefore does not allow to reach an exhaustive assessment of the issues analysed, however, from Table 4 it is possible to see very easily that these transactions did not involve any average performing FinTech, but only firms belonging to cluster 1 (poorly efficient firms) or cluster 3 (highly efficient firms). The chi-square, Cramer's V values and their significance in Table 4 show very clearly the absence of a link between the two topics of interest. Thus, it would seem that the rationale behind the deals was trivially to opt for a merger with very efficient yet healthy targets and for an acquisition of firms that are characterized by a good business idea but bad management, exploiting the likely opportunity to acquire these latter FinTechs at a cheap price.

The presence of a link between the core businesses of the deal firms was also tested; the result (chi-square 6.45; Cramer's V = 0.62; p-value 0.14) only allowed a glimpse that the M&A firms associated with the lowest levels of efficiency in fact operate in the lending and payment sector while most of the most efficient firms belong to the TechFin.

6. Conclusions

Understanding the relationship between the level of efficiency achieved by FinTechs firms and their greater or lesser involvement in M&A deals is a topic particularly important for a wide range of financial stakeholders.

The obtained results show that, probably, the reasoning behind the transactions is straightforward: to choose mergers with highly efficient and stable FinTechs, while acquiring firms that have promising projects but poor management, so benefiting from the opportunity to purchase them at a low cost.

For regulatory and supervisory purposes, these findings could be relevant for several reasons. First of all, what emerged from the analysis would seem to point to a tendency to form increasingly systemically relevant players; consequently, supervisory authorities will be increasingly called upon to assess the potential impact of these bigger players on systemic risk and, in general, on the competitive balance of the market, due, if nothing else, to the reduction in the number of players and the increase in market concentration. In addition, if particularly efficient FinTechs are indeed more attractive for M&A, objective criteria (e.g. performance indicators) could be created to identify who are the strategic players to be subjected to enhanced supervision. The most efficient FinTechs could then exploit M&A to move into more favourable regulatory environments; in such an eventuality, it becomes essential for regulators to monitor these movements and coordinate internationally to prevent regulatory arbitrage. Also not to be underestimated is the fact that the integration of highly efficient FinTech platforms may generally entail greater technological and governance risks, with the consequent need for regulators to ensure that appropriate controls are in place in the post-merger integration and transition process. Finally, if indeed the achievement of higher levels of efficiency leads to an increase in M&A transactions, this may indicate that the market actually rewards innovation and scalability and thus authorities may incentivise responsible

Table 3

Average values of the characteristics describing the FinTechs' profile by efficiency groups and year.

Variable	Cluster	2021	2022	2023
Geographic area	1	Lombardia Region	Lombardia Region	Lombardia Region
	2	Lombardia Region	Lombardia Region	Lombardia Region
	3	Lombardia Region	Lombardia Region	Lombardia Region
Core business	1	Techfin – Payments	Techfin – Payments	Techfin – Payments
	2	Techfin	Techfin	Lending – InsurTech
	3	Techfin	Techfin	Techfin
Financial assets	1	0.002	0.006	0.017
	2	0.004	-	0.026
	3	0.015	0.028	0.033
Receivables	1	28.40	25.48	25.97
	2	27.47	33.79	27.67
	3	32.58	24.56	26.24
Financial fixed assets	1	3.44	2.95	4.04
	2	2.50	4.16	3.28
	3	3.21	3.28	4.75
Tangible assets	1	2.57	2.06	2.56
	2	2.88	2.33	1.81
	3	2.72	1.20	2.36
Intangibles	1	32.28	31.37	27.22
	2	34.84	28.97	34.20
	3	26.11	28.01	31.71
Total fixed assets	1	38.29	36.39	33.81
	2	40.23	35.45	38.93
	3	31.57	32.38	38.81
Sales	1	58.83	77.89	64.75
	2	49.96	56.98	74.13
	3	63.75	51.43	75.11
Number of employees	1	0.69	0.57	0.67
	2	0.78	0.58	0.63
	3	0.44	0.52	0.46
Leverage	1	2.12	2.02	5.21
	2	2.13	1.91	3.52
	3	1.93	1.73	2.59
Liquidity ratio	1	28.86	33.36	25.41
	2	28.65	26.97	26.66
	3	30.14	36.28	35.20
ROA	1	-12.86	-15.08	-15.88
	2	-10.95	-9.38	-13.65
	3	-4.03	-6.02	-10.8
ROE	1	-50.15	-62.39	-139.86
	2	-98.39	-42.00	-69.39
	3	-14.54	-21.89	-42.35

innovation, ensuring that the balance between growth and stability is maintained.

