

# Assessing the Impact of Banks' High-Tech Investments on Efficiency: What Is the Actual Relationship Direction?

Francesca Pampurini<sup>1</sup> & Anna Grazia Quaranta<sup>2</sup>

<sup>1</sup> Department of Economics and Business Management Sciences, Catholic University of the Sacred Heart of Milan, Italy

<sup>2</sup> Department of Economics and Law, University of Macerata, Italy

Correspondence: Anna Grazia Quaranta, Department of Economics and Law, University of Macerata, Macerata, Italy. E-mail: [annagrazia.quaranta@unimc.it](mailto:annagrazia.quaranta@unimc.it)

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## Abstract

This paper analyses whether there is any relationship between the efficiency level achieved by Euro Area banking groups and their attitude toward high-tech investments proxied by high-tech patents. We measure banking efficiency via Data Envelopment Analysis (DEA). The period considered is the decade between 2012 and 2021. The results obtained show that there is a generally negative relationship between the two topics under investigation. The evidence obtained justifies the importance of an appropriate level of attention by regulators since increasing levels of technological innovation pursued through significant growth in intangible assets, could negatively affect the overall financial system efficiency.

**Keywords:** banks, high-tech investments, high-tech patents, data envelopment analysis, cluster analysis

## 1. Introduction

In recent years, it became increasingly evident that European banks, in order to compete with new FinTech players characterised by the adoption of particularly aggressive strategies, had necessarily to reply with increasing, direct or indirect, investments in technological innovation.

Actually, this competition between banks and FinTech firms can stimulate efficiency in the financial sector and, first and foremost, the overall efficiency of banks through the adoption of innovative technologies, improved services, reduced operating costs and access to new markets (Stulz, 2019).

In more detail, competition with FinTech is pushing banks to adopt innovative technologies to improve operational efficiency. Indeed, the adoption of advanced technology solutions can undoubtedly simplify processes, automate procedures and reduce operating costs, thereby increasing banks' overall efficiency (Jakšič & Marinč, 2019).

Competition with FinTech then forces banks to improve their services' quality and variety. Banks can invest in technology to offer more convenient and tailor-made digital services that meet customers' expectations. The implementation of tools, such as intuitive mobile applications, advanced payment platforms and automated wealth management services, can indeed improve efficiency in the delivery of financial services.

FinTech firms, due to their lightweight structure and operational agility, can offer financial services at a lower cost than banks. This competition pushes banks to reduce their operating costs and adopt more efficient business models to remain competitive. Automating processes, simplifying procedures and using technologies that are more advanced, can therefore achieve operational efficiency.

As FinTechs can introduce innovative financial solutions and reach market segments previously neglected by banks, competition with them can push the latter to expand their operations and adapt to new markets, thus increasing the overall efficiency of the financial sector.

Despite competition, many banks choose to collaborate with FinTechs through strategic partnerships, investments or acquisitions. This collaboration can enable them to benefit from the technological innovation of FinTechs and integrate efficient solutions into their business models (Navaretti et al., 2017).

However, it is important for banks to adapt their strategy to exploit the opportunities offered by competition with

FinTech and to maintain a competitive advantage.

This situation undoubtedly had (and has) an important effect in the traditional banking system, at least because banks need to manage a large amount of customer information and transaction data (Dorfleitner et al., 2017). In this context, efficient handling of big-data held by banks can, for example, produce positive effects for them in terms of potential customer research and risk management (Pérez-Martíet et al., 2018).

In this scenario, this paper aims to investigate the existence of a real relationship between the efficiency achieved by Euro Area banking groups and their investments in technology. Indeed, we think it is useful to understand whether banks' efforts in high-tech investment actually led to improvements in their overall efficiency.

Actually, it comes as no surprise that more investment in technology can only increase the level of efficiency of banks. Indeed, overall, the adoption and implementation of advanced technology solutions undoubtedly enable them to reduce costs, improve customer experience, remain competitive in the financial market and improve operational efficiency.

First, trivially, investments in technology can in fact save banks costs in various ways. Indeed, automated processes reduce the need for manual labour and its associated costs, just as digitisation reduces paper documentation, storage requirements and physical infrastructure needs. By streamlining operations and reducing expenses, banks can thus allocate resources more productively, improving efficiency.

Immediately linked to this is another aspect: technology enables the automation of various banking processes (such as, for example, the entry of customers in the registry, transaction processing and document management). Moreover, by reducing manual intervention, technology streamlines operations, minimises errors and numerous causes affecting operational risk, and, once again, can improve overall efficiency. Tasks that previously required significant time and resources can now be completed quickly and accurately with the help of advanced software systems.

By exploiting technology and data analysis, banks can then gain valuable insights into customer behaviour identify patterns and make decisions based on information from transactions, market trends and internal operations. This can also contribute to targeted marketing, risk assessment, fraud detection and general improvement of operational efficiency.

Finally, technology can also play a crucial role in assessing and reducing risks for banks. Advanced algorithms and artificial intelligence can in fact analyse complex data sets, identify potential risks and facilitate real-time monitoring of transactions.

In order to realise the efficiency gains from the above-mentioned technology investments, banks should therefore focus on adopting robust and secure technology platforms in line with business needs and scalability requirements, and on solutions that ensure seamless integration between the various systems and channels. Banks should focus also on regularly updating the technology infrastructure, on investing in cybersecurity measures, on continuous training and support for employees, and on monitoring and evaluating the impact of technology investments on efficiency.

While on the one hand, as mentioned and in general, adequate investments in technology naturally lead one to think about improving the efficiency of banks, at the same time it is also true that they must take into due consideration that the large initial cost commitment required by high-tech investments and the need to constantly provide with periodic updates to ensure the necessary upgrading of the acquired instruments can require time for the investments to be considered profitable. Moreover, banks must also carefully evaluate the technological choices, plan their implementation strategically and ensure that personnel are adequately trained to maximise the benefits obtained from the investments. Should these circumstances not materialise, an inverse relationship between banking efficiency and investment in technology may even become manifest. (Chai et al., 2016).

Stating the above, how can we measure banks investments in technology? Previous studies (Acs et al., 2002) showed that patents provide a reliable measure of the propensity to innovate business, and banks that made significant investments in technological innovation followed three main strategies: buying patents, buying technology firms, or setting up an ad hoc firm within their group that can provide innovative tools or knowledge related to the high-tech world.

