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CAN HIGH-TECH INVESTMENTS IMPROVE BANKING EFFICIENCY?

GIULIANA BORELLO
Università degli Studi di Verona, Italy
Giuliana.borello@univr.it

FRANCESCA PAMPURINI
Università Cattolica del Sacro Cuore, Italy

ANNA GRAZIA QUARANTA
Università di Macerata, Italy

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This study examines the high-tech investment activity of the banking system in the period following the Global Financial Crisis, from 2009 to 2020. To gain an understanding of the effect of the increasing interest of banks in high-tech investments, this research provides evidence of the relationship between the level of efficiency achieved by Euro Area banking groups and their high-tech investment aptitude. This paper is purely exploratory given that, to the best of our knowledge, it is one of the first to address this specific research question. We analyze in detail the association between bank efficiency (measured using a stochastic frontier approach) and different high-tech investment indicators, as well as the direction of this connection to provide an explanation for the relationship. We find a stable and overall significant relationship between banks' efficiency and their high-tech investment aptitude. Moreover, we find that only medium efficiency banking groups that adopt a more diversified investment acquisition strategy have a positive relationship with high-tech investment aptitude; otherwise, the relationship between bank efficiency and high-tech investment indicators seems to be negative. Regulators should be aware of this bank acceleration in the enhancement of high-tech investment because it can reduce the stability of banking groups and because an increase in intangibles assets (e.g. patents) could also be motivated by an interest rather than an earnings management strategy.

Keywords: Banking groups; efficiency; cluster analysis; high-tech; patents.

JEL Classifications: G21, O34, C58, C23, F65

1. Introduction

In the past two decades, banking, as with the entire financial sector, has been the object of important transformations. Banks have been forced by customers to improve technology to provide their services 24/7 in every part of the world, and, *pari passu*, they had to improve information security.[a] In the past decade, as a consequence of the Global Financial Crisis, the interest margin has been reduced almost to zero. In addition, in Southern Europe during this period, the sovereign debt crisis intensified bank funding risk, forcing banks to increase deposit rates to attract depositors and increase alternative stable funds (European Central Bank 2011).

In this context of difficulties for the banking sector, particularly for European banking groups, fintech start-ups and techfin giants have emerged. Puschmann (2017) provides a simple definition of fintech as an industry consisting of organizations that use sophisticated financial technology to enable fast financial services to be delivered without long procedures. The Financial Stability Board (FSB 2017) provides a broader definition of fintech as a 'financial innovation that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services'.

In contrast to fintech firms, tech giants (such as Google, Amazon, Apple, Alibaba) are referred to as 'techfin' operators because they 'start with technology, data and access to customers. Then they move into the world of finance by leveraging their access to data and customers and seek to out-compete incumbent financial firms or FinTech startups' (Zetzsche *et al.* 2017).

Once new entrants (fintech and techfin) arrived in the financial market, the market itself was compelled to cope with a sudden change in the competition environment because these new market entrants were able to break pipeline value chains, unbundling them into different modules of products or services, and combining among themselves (Omarini 2018). An acceleration versus an open paradigm between new entrants and incumbent banks was encouraged by regulators, for example, through Revised Payment Services Directive (PSD2, Directive [EU] 2015/2366). In the European Union, the development of cost-saving technology, together with deregulation, intensified financial sector competition (Beccalli 2007). Within this context, banks shifted significantly from a conservative paradigm, in which the service's value begins with a banking relationship with customers, to open banking models, where modularity can be an alternative source of revenue.

The competitive landscape between incumbent banks, techfin and fintech startups became more challenging as digital technology lowered barriers to entry into the banking sector. Fintech companies began to offer financial products that had been

[a] In 2016, the frequency of cyberattacks affecting the financial sector was 65% higher than that of any other sector. There were more than 200 million breaches, which was a 937% increase from 2015, when such attacks amounted to just under 20 million. *Source*: IBM, Security trends in the financial services sector, April 2017.

the exclusive domain of traditionally licensed credit institutions (e.g. payment services and loans) (Thakor 2020, European Banking Authority 2017).