On the side of practitioners, the results of the analysis may then be of interest if one takes into account that efficiency should not only be seen as an operational advantage, but can become a strategic communication lever to attract investments, increase visibility as well as facilitate a profitable exit strategy via M&A for founders and early-stage investors.

As already pointed out, as far as we know, there is still no other work that can confirm or disprove the results just presented. However, the results obtained should be considered preliminary due to the limited number of M&A deals during the observed period involving the firms included in the FinTech District data set. As time passes, more FinTechs may nevertheless become part of that data set and it will certainly be possible to observe additional M&A deals, with the consequence that more statistically significant results can be commented on.

We also aim to overcome some, at the moment for us unavoidable, limits of this research which, we repeat, shows a preliminary nature; to this end, we intend to proceed by extending the analysis to a larger number of countries and markets and by considering a longer time span.

Author contribution

We the undersigned declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We understand that the Corresponding Author is the sole contact for the Editorial process. He/she is responsible for communicating

Table 4
Analysis of the relationship between the level of efficiency achieved by FinTech firms and their involvement in M&A transactions.

M&A 2021	Cluster 1	Cluster 2	Cluster 3	Totale
NO	65	42	42	149
YES	2	0	1	3
	67	42	43	152
chi-square	1.23			
Cramer's V	0.09			
p-value	0.54			
M&A 2022	Cluster 1	Cluster 2	Cluster 3	Totale
NO	72	48	48	168
YES	2	0	2	4
	74	48	50	172
chi-square	1.81			
Cramer's V	0.11			
p-value	0.40			
M&A 2023	Cluster 1	Cluster 2	Cluster 3	Totale
NO	82	13	86	181
YES	9	0	3	12
	91	13	89	193
chi-square	4.23			
Cramer's V	0.15			
p-value	0.22			

with the other authors about progress, submissions of revisions and final approval of proofs.

CRedit authorship contribution statement

Grazia Onorato: Writing – review & editing, Writing – original draft, Validation, Methodology, Data curation, Conceptualization.
Anna Grazia Quaranta: Writing – review & editing, Writing – original draft, Validation, Methodology, Data curation, Conceptualization.
Francesca Pampurini: Writing – review & editing, Writing – original draft, Validation, Methodology, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Let us consider $K(1 < k, l < K)$ DMUs, and refer to DMU l .
 The SDEA general model involves f_j ($j : 1, \dots, N$) inputs and o_w ($w : 1, \dots, M$) outputs. For each DMU, this approach adopts both the inputs and outputs random vectors, respectively, of dimension $(N \times 1)$ and $(M \times 1)$ – i.e. $\tilde{f}_l = (\tilde{f}_{l1}, \dots, \tilde{f}_{lN})^T$ and $\tilde{o}_l = (\tilde{o}_{l1}, \dots, \tilde{o}_{lM})^T$ – and the expected inputs and outputs vectors – e.g., $\bar{f}_l = (\bar{f}_{l1}, \dots, \bar{f}_{lN})^T$ and $\bar{o}_l = (\bar{o}_{l1}, \dots, \bar{o}_{lM})^T$.
 Moreover, it identifies the conjunct probability distribution of $(\tilde{f}_l, \tilde{o}_l)$ considering the inputs and outputs historical data.