To the best of our knowledge, there are currently only two papers in the literature that studied the link between patents and efficiency in the banking sector; this, despite the fact that the relationship between the efficiency achieved by banks and their investments in technology is undoubtedly an interesting topic to analyse. The first, by Zhao et al. (Zhao et al., 2022), is devoted to the Chinese market and uses CAMEL (Capital adequacy, Asset quality, Management, Earnings, Liquidity, and Sensitivity) performance indicators; the second, by Borello et al.

(Borello et al., 2022) is instead focused on the European banking market after the Global Financial Crisis.

Therefore, this paper aims to contribute to the analysis of this relationship by focusing on the first two investment strategies followed by banks suggested by Acs et al. (Acs et al., 2002), i.e. direct investments (buying patents) and acquisitions of high-tech firms. For this purpose, we will use information on 72 banking groups in the main Euro Area countries over the period 2012-2021.

In particular, the paper is a first extension of Borello *et al.* 2022. Indeed, we had a twofold aim. On the one hand, to verify whether what was found in that mentioned work and related to observations referring to the period 2009-2020 was still valid in a different time period (2012-2021), and moreover considering a dataset containing information from the year immediately following the Covid-19 Pandemic. On the other hand, we measure banks' efficiency via a quantitatively more robust approach than the use of the Stochastic Frontier Approach (employed in the aforementioned contribution by Borello *et al.*, 2022). This was done in order to exclude that the results achieved in that work might have been influenced by the constraints intrinsic in the methodology there adopted.

The remainder of the paper is organized as follows. In Section 2 the literature review; Section 3 presents the data and the methodology used, Section 4 illustrates and discusses the analysis empirical results, while Section 5 concludes.

## 2. Literature Review

New FinTech entrants have been able to change the value chain that is characteristic of several financial products by breaking it down into elementary parts and recombining these parts in different ways (Omarini, 2018).

In fact, the Schumpeterian theory known as "creative destruction" (Schumpeter, 1942) which attributes such a dual effect to innovation, would seem to be appropriate in this new context. Indeed if, on the one hand, the innovation introduced by FinTech is clearly a threat to banking institutions, consequently leading to the 'destruction' of the business models they have adopted so far, on the other, it can instead 'create' new business methods and opportunities.

That notwithstanding, competition between banks and FinTech players has become increasingly relevant in recent years as FinTechs have undoubtedly revolutionised the financial sector by introducing innovative digital solutions. Moreover, these players are notoriously agile and able to innovate quickly, introduce new business models, digital financial services, improve user experiences and, in general, adopt simplified processes. All this, of course, could only induce banks to adapt and thus improve their services; thereby, challenging the traditional service models they had previously implemented (Jakšič & Marinč, 2019, Arnaudo et al, 2022).

In this new environment, the traditional model based on the bank-customer relationship as the starting point for offering a wide range of products and services has been partly replaced by the open banking model inspired by the concept of product modularity (Bofondi & Gobbi, 2017). This model also proved to be particularly suitable for traditional products, such as financing and payment services, which are now offered not only by banks but also by a number of new entrants thanks to the lowering of many barriers made possible by new technologies (EBA, 2017). Indeed, banks, in order to remain competitive, have inevitably had to respond to new customer expectations in terms of speed, ease of use and accessibility of financial services, linked to the new FinTech offerings and all aimed at improving the customer experience (Boot, 2017; Kumar & Balaramachandran, 2018).

Although banks had always privileged access to data, with the development of open banking and regulation requiring them to share the information they hold with third-party service providers, FinTechs have easily gained access to bank customers' information and thus have been able to offer increasingly personalised and innovative services in direct competition with banks (Babina et al., 2022). The latter are, however, subject to strict regulation and compliance requirements that may slow down their innovation process and, thus, their agility in providing services to customers (He et al., 2020; Parlour et al., 2020). In contrast, FinTechs can still avoid some of these restrictions and benefit from rules that are more flexible in particular areas. Despite the fact that regulation, also to ensure the stability of the financial system and the protection of consumers, is becoming increasingly aware of the delicate coexistence of these two competing actors, banks currently remain constrained (Zveryakov et al., 2019).

The undoubtedly greater specialisation of FinTechs in some particular sectors and financial services (including, for example, peer-to-peer lending, automated financial advice, including through robo-advisory, digital payments and cryptocurrencies) has clearly challenged banks, which have either tried to compete directly on several fronts by adapting to the new situation, or to adopt strategies aimed at integrating these specialised solutions through partnerships. In fact, many banks have chosen to collaborate with FinTech rather than compete (Shah Hosseini et al., 2022; Navaretti et al., 2017) and, having become aware of the extent of the FinTech phenomenon and the

opportunities that could arise from it, innovation has taken on a very different meaning in the banking sector.

As already highlighted in Section 1, competition between banks and FinTech firms can stimulate banks' overall efficiency through the adoption of innovative technologies, improved services, reduced operating costs and access to new markets. Different authors (Stulz, 2019; Jakšič & Marinč, 2019) have addressed these aspects, as already mentioned.

It is quite natural to link the idea of increased investment in technology to improved bank efficiency, and this is only because the adoption of advanced technology solutions can simplify processes, improve automation and optimise internal operations.

Some key points highlighting the relationship between technology and operational efficiency in banks are process automation, digitisation of services, improved data management, security and compliance in the banking sector (Talluri et al., 2013).

Clearly, technology allows banks to automate a number of processes that were previously performed manually. This reduces human error, increases the speed of operations and allows higher volumes of work to be handled. For example, automation can be applied to back-office processes such as document management, payment processing, register updating and other repetitive tasks (Romao et al., 2019).

Banks can use technology to offer digital financial services to their customers, such as online access to accounts, digital payments, online account opening and customer support through chatbots or virtual assistants. This digitisation simplifies customer interaction, reduces waiting times and improves accessibility to financial services, thus contributing to overall operational efficiency (Villar & Khan, 2021, Campanella et al., 2022).

Technology enables banks to manage and analyse large amounts of data more efficiently (Vives, 2017). Indeed, the adoption of data analysis, artificial intelligence and machine learning tools can enable them to obtain more in-depth information on customers, improve risk assessment models, customise service offerings and optimise portfolio management.

However, only with appropriate technological investments it is possible to address security and compliance issues in the banking sector. Indeed, banks are called upon to constantly ensure the security of financial transactions, the protection of sensitive data and the fulfilment of compliance regulations such as GDPR (General Data Protection Regulation) or KYC (Know Your Customer). Only the implementation of advanced technologies, such as encryption, two-factor authentication and fraud detection systems, therefore, helps to ensure a secure and compliant environment (Albrecht, 2020).