The advantages of fintech firms are the disadvantages of incumbent banks. Fintech firms are smaller, and they are therefore more agile and able to support a greater diversity of products and providers. Their business model is flexible and completely digitalized and, therefore, they are able to provide their services in cross-industries, allowing them vast access to many markets. However, fintech start-ups struggle to secure operating leverage, particularly the significant upfront investment required to build intellectual property (IP) (Lee & Shin 2018). Fintech companies are more likely to hold more types of IP than do banks because they are aware that they should protect their valuable inventions to raise more capital (Hall & Harhoff 2012), which is necessary to rapidly acquire banking market share and establish a trusted customer base. Most fintech IP is software protected by copyright through patenting; however, this protection option does not prevent rivals from reverse engineering computer programs.

Thus, traditional European banks, which were already under the strain of the Global Financial Crisis and its effects on business performance, had to adopt a strong and expensive investment strategy to exploit high-tech innovation benefits and to compete with fintech operators that were gaining market share.

Therefore, with this purely exploratory research, we aim to verify the following: (1) Whether there is a link between the high-tech investment strategies adopted by banks and the level of efficiency achieved by these banks; and (2) if such a link does exist, what is its direction (direct or indirect). By addressing these two studies, we seek to provide an explanation for the association between banking group efficiency and high-tech investment ability.

In the past two decades, many banking operators (new entrants and incumbents) have attempted to increase the number, value and quality of their patent portfolios. Levin *et al.* (1987) and Merges & Nelson (1990) state that generally, the relative effectiveness of a patent is greater in discrete or simple technology products than it is in complex products, which comprise numerous separately patentable elements. Given that in the banking sector, the innovation in the technology is simple, banks are encouraged to patent their innovations. However, according to La Belle & Schooner (2014), in the previous decade, financial institutions did not rely on patent rights to protect their innovations because financial innovation was seen as a fast-paced and constantly evolving phenomenon. The financial industry relied more on first-mover advantage and trade secrets as opposed to patents, which take more time, effort and resources to secure the same advantages. Thus, in the past, banks did not use patents a great deal, and the few financial patents they did issue were not considered particularly interesting; however, banks are now increasingly seeking patent protection (La Belle & Schooner 2014).

Analyzing research and development (R&D) investment in China, Han *et al.* (2017) revealed that the increased R&D expenditure was associated with a dramatic increase in the number of patents; however, they found limited increase in the economic return from new products throughout the high-tech industry. This finding suggests that an increase in R&D inputs leads to improvements in technology production efficiency, but that has not yet led to an equivalent improvement in technology commercialization efficiency. R&D plays a crucial role in enhancing the competitiveness of companies in achieving sustained and rapid growth (Zhong *et al.* 2011). Although R&D expenditure is often used as a proxy for innovation, we prefer to use patents rather R&D expenditure as this proxy because, as suggested by Nagaoka *et al.* (2010), R&D expenditure is an input for innovation rather than an output.

Moreover, Cloodt *et al.* (2006) demonstrated that acquiring different external knowledge bases and making proper use of this new knowledge are important contributions to a firm's post-merger and acquisition (M&A) innovative performance. Therefore, it is the firm's ability to acquire, transfer, and integrate the acquired knowledge base into its existing knowledge base that creates sustainable competitive advantage (Barney 1986). These considerations motivate firms to prefer technological acquisitions that are more likely to provide technological knowledge to the acquiring firm.

Patents contain valuable information to identify emerging markets, give insights into the actions of competitors, and inform the company about which parts of its portfolio are most valuable. Patenting an invention is not free given that it requires the payment of a fee (or a royalty) to grant a licence and obtain a return on the investment if somebody wishes to use the invention. Patenting has costs related to numerous factors, for example, the number of countries in which the invention is protected and the patent maturity.[b]

The patents portfolio is often used as a proxy of knowledge capital stock (Furman *et al.* 2002; Hu & Mathews 2008). Recently, patent information is increasingly used by statistician to analyze innovation and the innovation process, and therefore patent statistics are increasingly used as a measure of innovation.[c] Patents might be the most appropriate proxy of technical improvement that creates economic benefits (Han *et al.* 2017; Han *et al.* 2017,Guan & Chen 2010; Wang & Huang 2007). Former studies (Acs *et al.* 2002; Pakes & Griliches 1984) have demonstrated that patents provide a fair and reliable measure of innovation production activities. All the above easily explains occurrences such as the fact that in 2021, the Bank of America[d] filed the highest number of patents (512) since the beginning of its activity, obtaining a patent portfolio comprising more than 5191 inventions, created by more than 6000 inventors across 42 states and 13 different countries. Similarly, according to

[b] The cost of patenting an invention depends on factors such as the nature of the invention, its complexity, the patent attorney's fees, the length of the application, and possible objections raised during the examination by the patent office (see https://www.wipo.int/patents/en/faq_patents.html).