Hence, the following structure

$$\begin{aligned}
 &\text{minimize } EFF_1 + \delta \left(\sum_{j=1}^N s_j^- + \sum_{w=1}^M s_w^+ \right) \\
 &\text{subject to } P \left\{ \sum_{l=1}^K \pi_l \tilde{f}_{jl} + s_{jl}^- \leq EFF_1 \tilde{f}_{jl} \right\} = (1 - \beta), j = 1, \dots, N \\
 &P \left\{ \sum_{l=1}^K \pi_l \tilde{o}_{wl} - EFF_1 \tilde{o}_{wl} \geq s_{wl}^+ \right\} = (1 - \beta), w = 1, \dots, M \\
 &s_{jl}^-, s_{wl}^+, \pi_l \geq 0.
 \end{aligned} \tag{1}$$

This model is a constrained linear optimisation problem with stochastic variables; EFF_0 indicates efficiency, δ represents a not

Archimedean positive infinitesimal, π_1 quantifies the input utilisation rate, s_j^- and s_w^+ are slack variables and, finally, β is a parameter that may be chosen at will, taking into account that a higher results accuracy can be obtained in relation to its lower values. According to this approach, a DMU is totally efficient in a stochastic sense if and only if the EFF value is equal to one and, at the same time, the slack variables are zero in all alternative solutions to the optimal one.

As for the SIODEA model, first of all it is fundamental to underline that the words ‘Input-Oriented’ refer to any numerical vector used in the model as input data (and thus they refer to the variables’ values representing both the inputs and outputs of the FinTech firms’ production process).

Stating the above, let F_D (resp. O_D) be the set of indices c (resp. d) for which $(f_{ck})_{1 \leq k \leq K}$ (resp. $(o_{dk})_{1 \leq k \leq K}$) is a vector of deterministic inputs (resp. outputs) and F_R (resp. O_R) be the set of indices h (resp. t) for which $(f_{hk})_{1 \leq k \leq K}$ (resp. $(o_{tk})_{1 \leq k \leq K}$) is a stochastic input variable (resp. stochastic output variable), with R that indicates the set of random variables. In this context, it is possible to define the union set of all input and output indices as, respectively, $F_D \cup F_R = \{1, \dots, n_F\}$ and $O_D \cup O_R = \{1, \dots, n_O\}$.

The SIODEA model with variable returns to scale assumes stochastic variables to be normally distributed in relation to their own mean and variance. It belongs to the family of the so-called chance-constrained programming (CCP) and it takes the following form:

$$\begin{aligned}
 & \text{EFF}_1 = \min(\theta_1) \\
 & P \left\{ \sum_{k=1}^K \lambda_k f_{hk} \leq \theta_1 f_{hl} \right\} \geq (1 - \beta), \quad h \in F_R \\
 & \sum_{k=1}^K \lambda_k f_{ck} \leq \theta_1 f_{cl}, \quad c \in F_D \\
 & P \left\{ \sum_{k=1}^K \lambda_k o_{tk} \leq o_{tl} \right\} \geq (1 - \beta), \quad t \in O_R \\
 & \sum_{k=1}^K \lambda_k o_{dk} \geq o_{dl}, \quad d \in O_D \\
 & \sum_{k=1}^K \lambda_k = 1 \\
 & \lambda_k \geq 0, \quad 1 \leq k \leq K
 \end{aligned} \tag{2}$$

where θ_1 is the ratio of outputs to inputs, $\text{EFF}_1 \in [0, 1]$ is the relative efficiency score for the l -th DMU, λ_k measures the rate of input/output utilisation and $\beta \in [0, 1)$ is a small prescribed real number.

This model:

- can consider all variables as stochastic, or that only some of them have a random nature;
- assumes that, in case of stochastic variables, every input $f_{hk}, h \in F_R$ (and every output $o_{tk}, t \in O_R$) is normally distributed with mean μ_h (resp. μ_t) and variance σ_h^2 (resp. σ_t^2) for each DMU;
- refers to $\text{cov}(f_{hk}, f_{hl}) \neq 0$ and to $\text{cov}(o_{tk}, o_{tl}) \neq 0$ since it considers the existence of a relationship between the same stochastic input and output variable through different DMUs.