This part of the literature, however, is complemented by another branch pointing that if certain specific circumstances do not materialise, a negative relationship between banking efficiency and investment in technology may even emerge. In a nutshell, these circumstances are attributable to the specificity of the technological choices made, their strategic implementation, and the adequate training and collaboration of the personnel involved (Chen & Zhu, 2004; Shu & Strassmann, 2005; Beccalli, 2007; Casolaro & Gobbi, 2007; Chai et al., 2016).

Stating the above, as anticipated in Section 1, the literature says that to measure banks' technological investments, patents provide a reliable measure of the propensity to innovate business. Moreover, banks that made significant investments in technological innovation followed three main strategies: buying patents, buying technology firms, or setting up an ad hoc firm within their group that can provide innovative tools or knowledge related to the high-tech (Acs et al., 2002). Indeed, also in order to compete with the mentioned new type of player in the markets and to preserve their customer relationships, banks faced important strategic investments in new technologies that impacted the value and quality of their patent portfolio (Zhao et al. 2022).

Some authors (Lerner et al., 2015; Hall et al., 2009) analysed the characteristics that distinguish financial patents from non-financial ones (Note 1) observing that FinTech-type patents have a direct impact on the firm's value. In particular, their analysis showed that financial patents exhibit a higher economic value than non-financial patents.

Actually, the identification of FinTech patents can be done using different approaches (Xu et al., 2020). The first is based on the criteria identified by well-known organisations – including the World Intellectual Property Organisation (WIPO) or the United States Patent and Trademark Office (USPTO) – that use specific classification systems to identify FinTech patents. For example, the IPC (International Patent Classification) proposed by WIPO has specific categories for financial technology, such as 'G06Q' which covers financial data processing methods or systems. A second approach for identification is based on the use of keywords and specific terminology can be useful to identify FinTech patents in the literature. These keywords may include, for

example, 'FinTech', 'financial technology', 'digital financial services', 'digital payments', 'blockchain', 'artificial intelligence in the financial sector', 'peer-to-peer lenders', 'online financial services' and other related items. Another method for identifying FinTech patents is citation analysis, i.e. searching for FinTech patents cited in other patents or studies. This method is based on the assumption that FinTech patents are often cited in studies or other related patents. Working with FinTech experts or industry professionals can be another way to identify FinTech patents as these experts are generally familiar with the latest innovations and trends in the financial field.

Hall et al. (Hall et al., 2009) and Lee and Sohn (Lee & Sohn, 2017) studied the FinTech patents status in the financial and non-financial industries. The conclusion from their analysis is that there is a relationship between FinTech patents and bank performance. While Hall et al. (Hall et al., 2009) suggested that technology patents differ between the financial and non-financial industries (finding, moreover, that non-financial firms hold a large share of financial patents), Lee & Sohn (Lee & Sohn, 2017) pointed out that there are more applications for the use of financial patents in the financial industry than in the non-financial industry.

Actually, few studies in the literature investigate the impact of financial technology on bank performance. Generally, previous studies mainly focus on the existing relationships between bank performance and particular types of technological innovation, however, offering only a qualitative description of the potential threats and opportunities arising from them (Anagnostopoulos, 2018; Drasch et al., 2018).

For example, the paper by Akhisar et al. (Akhisar et al., 2015) shows that investments in internet banking services significantly improved the ROE and ROA of banks in 30 European countries during 2005-2013. Campanella et al. (Campanella et al., 2017) obtained similar results in their analysis related to the development of the Internet of Things (IoT) in finance. Next, a paper by Md Hamid et al. (Md Hamid et al., 2020) verifies the existence of some relationship between both the variability of net profits and bank capital endowment, on the one hand, and investment in cybertechnology, on the other. Rega (Rega, 2017) finds the existence of a positive and significant relationship between investment in FinTech innovation and profitability.

To the best of our knowledge, in the scientific literature, the topic of the link between patents and efficiency in the banking sector is still little investigated; in fact, only the aforementioned study by Zhao et al. (Zhao et al., 2022) and the purely exploratory work by Borello et al. (Borello et al., 2022) can be mentioned.

### 3. Methodology

The goal of this paper is to investigate if a relationship exists between the efficiency achieved by European banks and their investments in technology, by focusing only on direct investments in patents and on the acquisitions of high-tech firms. To this aim, we will use information on 72 banking groups in the main Euro Area countries (Austria, Belgium, Germany, Spain, France, Italy, the Netherlands, and Portugal) for each year in the period 2012-2021.

All in all, the analysis will be conducted via connection indices between the average level of efficiency achieved each considered year by the banking groups belonging to three particular clusters of banks (respectively characterized by a high, medium or low efficiency level in the whole studied period) and the values of particular high-tech investment indicators, such as the Total Intellectual Property-quality index (Total IP-quality index, that can be considered a patent quality indicator for high-tech investments) and the number of High-tech firms/patents transacted.

Indeed, as suggested by Nagaoka et al. (Nagaoka et al., 2010) and coherently with Acs et al. (Acs et al., 2002), we will use the patent portfolio to measure the level of investment in technological innovation. This, because many researchers agree that patents might be the most appropriate proxy for technical improvement that creates economic benefits (Pakes & Griliches, 1984; Acs et al., 2002; Furman et al., 2002; Wang & Huang, 2007; Hu & Mathews, 2008; Guan & Chen, 2012; Han et al., 2017).

The abovementioned patent information was extracted from Bureau Van Dijk's Orbis Intellectual Property (Orbis IP). This provider gives some patent quality indicators related to different aspects, including market attractiveness, market coverage, technical quality, assignee score and legal score.

These indicators vary between 0 (lowest quality) and 100 (best quality). The above five indicators are also combined together by the provider in order to obtain the mentioned Total Intellectual Property-quality index (Total IP-quality index). If it approaches 100, it means that patents play a very important role for the firm; on the contrary, if it approaches 0, it means that patents play only a marginal role.

On the other hand, data on high-tech firms/patents transactions that occurred between 2012 and 2021 come from Zephyr (Bureau van Dijk).

In particular, we expect to find evidence of a relationship between high-tech banks' investments and the technical-operational efficiency they achieved. We also expect to find that, at present, because of the reasons already announced in previous Section 1, there is an indirect link between the two topics investigated.

The efficiency values for each banking group for each year will be obtained via Data Envelopment Analysis (Cooper et al., 2002). All in all, as it is well known, Data Envelopment Analysis (DEA) is a non-parametric method used to evaluate the relative efficiency of a set of decision-making units (DMUs) that consume inputs to produce outputs. Charnes, Cooper, and Rhodes first introduced it in the late 1970s (Charnes et al., 1978).