[c] The reasons for the increasing use of patent data in recent years is the development of patent databases for the analysis of innovation (e.g. National Bureau of Economic Research and the European Patent Office).

[d] Bank of America news release 14 February 2022, 08:00 ET.

Intellectual Properties-Business Innovation (IP-BI),[e] a company specializing in patent tracking and evaluation, in 2020, Deutsche Bank transacted in 6152 patents.

More recently, to compete with new entrants, traditional banks have had to accelerate the improvement of their high technology. They have adopted three high-tech investment strategies: (1) buy high-tech patents, (2) acquire high-tech companies, (3) constitute internally to their group a specialized high-tech company that could provide innovative high-tech instruments or knowledge to the group's companies. Regardless of the strategy, given that interest in high-tech investments has become increasingly important for banks, we believe it is useful to understand whether the efforts made by banks in high-tech investment have led to improvements in efficiency. In the literature, only Zhao *et al.* (2022) have explored the link between patents and efficiency in the Chinese banking sector, using CAMEL performance indicators and patent data.

To achieve this aim, the paper provides empirical evidence about the relationship between banks' high-tech investment and efficiency, starting from the consideration of data on direct investments in high-tech patents and in acquisitions of high-tech companies as indicators of the banks' interest in high-tech investment. This preliminary, exploratory study contributes to the literature by examining what occurs in the relationship between high-tech investment and banks' efficiency using data from Euro Area banking groups in the period 2009–2020. The study analyzes a comprehensive set of data on high-tech investment patent quality indicators (market attractiveness, market coverage, technical quality, assignee score, legal score, and total IP quality), patent portfolio values, the number of inventions, the number of high-tech patent transactions, and high-tech investment acquisitions. Specifically, we expect to find evidence of a relationship between high-tech banks' investments (in terms of the quality, dimension and high-tech specialization of their patent portfolio; and their acquisition of high-tech companies) and efficiency. We also expect to find that, currently, there is a negative connection between these two figures because these kinds of investments are very recent and, consequently, they have not yet been able to fully amortize their costs and cash in their benefits. The remainder of the paper is organized as follows. Section 2 presents the data and methodology, Sec. 3 presents the empirical results of the analysis, and Sec. 4 provides conclusions.

2. Data and Methodology

As previously stated, this study aims to investigate whether there is a relationship between banks' efficiency level and high-tech investment strategies across Euro Area banking groups in the period 2009–2020 and, if this relationship exists, to discover its direction to create understanding of the underlying reasons for the relationship.

[e] IP-BI BV is a Dutch company focusing on IP valuation, IP big data processing and IP data in general. To achieve its business aims, IP-BI has processed datasets of different official patent offices worldwide with different algorithms and rule sets; it has processed more than 60 million IP worldwide and valued it for different years.

We decided to refer to banking groups, instead of single banks, because banking groups are independent business units whose data are not affected by accounting distortions deriving from intragroup operations (Beaver *et al.* 2018; Bonacchi *et al.* 2017; Pampurini & Quaranta 2021).

The research will begin evaluating the efficiency levels of the considered banking groups from the beginning of the Global Financial Crisis in 2009–2020 (which is the last year of the Covid-19 pandemic period for which balance-sheet data are available).

To obtain efficiency values for each unit and for each year, we will employ a stochastic cost frontier[f] (in translogarithmic form). This is one of the most common parametric approaches based on the regression of production costs on input and output factors, the approach chosen in agreement with the intermediation approach (Berger & Humphrey 1997). According to the authors, outputs will be measured by loans, total financial assets, and off-balance-sheet items, while inputs will be represented by human, financial and fixed capital, and equity will be considered a netput. The proxies of the input quantities will be taken from the financial statements of each banking group and refer to the following:

(1) Staff, interest, and other operating expenses (to quantify total costs);
(2) Net loans, total securities, and off-balance-sheet items (to measure the three outputs);
(3) Staff expenses to total assets, interest expenses to total liabilities, amortization, and other operating expenses to total fixed assets and total equity (to quantify the inputs, respectively).