Stating the above, after some mathematical steps, a second-order conic optimization problem can be obtained that allows to manage stochastic variables in order to handle in a suitable way both the possible financial statements values’ variability as well as any possible error in data collection:

$$\begin{aligned}
 & \min(\theta_1) \\
 & \sum_{k=1}^K \lambda_k \mu_{hk} - \theta_1 \mu_{hl} \leq e \sqrt{\sum_{k=1}^K \lambda_k^2 \sigma_{hk}^2 + (\lambda_1 - \theta_1)^2 \sigma_{hl}^2 + 2 \text{cov}(f_{hk}, f_{hl})}, \quad \forall h \in F_R \\
 & \sum_{k=1}^K \lambda_k f_{ck} \leq \theta_1 f_{cl}, \quad \forall c \in F_D
 \end{aligned}$$

$$\sum_{k=1}^K \lambda_k \mu_{tk} - \mu_{tl} \geq e \sqrt{\sum_{k=1}^K \lambda_k^2 \sigma_{tk}^2 + \lambda_k^2 \sigma_{tl}^2 + 2\text{cov}(\sigma_{tk}, \sigma_{tl})}, \quad \forall t \in O_R$$

$$\sum_{k=1}^K \lambda_k o_{dk} \geq o_{dl}, \quad \forall d \in O_D$$

$$\sum_{k=1}^K \lambda_k = 1$$

$$\lambda_k \geq 0, \quad (k = 1, \dots, K)$$
(3)

where the cumulative density function for standard normal distribution $\Phi_z(\text{EFF}) = \beta$ was used to derive EFF_1 .

Data availability

The data that has been used is confidential.