The main idea behind DEA is to identify the best-performing DMUs, known as efficient units, based on their ability to produce the same or more output while consuming the same or fewer inputs than their counterparts. The DEA model calculates a score for each DMU, called efficiency score, which is the ratio of its weighted output to weighted input. The model determines the weights such that the sum of the weights of the inputs for each DMU is equal to 1, and the sum of the weights of the outputs for each DMU is also equal to 1. The efficiency score ranges from 0 to 1, where a score of 1 indicates that the DMU is fully efficient.

With more details, a DEA model consists of three main components:

- 1) Decision-Making Units (DMUs): DMUs are the entities being evaluated for their efficiency, (in our case the banks). Each DMU consumes inputs to produce outputs;
- 2) Input and Output Variables: the inputs and outputs are measured in the same units of measurement and are often standardized to account for differences in scale and units;
- 3) Efficiency Scores: Efficiency scores are the main output of the DEA model. They represent the relative efficiency of each DMU compared to the others. As anticipated, the efficiency score ranges from 0 to 1, where a score less than 1 indicates the degree of inefficiency.

The following model describes the structure of the original DEA model known as Charnes, Cooper, Rhodes-Input Oriented Ratio Form (CCR-IR – Charnes et al., 1994)

$$\max h_k(w, v) = \frac{\sum_{j=1}^m w_j y_{k,j}}{\sum_{i=1}^n v_i x_{k,i}} \quad (1)$$

subject to the constraints

$$\frac{\sum_{j=1}^m w_j y_{k,j}}{\sum_{i=1}^n v_i x_{k,i}} \leq 1 \quad k = 1, 2, \dots, K \quad (2)$$

$$w_j, v_i > 0 \quad (3)$$

where:

- $w_j$  is the output  $j$  weight;
- $v_i$  is the input  $i$  weight;
- $y_{k,j}$  is the observed value of output  $j$  in relation to DMU  $k$ ;
- $x_{k,i}$  is the observed value of input  $i$  in relation to DMU  $k$ ;
- $K$  is the number of the DMUs considered.

Actually, the statements from [1] to [3] define a fractional programming problem (Quaranta, 2016); in order to simplify the calculations, the model was therefore led to the following equivalent linear programming problem (Charnes et al., 1994)

$$\max \sum_{j=1}^m w_j y_{k,j} \quad (4)$$

subject to the constraints

$$\sum_{j=1}^m w_j y_{k,j} - \sum_{i=1}^n v_i x_{k,i} \leq 0 \quad k = 1, 2, \dots, K \quad (5)$$

$$\sum_{i=1}^n v_i x_{k,i} = 1 \quad (6)$$

$$w_j, v_i > 0 \quad (7)$$

The DEA model then uses linear programming techniques to find the weights for each input and output that maximize the efficiency score of each DMU. This involves solving a linear programming problem for each DMU, subject to the constraints that the weighted inputs for the DMU are less than or equal to the weighted inputs for all other DMUs, and the weighted outputs for the DMU are greater than or equal to the weighted outputs for all other DMUs.

Overall, the DEA model provides a way to evaluate the relative performance of multiple DMUs with multiple inputs and outputs, taking into account the different ways in which they use their resources to produce outcomes.

DEA – that has been widely used in various fields, within them finance, to evaluate the performance of organizations and to identify areas for improvement (Quaranta et al., 2018) – has several advantages over traditional methods for measuring efficiency, such as regression analysis and linear programming. Indeed, it does not require any assumptions about the functional form of the production function or the distribution of the errors, and it can handle multiple inputs and outputs simultaneously.

In terms of defining inputs and outputs needed to obtain the efficiency indices, we will follow the well-known Intermediation Approach (Berger & Humphrey, 1997) since it is still the most widely used method to evaluate the performance of financial institutions (commercial banks, investment banks, insurance companies, and pension funds) in different contexts. This approach can help identify the sources of inefficiency in the intermediation process and provide insights into how to improve the resources allocation in the financial system (Boda & Piklovà, 2018) (Note 2).

With more details, the Intermediation Approach suggests that financial intermediaries play a critical role in the efficient allocation of financial resources in an economy. Financial intermediaries collect funds from savers and channel them to borrowers, enabling the transfer of funds from those who have excess capital to those who need it. Since financial intermediaries perform several key functions in the economy, and, overall, the Intermediation Approach highlights their importance in promoting economic growth by facilitating the efficient allocation of capital in the economy.

The Intermediation Approach considers financial institutions as intermediaries that collect funds from savers and allocate them to borrowers or invest them in financial assets. The inputs and outputs are not defined in physical or monetary units, but in terms of the intermediation function. This means that the inputs are the funds collected from the savers, and the outputs are the financial services provided to the borrowers or the investors. As a consequence, outputs are represented by loans, financial assets, and off-balance sheet items (respectively, generally proxied by Net Loans, Total Securities and Off-Balance Sheet items), while inputs are represented by Human Capital, Financial Capital, Fixed Capital and Equity (respectively proxied by Staff Expenses, Financial Expenses, Other administrative Expenses, and Equity).

In this paper, we will derive the proxies for all the outputs and inputs just listed above from the balance sheets of each banking group provided by Bank Focus (Bureau Van Dijk).

Based on the efficiency levels obtained for each year in the analysis, we will divide the banking groups into three clusters by implementing a k-square cluster analysis (Johnson & Wichern, 2007; Izenman, 2008). The three clusters will be respectively characterized by a high, medium or low efficiency level achieved by the banking groups belonging to each of them (Pampurini & Quaranta, 2018).

For each cluster obtained in this way, the relationship, measured by means of connection indices – Pearson's  $\chi^2$  and Cramer's V – and a correlation index – Bravais-Pearson's r – between the average level of efficiency achieved by the banking groups belonging to each of them each year considered and the contextual values assumed by the specific high-tech investment indicators used will be studied.

#### 4. Empirical Results

Table 1 shows the results obtained for the average efficiency levels reached each year in the period 2012-2021 in relation to the size (small, medium and large) and country of the banking groups considered.

As for the size category, we followed what many ECB reports suggest. In more detail, we referred to the ratio of each banking group total assets to the total assets of the whole Euro Area banking system (Source ECB) and then, a 'large' bank is a unit for which this indicator is greater than 0.5%, while 'small' is a bank for which the ratio considered was lower than 0.005%. We considered 'medium' all the remaining banking groups.