Referring to the levels of efficiency reached in each year by each bank, via a (k-square) cluster analysis (Bolasco 1999; Fabbris 1983), we will identify three clusters of banking groups characterized by the highest, medium and lowest levels of overall efficiency during time (Pampurini & Quaranta 2018).

After having identified the profile that differentiates the banking groups belonging to each efficiency cluster obtained in this way, the analysis will verify the possible presence of a link between the overall efficiency level achieved over time by the considered banking groups and their high-tech investments, also evaluating the intensity of the link. To achieve this aim, within each cluster obtained, we will analyze the relationship (measured via connection [Pearson's χ^2 and Cramer's V] and correlation [Bravais–Pearson's r] indices) that, over time, may have been

[f] Previous literature (Aigner *et al.* 1977; Forsund *et al.* 1985; Berger *et al.* 1997; Coelli *et al.* 2005) has widely described the advantages of stochastic frontiers, in relation to non-parametric methods, that derive from the fact that they are able to separate the efficiency component directly linked to managerial skills from the component deriving from random factors, measurement inaccuracy or other kinds of circumstances that cannot be captured by accounting measures. To separate these two factors, the error term of the regression is split into two components. The first one, distributed as a normal random variable, mainly considers some random factors and the measurement errors. The second component, that generally follows a one-side normal distribution assuming values lower or equal to zero in a cost function, refers to technical inefficiency.

registered between the average level of efficiency achieved by banking groups and the values assumed by specific high-tech investments indicators.

As stated, we focus on a wide time window, from 2009 to 2020, because it allows us to consider all the main events that have affected financial markets recently: The Global Financial Crisis and its spread from the United States to the Euro Area, the sovereign debt crisis, the non-performing loans crisis, and the first year of the Covid-19 pandemic.

Our dataset is composed of all the banking groups belonging to the main Euro Area countries characterized by a similar social and economic environment, that is, Austria, Belgium, Germany, Spain, France, Italy, Holland, and Portugal. To obtain robust results, we worked on a balanced dataset[g] that consists of 73 units of banking groups: 9 Austrian, 3 Belgian, 16 German, 11 Spanish, 8 French, 14 Italian, 10 Dutch, and 3 Portuguese. Accounting data are taken from Bank Focus database (Bureau van Dijk), while the gross domestic product deflator values were obtained from the World Bank database.

Because it is not clearly reported whether a banking group has constituted a specialized high-tech division or company, to define high-tech investments for each banking group, we use the following factors: (1) Patent portfolio quality indicators; (2) patent transactions data, also providing a high-tech classification of patent; and (3) acquisitions of companies defined as 'high technology' according to the Eurostat classification. We collected data variables of patents from Bureau van Dijk's Orbis Intellectual Property (Orbis IP) database, which provides company and patent information. This database allows us to obtain, for each banking group, all the patents that are directly owned (at a consolidated level) and all the patents of the 100% owned subsidiaries.[h] It is important to note that analyzing banking groups operating in the Euro Area means that the groups under study are not affected by significant differences in patent systems.[i]

[g] See Roengpitya *et al.* (2014).

[h] Orbis IP specifies in their guide the following 'A public database of all patent transactions is not available: Most transactions are embedded into confidential M&A deals where the transaction conditions are not public and so [neither are] the patent values. Also, direct patent transactions are normally confidential information because the contracts may include additional aspects, e.g. sale and lease back, payment in stocks or certain payment terms etc. Some auctions providers have transaction values regarding single patents or patent families but this is because just a limited vies and also includes strategic prices. Utilization companies will also have internal information regarding the transactions they have been pushing but there is always a complete package of patents sold (e.g. a small portfolio) where a package price was finally paid'.

[i] Nagaoka (2010) provides a comprehensive discussion of some of the differences in patent systems around the world: 'One major difference is while there is an examination request system in Europe and Japan, there is no such system in the United States where all applications are examined. As a result, in Europe and Japan, a firm can apply for a patent but still has the option to request a patent examination. Since the application fee is low, the examination request system tends to encourage firms to apply for a large number of patents. The second major related difference is that all patent applications are automatically disclosed in Europe and Japan but not in the United States (disclosure of patent applications was introduced in 1999, but only partially). As a result, while the published patent applications provide comprehensive information on the inventive activities in Europe and Japan, they do not in the United States'.