References

- Aigner, D., Lovell, C.K., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. *J. Econ.* 6 (1), 21–37.
- Akhtar, Q., Nosheen, S., 2022. The impact of fintech and banks M&A on Acquirer's performance: a strategic win or loss? *Borsa Istanbul. Rev.* 22 (6), 1195–1208.
- Alhenawi, Y., Stilwell, M., 2017. Value creation and the probability of success in merger and acquisition transactions. *Rev. Quant. Financ. Account.* 49, 1041–1085.
- Appadu, N., Faelten, A., Moeller, S.D., Vitkova, V., 2016. Assessing market attractiveness for mergers and acquisitions: the M&A Attractiveness Index Score. *Eur. J. Financ.* 22 (8-9), 732–755.
- Balak, S., Behzadi, M.H., Nazari, A., 2021. Stochastic copula-DEA model based on the dependence structure of stochastic variables: an application to twenty bank branches. *Econ. Anal. Policy.* 72, 326–341, 487–499.
- Battese, G.E., Coelli, T.J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empir. Econ.* 20, 325–332.
- Bellardini, L., Del Gaudio, B.L., Previtali, D., Verdoliva, V., 2022. How do banks invest in FinTechs? Evidence from advanced economies. *J. Int. Financ. Mark. Inst. Money* 77, 101498.
- 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.
- Bianconi, M., Tan, C.M., 2019. Evaluating the instantaneous and medium-run impact of mergers and acquisitions on firm values. *Int. Rev. Econ. Financ.* 59, 71–87.
- Calipha, R., Tarba, S., Brock, D., 2010. Mergers and acquisitions: a review of phases, motives, and success factors. *Adv. Mergers Acquis.* 9, 1–24.
- Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision-making units. *Eur. J. Oper. Res.* 2 (6), 429–444.
- Chiu, W.H., Shih, Y.S., Chu, L.S., Chen, S.L., 2022. Merger and acquisitions integration, implementation as innovative approach toward sustainable competitive advantage: a case analysis from Chinese sports brands. *Front. Psychol.* 13, 869836.
- Coelli, T.J., Rao, D.S.P., O'Donnell, C.J., Battese, G.E., 2005. *An Introduction to Efficiency and Productivity Analysis*. Springer, Berlin.
- Collecchio, F., Cappa, F., Peruffo, E., Oriani, R., 2024. When do M&As with FinTech firms benefit traditional banks? *Br. J. Manag.* 35 (1), 192–209.
- Cummins, J.D., Xiaoying, X., 2008. Mergers and acquisitions in the US property-liability insurance industry: Productivity and efficiency effects. *J. Bank. Financ.* 32 (1), 30–55.
- Dasilas, A., Karanović, G., 2023. The impact of FinTech firms on bank performance: evidence from the UK. *Eur. J. Bus.*
- Demerdash, B.E., Khodary, I.A., Tharwat, A.A., 2013. Developing a stochastic input oriented data envelopment analysis (SIODEA) model. *Int. J. Adv. Comput. Sci. Appl.* 4 (4), 40–44.
- Eisenmann, T.R., Parker, G., Van Alstyne, M., 2009. Opening platforms: how, when and why. *Platf. Mark. Innov.* 6, 131–162.
- Feng, C., Zhong, S., Wang, M., 2024. How can green finance promote the transformation of China's economic growth momentum? A perspective from internal structures of green total-factor productivity. *Res. Int. Bus. Financ.* 70, 102356.
- Fethi, M.D., Pasiouras, F., 2010. Assessing bank efficiency and performance with operational research and artificial intelligence techniques: a survey. *Eur. J. Oper. Res.* 204, 189–198.
- Fidrmuc, J.P., Xia, C., 2019. M&A deal initiation and managerial motivation. *J. Corp. Financ.* 59, 320–343.
- Giglio, F., 2021. Fintech: a literature review. *Eur. Res. Stud. J.* 24 (2B), 600–627.
- 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.
- Harjoto, M.A., Yi, H.C., Chotigeat, T., 2012. Why do banks acquire non-banks? *J. Econ. And. Financ.* 36 (3), 587–612.
- Hay, D.A., Guy, S.L., 1997. The efficiency of firms: what difference does competition make? *Econ. J.* 107 442 (1997), 597–617.
- Herbert, D., Reimann, M., 2005. Evaluating market attractiveness: individual incentives versus industry profitability. *Comput. Econ.* 24, 321–355.
- Hornuf, L., Klus, M.F., Lohwasser, T.S., Schwienbacher, A., 2021. How do banks interact with FinTech startups? *Small Bus. Econ.* 57 (3), 1505–1526.
- Huang, Z., Li, S.X., 2001. Stochastic DEA models with different types of input-output disturbances. *J. Prod. Anal.* 15, 95–113.
- Kao, C., Liu, S.T., 2004. Predicting bank performance with financial forecasts: a case of Taiwan commercial banks. *J. Bank. Financ.* 28, 2353–2368.
- Kao, C., Liu, S.T., 2009. Stochastic Data Envelopment Analysis in measuring the efficiency of Taiwan commercial banks. *Eur. J. Oper. Res.* 196 (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.
- Kini, A.N., Savitha, B., Hawaldar, I.T., 2024. Brand loyalty in FinTech services: the role of self-concept, customer engagement behavior and self-brand connection. *J. Open Innov. Technol. Mark. Complex.* 10 (1), 100240.
- Klus, M.F., Lohwasser, T.S., Holotiu, F., Moormann, J., 2019. Strategic alliances between banks and FinTechs for digital innovation: motives to collaborate and types of interaction. *J. Entrep. Financ.* 21 (1), 1–23.
- KPMG, 2018. *Continuing to climb. Global banking M&A trends 2018*.
- Kwon, K.Y., Molyneux, P., Pancotto, L., Reghezza, A., 2024. Banks and FinTech acquisitions. *J. Financ. Serv. Res.* 65 (1), 41–75.
- Li, X., 2024. The impact of technology mergers and acquisitions on enterprise sustainable competitiveness. *Sustainability* 16 (6), 2291.