Table 1. Efficiency values averages of banking groups by size and by country.

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
<b>Large</b>	0.92	0.91	0.87	0.82	0.82	0.84	0.81	0.82	0.96	0.86
<b>Medium</b>	0.96	0.95	0.89	0.85	0.87	0.86	0.86	0.87	0.97	0.88
<b>Small</b>	0.93	0.91	0.85	0.83	0.84	0.85	0.85	0.82	0.97	0.87
<b>Austria</b>	0.91	0.87	0.83	0.76	0.80	0.79	0.84	0.86	0.98	0.90
<b>Belgium</b>	0.98	0.93	0.91	0.91	0.87	0.89	0.88	0.90	1.00	0.99

<b>Germany</b>	0.95	0.91	0.88	0.82	0.80	0.85	0.81	0.82	0.97	0.86
<b>Spain</b>	0.90	0.93	0.79	0.78	0.80	0.81	0.69	0.79	0.96	0.79
<b>France</b>	0.96	0.91	0.87	0.86	0.87	0.86	0.81	0.86	0.97	0.97
<b>Italy</b>	0.95	0.96	0.96	0.89	0.89	0.87	0.85	0.87	0.97	0.81
<b>The Netherlands</b>	0.96	0.90	0.88	0.84	0.86	0.88	0.89	0.85	0.98	0.92
<b>Portugal</b>	0.91	0.95	0.93	0.87	0.97	0.93	0.95	0.93	0.96	0.97

Consistent with evidence from previous empirical analyses (Wheelock & Wilson, 2012; Batir et al., 2017; Pampurini & Quaranta, 2022; Borello et al., 2022), these results clearly show that larger banking groups are those that have systematically achieved the lowest efficiency levels, while medium-sized banking groups are those that are characterized by higher efficiency levels.

As can be seen from the values shown in the mentioned table, the variability of the average values of the efficiency indices obtained in relation to the different years analysed is low.

As anticipated in Section 2, starting from the efficiency values described above, a non-hierarchical cluster analysis was performed to group the considered units into three homogeneous sets, in order to separate the banking groups that showed higher (cluster 1), medium (cluster 2) and lower (cluster 3) efficiency values during the studied period. A deeper analysis (Note 3), confirming what Table 1 already shows, highlighted that the banking groups characterised by the highest efficiency values were predominantly medium-sized. Moreover, a traditional business model, an appropriate liquidity level, lowest cost to income ratio levels (further confirmation of the best levels of overall efficiency achieved) and medium to high values of profitability ratios, also characterizes them.

Information about size, the business model adopted (proxied via total loans to total assets and total financial assets to total assets), liquidity (measured by liquid assets to total assets), cost to income ratio and profitability (quantified by ROAA) for each considered banks were extracted, also in this case, from Bank Focus (Bureau Van Dijk).

Table 2 shows patent quality average and number of firms/patents transacted by cluster. The results show that banking groups in cluster 1, i.e., the most efficient ones, invested in patents associated with the highest technical quality. In addition, the number of high-tech patents in banks' portfolios between 2012 and 2021 is clearly high in relation to the most efficient banking groups again.

Table 2. Patent quality average and number of firms/patents transacted by cluster

	Cluster 1	Cluster 2	Cluster 3
<b>Total IP quality index (2021) average</b>	75	64	55
<b>Number of High-tech firms/patents transacted (2012-2021)</b>	42	12	1

Table 3 shows the relationship, over time in each cluster, between banking groups' efficiency average levels and Total IP quality index values (Note 4).

Table 3. Relationship between banking groups efficiency average levels and Total IP quality index values.

	Cluster 1	Cluster 2	Cluster 3
<b>Pearson's <math>\chi^2</math></b>	127 (0.02)	127 (0.02)	127 (0.02)
<b>Cramer's V</b>	1 (0.02)	1 (0.02)	1 (0.02)
<b>Contingency coefficient</b>	0.936 (0.02)	0.936 (0.02)	0.936 (0.02)
<b>Bravais-Pearson's r</b>	-0.757 (0.02)	-0.674 (0.046)	-0.712 (0.04)



The results obtained highlight a high value and high significance of Pearson's  $\chi^2$  index, of its normalized value  $V$ , as well as of the contingency coefficient. This confirms our intuition about the existence of a strong link between the banking groups' efficiency and their investments in high-tech. Regarding the direction of the relationship, the Bravais-Pearson  $r$ -index shows a negative sign, which was also expected.

This statement might even seem to be counter-intuitive since, in general, as anticipated in Section 1, increased investment in technology should tend to increase-rather than decrease-banks' level of efficiency from the outset. We argue that our result could be probably due to both the large initial cost commitment required by high-tech investments and the need to provide constantly with periodic updates to ensure the necessary upgrading of the acquired instruments. As a direct consequence, this can only require more time for the investments to be considered profitable.

However, in addition to the reason just highlighted, the existence of a possible inverse relationship between the two aspects analysed in this paper, in some specific cases, could also occur – this circumstance also anticipated several times since Section 1 – due to situations in which increased investment in technology may not automatically translate into improved efficiency. In fact, this could happen for a wide number of reasons ranging from lack of planning to resistance to change, from the use of unsuitable (or, worse, obsolete) technology to the absence of a proper IT security.

With more detail, if in fact investments in technology are made without proper planning or implementation strategy, there could be a lack of coordination and integration between different systems and a resulting operational inefficiency or creation of redundant and overlapping processes, rather than an overall improvement in efficiency. When new technology solutions are implemented, but bank staff are not adequately trained and/or are resistant to change, the full potential of the technology investment may then not be exploited. In fact, failure to adopt or inefficient use of technology tools could even reduce the overall efficiency of banking activities. If technology investments are then made on solutions that are not suited to banks' specific needs or on outdated systems, they may not generate the expected benefits. Indeed, choosing inappropriate technologies could lead to compatibility issues, reduced flexibility, or functional limitations, reducing efficiency rather than improving it. Finally, investments in technology should also include robust IT security measures. For if, at the same time, banks do not invest heavily enough in data protection and cybersecurity, they may be exposed to a wide range of risks that could adversely affect their operational efficiency.

## 5. Conclusions

This paper analysed the relationship between the efficiency level achieved by Euro Area banking groups and their investment activity in high technology in the decade between 2012 and 2021.

We expected to find an indirect relationship between the investment in technology made by banking groups and their efficiency.