To define the portfolio patent quality, the Orbis IP database provides variables estimated by IP-BI. Using a complex data-mining and indicator-based valuation method, IP-BI measures IP value qualitatively and quantitatively (i.e. monetarily), focusing on patents and utility models. IP-BI has built an own reference database for traded patents: Their estimation is based on 25 different types of IP and company-specific value indicators (such as forward–backward citations, family sizes, covered countries, patent age, and legal status). The valuation is conducted for all patent families of each company in the database, and the results are aggregated to a set of company-specific IP-related key figures that determine patent quality. Because not all inventions are patented, we also use the number of inventions, provided by Orbis IP, as indicators for inventive activities. Unfortunately, not all banking groups provide information related to their patent portfolio, therefore, in these cases (most of which are not listed banking groups), it is not possible to obtain data from Orbis IP.

Orbis IP provides five indicators of patent quality: Market attractiveness, market coverage, technical quality, assignee score, and legal score. All these indicators are stated on a scale from 0 (the lowest quality) to 100 (the best quality). The total IP quality indicator combines these five patent quality indicators. When total IP quality is close to 100, it means that patents play a very important role for the company and when they are close to 0, it means the patents play an unimportant role for the company. Further, we use the patent portfolio value average and the number of inventions for each banking group to understand their innovation strength and the monetary value of their patent investments. Table 1 offers a brief description of these variables.

All the patents transacted (acquired and sold) by each banking group were classified according to the patent approach, which identifies whether the patent is defined as 'high technology'. The patent approach is based on the high-tech classification provided by the European Commission, which is organized into several International Patent Classification (IPC)[j] subclasses (four-digit level), including a class devoted to patent applications in high-tech fields.[k]

Moreover, to identify high-tech investment through acquisitions, we use Zephyr (Bureau van Dijk), which provides data on M&A deals. We consider all banking acquisitions completed between 2009 and 2020 and classify them according to the sectoral approach. This approach was introduced by Eurostat; it categorizes manufacturing and services activities considering their technological intensity and classifies them according to the Statistical Classification of Economic Activities in

[j] IPC provides a detailed classification of the patents according to the different technical fields to which they refer.

[k] High-tech patents are classified following the criteria established by the Trilateral Statistical Report. The following are considered high-tech sectors: Computer and automated business equipment, micro-organism and genetic engineering, aviation, communication technology and semiconductors and lasers. https://ec.europa.eu/eurostat/cache/metadata/Annexes/pat_esms_an2.pdf.

Table 1. Definition of Orbis IP patent indicators.

Patent indicators (variables)	Definition
Market attractiveness (%)	This indicator reveals, from an IP perspective, the number of active competitors and innovations in the different technical fields of the company.
Technical quality (%)	This indicator is the degree of innovation that can be derived from a company's IP.
Legal score (%)	This indicator measures the legal strength of the IP in relation to the degree to which it can be protected.
Market coverage (%)	This indicator reveals the size of the market that is covered with the IP and in how many countries the patent is guaranteed protection.
Assignee score (%)	This indicator measures the R&D behavior of the company that results in the creation of IP.
Total IP quality (%)	This indicator combines the other five indicators (market attractiveness, market coverage, technical quality, assignee score and legal score) in one value.
Patent portfolio value average(€)	This variable reveals the value of a patent provided by IP-BI.
Inventions	This refers to the number of inventions.

the European Community code (abbreviation in NACE Rev.2[1]). In particular, manufacturing activities are grouped into four categories: (1) High technology, (2) medium–high technology, (3) medium–low technology, and (4) low technology. Services activities are grouped into two categories: (1) Knowledge-intensive services (KIS) and (2) less knowledge-intensive services (LKIS). Therefore, using NACE Rev. 2 (at the two-digit level), we can gain and discover whether the banking group acquired an equity stake in a high-tech company or in a different kind of company. According to the NACE Rev. 2 criterion, it is possible to classify firms using the following three concentric sets of high-tech investments: (1) The broader set comprises firms operating in high-tech manufacturing and the KIS sector; (2) the narrower set includes companies operating only in high-tech KIS and financial services (disregarding high-tech manufacturing firms); (3) the final set is the most narrow set that comprises only knowledge-intensive financial services firms, disregarding companies that have KIS in other sectors.