- Li, E., Mao, M.Q., Zhang, H.F., Zheng, H., 2023. Banks' investments in FinTech ventures. *J. Bank. Financ.* 149, 106754.
- Malik, M.F., Anuar, M.A., Khan, S., Khan, F., 2014. Mergers and acquisitions: a conceptual review. *Int. J. Account. Financ. Report.* 4 (2), 520.
- Mourad, N., 2022. Second-order conic programming for data envelopment analysis models. *Period. Eng. Nat. Sci.* 10 (2), 487–499.
- Nangin, M.A., Barus, I.R.G., Wahyoedi, S., 2020. The effects of perceived ease of use, security, and promotion on trust and its implications on FinTech adoption. *J. Consum. Sci.* 5 (2), 124–138.
- Nguyen, H.T., Yung, K., Sun, Q., 2012. Motives for mergers and acquisitions: ex-post market evidence from the US. *J. Bus. Financ. Account.* 39 (9-10), 1357–1375.
- Oberholzer, M., 2010. A model to compare firms' efficiency in creating shareholders' value. *South Afr. J. Account. Res.* 24 (1), 13–30.
- Olesen, O.B., Petersen, N.C., 2016. Stochastic data envelopment analysis. A review. *Eur. J. Oper. Res.* 251, 2–21.
- Onorato, G., Pampurini, F., Quaranta, A.G., 2024. Lending activity efficiency. A comparison between fintech firms and the banking sector. *Res. Int. Bus. Finance* 68, 102185.
- Pagano, M.S., 2021. The shrinking role of foreign operations at global financial institutions and its impact on efficiency. *Fin. Res. Lett.* 38, 101419.
- 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* 10 (1–16), 2237.
- Pandey, D.K., Hassan, M.K., Kumari, V., Zaied, Y.B., Rai, V.K., 2024. Mapping the landscape of FinTech in banking and finance: A bibliometric review. *Res. Int. Bus. Financ.* 67, 102116.
- Pramaswari, F., Nasution, A.P., Nasution, S.L.A., 2021. The effect of branding quality and service quality on customer satisfaction through Financial Technology (FinTech) at PT. WOM Finance branch Rantauprapat. *Bp. Int. Res. Crit. Inst. (BIRCIJ.) Humanit. Soc. Sci.* 4 (2), 2995–3004.
- Quaranta, A.G., Raffoni, A., Visani, F., 2018. A multidimensional approach to measuring bank branch efficiency. *Eur. J. Oper. Res.* 266 (2), 746–760.
- Ray, S.C., 2004. *Data envelopment. Analysis: Theory and techniques for economics and operations research.* Cambridge University Press.
- Restoy, F., 2019. Regulating FinTech: what is going on, and where are the challenges. *Bank Int. Settl.* 1–7.
- Rezaee, Z., 2011. *Financial Services Firms: Governance, Regulations, Valuations, Mergers, and Acquisitions.* John Wiley & Sons.
- Ryu, H.S., 2018. What makes users willing or hesitant to use FinTech?: the moderating effect of user type. *Ind. Manag. Data Syst.* 118 (3), 541–569.
- Santosooslo, P., 2014. Do efficiency ratios help investors to explore firm performances? Evidence from Italian listed firms. *Int. Bus. Res.* 7 (12), 111.
- Suryono, R.R., Budi, I., Purwandari, B., 2020. Challenges and trends of financial technology (FinTech): a systematic literature review. *Information* 11 (12), 590.
- Tarawneh, A., Abdul-Rahman, A., Mohd Amin, S.I., Ghazali, M.F., 2024. A systematic review of fintech and banking profitability. *Int. J. Financ. Stud.* 12 (1), 3.
- Thanassoulis, E., Portela, M., Allen, R., Cooper, W., Seiford, L., Zhu, J., 2004. Handbook on data envelopment analysis. *Int. Ser. Oper. Res. Manag. Sci.* 71, 99–138.
- Wang, Y., Nor, E., 2022. The impact of FinTech on the profitability of traditional banks. *Glob. Bus. Manag. Res.* 14.
- Wang, J., Yuan, X., Huang, X., Liu, C., Zhang, P., 2024. Can digitalization facilitate cross-border M&A? Evidence from Chinese A-share listed companies. *Res. Int. Bus. Financ.* 67, 102118.
- Wanke, P., Kalam Azad, M.A., 2018. Efficiency in Asian railways: a comparison between Data Envelopment Analysis approaches. *Transp. Plan. Technol.* 41 (6), 573–599.
- Wong, W.P., Deng, Q., Tseng, M.L., Lee, L.H., Hooy, C.W., 2014. A stochastic setting to bank financial performance for refining efficiency estimates. *Intell. Syst. Account. Financ. Manag.* 21 (4), 225–245.
- Zhao, Y., Ma, F., 2025. Will fintech enhance financial regulation? *Res. Int. Bus. Financ.*, 103005
- Zheng, H., Mao, M.Q., 2024. FinTech mergers and acquisitions. *J. Int. Money Financ.* 143, 103076.