The results of the analysis confirmed this intuition; in fact, with the data at our disposal, we were able to verify the existence of an overall negative and significative relationship between the investigated topics, moreover confirming results already obtained in other previous studies (Borello et al., 2022; Beccalli, 2007).

There are several possible explanations for these results. Among the others, as mentioned earlier, high-tech investments involve large acquisition and maintenance costs due to the high rate of obsolescence of the technological product, while the benefits from them are of later manifestation.

The acquisition of a high-tech firm could then be motivated by strategic choices aimed at preventing competitors from proceeding with the same acquisition or even with a partnership. This is without taking into account that an acquisition, under conditions of high competition, could lead to paying a price for the target that is higher than its fair value.

If the main objective of open banking was intended to be to increase competition among banks for the benefit of the prices charged to customers, the results so far would seem to show that, at the moment, competition has led to costs for banking groups that are investing in high technology that have not yet been followed by positive effects in terms of efficiency (Thakor, 2020; Omarini, 2018).

Regulators should be aware of these outcomes and monitor the situation closely both because, from the manifestation of lower levels of efficiency for the individual intermediary, a lower overall efficiency of the system could originate, and because the increase in intangible assets held by banks could also conceal specific interests (Hall & Harhoff, 2012; La Belle & Schooner, 2014) rather than an earnings management strategy.

**Informed consent**

Obtained.

**Ethics approval**

The Publication Ethics Committee of the Canadian Center of Science and Education.

The journal and publisher adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

**Provenance and peer review**

Not commissioned; externally double-blind peer reviewed.

**Data availability statement**

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

**Data sharing statement**

No additional data are available.

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**References**

- Acs, Z. J., Anselin, L., & Varga, A. (2002) Patents and innovation counts as measures of regional production of new knowledge. *Research Policy*, 31(7), 1069-1085. [https://doi.org/10.1016/S0048-7333\(01\)00184-6](https://doi.org/10.1016/S0048-7333(01)00184-6)
- Akhisar, I., Tunay, K. B., & Tunay, N. (2015) The effects of innovations on bank performance: the case of electronic banking services. *Procedia-Soc. Behav.Sci.*, 195, 369-375. <https://doi.org/10.1016/j.sbspro.2015.06.336>
- Albrecht, H. J. (2020). Data, data banks and security. *European Journal for Security Research*, 5(1), 5-23. <https://doi.org/10.1007/s41125-019-00062-9>
- Anagnostopoulos, I. (2018) Fintech and regtech: impact on regulators and banks. *Journal of Economic Business*, 100, 7-25. <https://doi.org/10.1016/j.jeconbus.2018.07.003>
- Arnaudo, D., Del Prete, S., Demma, C., Manile, M., Orame, A., Pagnini, M., & Soggia, G. (2022). The digital transformation in the Italian banking sector. *Bank of Italy Occasional Paper*, (682). Retrieved from <https://www.bancaditalia.it/pubblicazioni/qef/2022-0682/index.html?com.dotmarketing.htmlpage.language=1>
- Babina, T., Buchak, G., & Gornall, W. (2022). Customer data access and fintech entry: Early evidence from open banking. <http://dx.doi.org/10.2139/ssrn.4071214>
- Batir, T. E., Volkman, D. A., & Gungor, B. (2017). Determinants of bank efficiency in Turkey: participation banks versus conventional banks. *Borsa Istanbul Review*, 17(2), 86-96. <https://doi.org/10.1016/j.bir.2017.02.003>
- Beccalli, E. (2007) Does IT investment improve bank performance? Evidence from Europe. *Journal of Banking & Finance*, 31(7), 2205-2230. <https://doi.org/10.1016/j.jbankfin.2006.10.022>
- Berger, A. N., & Humphrey, D. B. (1990). The dominance of inefficiencies over scale and product mix economies in banking. *Finance and Economics Discussion Series*, 107. [https://doi.org/10.1016/0304-3932\(91\)90027-L](https://doi.org/10.1016/0304-3932(91)90027-L)
- Berger, A. N., & Humphrey, D. B. (1997). Efficiency of financial institutions: International survey and directions for future research. *European Journal of Operational Research*, 98(2), 175-212. [https://doi.org/10.1016/S0377-2217\(96\)00342-6](https://doi.org/10.1016/S0377-2217(96)00342-6)
- Boda, M., & Piklovà, Z. (2018). The Production or Intermediation Approach? In Jajuga et al. (Eds.), *Contemporary Trends and Challenges in Finance, Springer Proceedings in Business and Economics* (pp. 111-120). [http://dx.doi.org/10.1007/978-3-319-76228-9\\_11](http://dx.doi.org/10.1007/978-3-319-76228-9_11)