[1]NACE is a four-digit classification providing the framework for collecting and presenting a large range of statistical data according to economic activity in the fields of economic statistics. NACE Rev. 2 is the outcome of a major revision of the international integrated system of economic classifications that occurred between 2000 and 2007, and it reflects the technological developments and structural changes of the economy, enabling the modernization of the community statistics and contributing, through more comparable and relevant data, to better economic governance at both the community and national level.

3. Empirical Results

As a result of our empirical investigation, Figs. 1 and 2 present the average values of the efficiency indices related to each year in the study period, considering the geographical and dimensional distribution of the groups.[m]

The values in Figs. 1 and 2 clearly demonstrate that the variability between the average values of the efficiency indices is very low except for in the non-performing loan crisis period. The level of the banking groups' efficiency clearly tends to decrease until 2017, most likely reflecting the effect on efficiency of low profitability and a high incidence of costs. Then, after a rapid increase until 2019, there is a fast collapse that, almost surely, reflects the effects of the Covid-19 pandemic on the global economy.

In relation to the comparison of the different sizes of banking groups, Fig. 2 offers an interesting result: Large groups' efficiency seems to be systematically lower than the efficiency of the other banking group sizes. The best efficiency dynamics are seen in the medium-sized banking groups, which is in line with evidence from the previous literature (Avramidis *et al.* 2016; Delis *et al.* 2017; Batir *et al.* 2017).

Starting from the efficiency values described above, we ran a non-hierarchical cluster analysis to group the considered units into three homogeneous sets to distinguish the banking groups that showed higher (cluster 1), medium (cluster 2), and lower (cluster 3) overall efficiency values throughout the study period.[n]

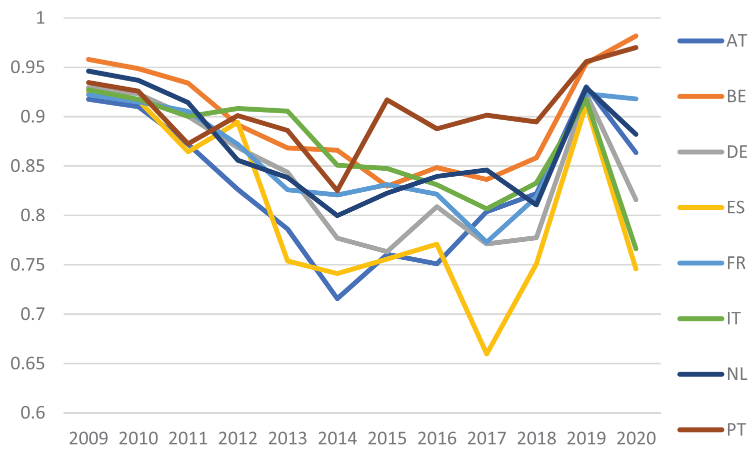

Fig. 1. Banking group efficiency across countries between 2009 and 2020.

[m] The efficiency data are available upon request. For the identification of the size of each unit, we referred to the ratio between the total assets of each banking group and the total assets of the whole banking system of the Euro Area. We defined as 'large' the units for which this indicator exceeded the 1% threshold and 'small' the units for which this indicator was below the 0.1% threshold. We defined all the other groups as 'medium'.

[n] Cluster classification is available upon request.

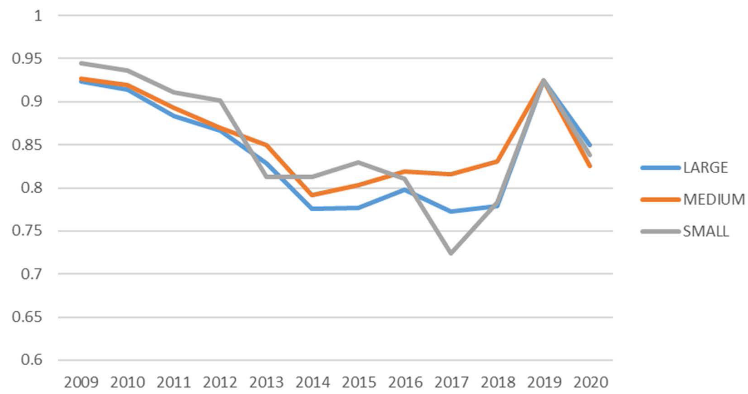

Fig. 2. Banking group efficiency across size classes between 2009 and 2020.