- Bofondi, M., & Gobbi, G. (2017). The big promise of FinTech. *European Economy Banks, Regulation, and the Real Sector*, (2), 107-119. Retrieved from <https://european-economy.eu/2017-2/the-big-promise-of-fintech>
- Boot, A. (2017). The Future of Banking: From Scale & Scope Economies to Fintech. *European Economy Banks, Regulation, and the Real Sector*, 3(2), 77-95. Retrieved from <https://european-economy.eu/2017-2/the-future-of-banking-from-scale-scope-economies-to-fintech>
- Borello, G., Pampurini, F., & Quaranta, A. G. (2022). Can High-tech investments improve banking efficiency? *Journal of Financial Management Markets and Institutions*, 10(1), 1-19. <https://dx.doi.org/10.1142/S2282717X22500037>
- Campanella, F., Della Peruta, M. R., & Del Giudice, M. (2017). The effects of technological innovation on the banking sector. *Journal of Knowledge and Economics*, 8(1), 356-368. <https://doi.org/10.1007/s13132-015-0326-8>
- Campanella, F., Serino, L., & Crisci, A. (2022). Governing Fintech for sustainable development: evidence from Italian banking system. *Qualitative Research in Financial Markets*. <https://doi.org/10.1108/QRFM-01-2022-0009>
- Casolaro, L., & Gobbi, G. (2007). Information technology and productivity changes in the banking industry. *Economic Notes*, 36(1), 43-76. <http://dx.doi.org/10.1111/j.1468-0300.2007.00178.x>
- Chai, B. B. H., Tan, P. S., & Goh, T. S. (2016). Banking Services that Influence the Bank Performance. *Procedia - Social and Behavioral Sciences*, 224, 401-407, <https://doi.org/10.1016/j.sbspro.2016.05.405>
- Charnes, A., Cooper, W. W., & Lewin, A. Y. (1994). *Data Envelopment Analysis*. Boston/Dordrecht/London: Kluwer Academic Publisher. <https://doi.org/10.1007/BF03183382>
- Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429-444. [https://doi.org/10.1016/0377-2217\(78\)90138-8](https://doi.org/10.1016/0377-2217(78)90138-8)
- Chen, Y., & Zhu, J. (2004). Measuring information technology's indirect impact on firm performance. *Information Technology and Management*, 5, 9-22. <https://doi.org/10.1023/B:ITEM.0000008075.43543.97>
- Cooper, W. W., L. M., & Seidorf, K. T. (2002). *Data Envelopment Analysis*, Boston, Kluwer Academic Publishers.
- Dorfleitner, G., Hornuf, L., Schmitt, M., & Weber, M. (2017). The Fintech Market in Germany. <https://doi.org/10.2139/ssrn.2885931>
- Drasch, B. J., Schweizer, A., & Urbach, N. (2018). Integrating the 'Troublemakers': a taxonomy for cooperation between banks and fintechs. *Journal of Economic Business*, 100, 2642. <https://doi.org/10.1016/j.jeconbus.2018.04.002>
- European Banking Authority. (2017). *Discussion paper on the EBA's approach to financial technology (FinTech)*. European Banking Authority, August 4. Retrieved from <https://www.eba.europa.eu/documents/10180/1919160/EBA+Discussion+Paper+on+Fintech+%28EBA-DP-2017-02%29.pdf>
- Ferrier, G. D., & Lovell, C. K. (1990). Measuring cost efficiency in banking: Econometric and linear programming evidence. *Journal of Econometrics*, 46(1-2), 229-245. [http://dx.doi.org/10.1016/0304-4076\(90\)90057-Z](http://dx.doi.org/10.1016/0304-4076(90)90057-Z)
- Furman, J. L., Porter, M. E., & Stern, S. (2002). The determinants of national innovative capacity. *Research Policy*, 31(6), 899-933. [https://doi.org/10.1016/S0048-7333\(01\)00152-4](https://doi.org/10.1016/S0048-7333(01)00152-4)
- Glodschmidt, A. (1981). On the definition and measurement of bank output, The Bank of Israel and the Hebrew University, Jerusalem, Israel. [https://doi.org/10.1016/S0378-4266\(81\)80010-6](https://doi.org/10.1016/S0378-4266(81)80010-6)
- Guan, J., & Chen, K. (2012). Modeling the relative efficiency of national innovation systems. *Research Policy*, 41(1), 102-115. <https://doi.org/10.1016/j.respol.2011.07.001>
- Hall, B. H., & Harhoff, D. (2012). Recent research on the economics of patents. *Annual Review of Economics* 4 (1), 541-565. <https://doi.org/10.1146/annurev-economics-080511-111008>
- Hall, B. H., Thoma, G., & Torrisi S. (2009). Financial Patenting in Europe. *European Management Review*, 6(1), 45-63. <https://doi.org/10.1057/emr.2009.3>
- Han, C., Thomas, S. R., Yang, M., Ieromonachou, P., & Zhang, H. (2017). Evaluating R&D investment efficiency in China's high-tech industry. *The Journal of High Technology Management Research*, 28(1),

- 93-109. <http://dx.doi.org/10.1016/j.hitech.2017.04.007>
- Hancock, D. (1985). Bank profitability, interest rates, and monetary policy. *Journal of Money, Credit and Banking*, 17(2), 189-202. <https://doi.org/10.2307/1992333>.
- He, Z., Huang, J., & Zhou, J. (2020). Open banking: Credit market competition when borrowers own the data. <https://doi.org/10.1016/j.jfineco.2022.12>
- Hu, M. C., & Mathews, J. A. (2008). China's national innovative capacity. *Research Policy*, 37(9), 1465-1479. <https://doi.org/10.1016/j.respol.2008.07.003>
- Izenman, A. J. (2008). *Modern Multivariate Statistical Techniques: Regression, Classification, and Manifold Learning*. Springer Texts in Statistics. New York: Springer-Verlag.
- Jakšič, M., & Marinč, M. (2019). Relationship banking and information technology: the role of artificial intelligence and FinTech. *Risk Management*, 21, 1-18. <https://doi.org/10.1057/s41283-018-0039-y>
- Johnson, R. A., & Wichern, D. W. (2007). *Applied Multivariate Statistical Analysis* (6th ed.). Prentice Hall.
- Kumar, K. N., & Balaramachandran, P. R. (2018). Robotic process automation-a study of the impact on customer experience in retail banking industry. *Journal of Internet Banking and Commerce*, 23(3), 1-27.
- La Belle, M. M., & Schooner, H. M. (2014). Big banks and business method patents.
- Lee, W. S., & Sohn, S. Y. (2017). Identifying emerging trends of financial business method patents. *Sustainability*, 9(9), 1670. <https://doi.org/10.3390/su9091670>
- Lerner, J., Seru, A., Short, N., & Sun, Y. (2020). Financial innovation in the 21st century: Evidence from US patenting. *NBER Working Paper*, 28980.
- Lerner, J., Speen, A., Baker, M., & Leamon A. (2015). *Financial Patent Quality: Finance Patents After State Street*. HBS Working Paper, Number: 16-068.
- Md Hamid, U., Sabur, M., & Md Hakim, A. (2020). Does cyber tech spending matter for bank stability? *International Review of Financial Analysis*, 72, 101587. <https://doi.org/10.1016/j.irfa.2020.101587>
- Nagaoka, S., Motohashi, K., & Goto, A. (2010). Patent statistics as an innovation indicator. In *Handbook of the Economics of Innovation* (pp. 1083-1127). Elsevier. [https://doi.org/10.1016/S0169-7218\(10\)02009-5](https://doi.org/10.1016/S0169-7218(10)02009-5)
- Navaretti, G. B., Calzolari, G., Mansilla-Fernandez, J. M., & Pozzolo A. F. (2017). FinTech and Banks: Friends or Foes?. In *European Economy. Banks, Regulation, and the Real Sector* (pp. 9-30). Europeye srl.
- Omarini, E. (2018). Banks and fintechns: How to develop a digital open banking approach for the bank's future, *International Business Research*, 11(9). <https://doi.org/10.5539/ibr.v11n9p23>
- Pakes, A., & Griliches, Z. (1984). *Patents and R&D at the Firm Level: A First Look*.
- 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, 2237(1-16). <https://doi.org/10.3390/su10072237>.
- Pampurini, F., & Quaranta, A. G. (2022). European banking groups efficiency in a decade: An empirical investigation on the determinants, *International Journal of Productivity and Quality Management*, (1), 1-17. <https://doi.org/10.1504/IJPQM.2022.124383>
- Parlour, C. A., Rajan, U., & Zhu, H. (2022). When FinTech Competes for Payment Flows. *The Review of Financial Studies*, 35(11), 4985-5024. <https://doi.org/10.1093/rfs/hhac022>
- Pérez-Martín, A., Pérez-Torregrosa, A., & Vaca, M. (2018). Big Data techniques to measure credit banking risk in home equity loans. *Journal of Business Research*, 89, 448-454. <https://doi.org/10.1016/j.jbusres.2018.02.008>
- Quaranta A. G. (2016). "La produttività delle Banche. Questioni di metodo, misure ed applicazioni" - Prefazione Prof. Roberto Tasca - Economia e Gestione delle Imprese - n° 12 - Aracne Editrice int.le - Roma - Giugno 2016.
- Quaranta A. G., Raffoni, A., & Visani, F. (2018). A multidimensional approach to measuring bank branch efficiency. *European Journal of Operational Research*, 266, 746-760. <https://doi.org/10.1016/j.ejor.2017.10.009>
- Rega, F. G. (2017). The bank of the future, the future of Banking - an empirical analysis of European banks. Unpublished working paper. <https://doi.org/10.2139/ssrn.3071742>

- Romao, M., Costa, J., & Costa, C. J. (2019). Robotic process automation: A case study in the banking industry. *In 14th Iberian Conference on information systems and technologies (CISTI)* (pp. 1-6).
- Schumpeter, J. A. (1942). *Can capitalism survive? Creative destruction and the future of the global economy*. New York: Harper Collins Publishers.
- Shah Hosseini, M. A., Keimasi, M., Shami Zanjani, M., & Haghhighikhah, M. (2022). A Systematic Literature Review of Bank-fintech Collaboration. *Journal of Business Management*, 14(2), 199-227. <https://doi.org/10.22059/ijbm.2022.328496.4191>
- Shu, W., & Strassmann, P. A. (2005). Does information technology provide banks with profit? *Information & management*, 42(5), 781-787. <https://doi.org/10.1016/j.im.2003.06.007>.
- Stulz, R.M. (2019). FinTech, BigTech, and the Future of Banks. *Journal of Applied Corporate Finance*, 31(4), 86-97. <https://doi.org/10.1111/jacf.12378>
- Talluri, S., Kim, M. K., & Schoenherr, T. (2013). The relationship between operating efficiency and service quality: are they compatible? *International Journal of Production Research*, 51(8), 2548-2567. <https://doi.org/10.1080/00207543.2012.737946>
- Thakor, A. V. (2020). Fintech and banking: What do we know? *Journal of Financial Intermediation*, 41, 100833. <https://doi.org/10.1016/j.jfi.2019.100833>
- Tulkens, H. (1993). On FDH Efficiency Analysis: Some Methodological Issues and Applications to Retail Banking, Courts and Urban Transit. *Journal of Productivity Analysis*, 4, 183-210. <https://doi.org/10.1007/BF01073473>
- Villar, A. S., & Khan, N. (2021). Robotic process automation in banking industry: a case study on Deutsche Bank. *Journal of Banking and Financial Technology*, 5(1), 71-86. <https://doi.org/10.1007/s42786-021-00030-9>
- Vives, X. (2017). The impact of FinTech on banking. *European Economy. Banks, Regulation, and the Real Sector*, (2), 97-105.
- Wang, E. C. & Huang, W. (2007). Relative efficiency of R&D activities: A cross-country study accounting for environmental factors in the DEA approach. *Research Policy*, 36(2), 260-273. <https://doi.org/10.1016/j.respol.2006.11.004>.
- Wheelock, D. C., & Wilson, P. W. (2012). Do large banks have lower costs? New estimates of returns to scale for US banks. *Journal of Money, Credit and Banking*, 44(1), 171-199. <https://doi.org/10.1111/j.1538-4616.2011.00472.x>
- Xu, L., Lu, X., Yang, G., & Shi, B. (2020). Identifying fintech innovations with patent data: A combination of textual analysis and machine-learning techniques. In *Sustainable Digital Communities: 15th International Conference* (pp. 835-843). Cham: Springer International Publishing.
- Zhao, J., Li, X., Yu, C. H., Chen, S., & Lee, C. C. (2022). Riding the FinTech innovation wave: FinTech, patents and bank performance, *Journal of International Money and Finance*, 122, 102552. <https://doi.org/10.1016/j.jimonfin.2021.102552>
- Zveryakov, M., Kovalenko, V., Sheludko, S., & Sharah, E. (2019). FinTech sector and banking business: competition or symbiosis? *Економічний часопис*, 175(1-2), 53-57. <https://doi.org/10.21003/ea.V175-09>

## Notes

Note 1. In the literature, the difference between financial and non-financial patents mainly concerns the subject matter of the patent and the field of application (obviously only financial). With regard to the first point, patents covering new financial products, risk assessment and management processes, trading algorithms, payment methods and banking technologies are definitely financial in nature (Lerner et al., 2020). It is important to note that the classification of financial and non-financial patents may vary depending on the context and specific legislation. In addition, some patents may have an intersection between the financial sector and other sectors, for example, patents involving financial technologies in the health or energy sector.

Note 2. Other methods used in the literature to identify the inputs and outputs of a financial intermediary are (i). the Production Approach, (ii). the Asset Approach, (iii). the Value Added Approach, and (iv). the User Cost Approach. The first emphasises that the production of financial services, like that of any other good, requires the use of labour and capital (Goldschmidt, 1981; Tulkens, 1993). The so-called Asset Approach (as classified by Berger & Humphrey, 1990). Tends to coincide with the Intermediation Approach in that the liability is

considered as the set of inputs while the asset represents the output. On the other hand, according to the scholars of the Value Added Approach (Ferrier & Lovell, 1990), if a balance sheet item generates a relevant share of value added then it is an output, otherwise it should be considered as an input or as a non-essential output. Finally, for authors whose contributions fall under the so-called User Cost Approach, if a balance sheet item makes a positive contribution to the operating margin (i.e. costs less or yields more than its opportunity cost), then it is an output, otherwise it should be considered as an input (Hancock, 1985).

Note 3. Data available upon request.

Note 4. Unfortunately, it was not possible to study the relationship between banking groups' efficiency average levels and the number of firms/patents transacted since these latter were too few.

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