We provide a profile for each of the previously identified efficiency clusters considering some variables are able to describe important managerial aspects, that is, size (small, medium, large); liquidity (using as a proxy the ratio between liquid assets and total assets); profitability (measured by the return on average assets (ROAA)); efficiency (quantified by the cost-to-income ratio); the business model adopted (described both via the ratio of loans to total assets and the ratio of securities to total assets); and the organizational complexity of the banking group (using as a proxy the number of companies in the group). Table 2 shows the average values reached by the variables in 2020 in each cluster.[o]

As illustrated in Table 2, 62% of the banking groups that exhibit the highest overall efficiency values in the 12 years considered (cluster 1) are medium sized and adopted a traditional business model. They are characterized by the lowest levels of liquidity ratio, cost-to-income ratio, and complexity of the group. At the same time, they show mid values of ROAA.

Table 2. Overall banking group efficiency clusters and managerial aspects.

		Cluster 1	Cluster 2	Cluster 3
Size	Small	15%	33%	17%
	Medium	62%	33%	33%
	Large	23%	33%	50%
Liquidity	Liquid assets/total assets	21.87%	31.80%	32.49%
Profitability	ROAA	0.20%	0.10%	0.40%
Efficiency	Cost-to-income ratio	62.54%	69.11%	79.70%
Business model	Loans/total assets	64.12%	51.38%	49.91%
	Total financial assets/total assets	15.54%	17.16%	23.49%
Complexity of the group	Number of companies in the group	231	388	1385

[o] We conducted the usual significance tests on the difference between the averages of the different variable values in the three clusters.

Table 3. Patent quality, value and number of transactions by cluster.

		Cluster 1	Cluster 2	Cluster 3
Mean patent quality (2020)	Market attractiveness (%)	83	68	68
	Technical quality (%)	82	80	74
	Legal score (%)	74	81	78
	Market coverage (%)	80	100	99
	Assignee score (%)	35	41	7
	Total IP quality (%)	62	62	51
Mean patent value (2020)	Portfolio value average (€)	7.613.590	155.640.769	3.839.000
Inventions (2016–2020)	Number of inventions	28	1249	10
Number of High-tech patents transacted (2016–2020)	High-tech patents: acquired	359	2390	1
	High-tech patents: sold	277	2358	0
	Net high-tech patents (acquired minus sold)	82	32	1

The banking groups belonging to cluster 2, characterized by medium overall efficiency values, are equally distributed among size classes. They highlight a medium level of group complexity, liquidity ratio and cost-to-income ratio.

Finally, 50% of the banking groups in cluster 3, which are the groups with the lower overall efficiency values, are large. Compared with clusters 1 and 2, the banking groups in this cluster show higher values of the cost-to-income ratio and the liquidity ratio, as well as significantly higher levels of group complexity. Moreover, the banking groups in cluster 3 exhibit a business model that is more oriented towards investment banking.

Table 3 shows patent quality, value, and number of transactions by cluster. The patent quality indicators refer to the entire patent portfolio (i.e. both high-tech and non-high-tech patents) in 2020. The market attractiveness indicator highlights that banking groups in cluster 1 have invested in patents that are considered of higher quality because they proved to be useful for several different fields of applications. Moreover, in the case of the technical quality indicator, the banking groups belonging to cluster 1 exhibit the highest values, which means that their patents are more likely to have a higher degree of innovation than do the patents owned by the other banking groups.

The legal score and the market coverage indicators demonstrate that the highest values refer to banking groups in clusters 2 and 3, respectively. The patents owned by medium and low-efficiency banks seem to provide a higher degree of legal protection and almost full geographical protection.

The assignee score demonstrates that, on average, clusters 1 and 2, implement a better R&D strategy that can provide a higher level of IP relevance. Finally, the total IP quality indicator, which is a combination of the five other indicators of patent quality, reveals lowest patent quality values for banking groups in cluster 3.

Table 4. M&A deals in different Bureau van Dijk (BvD) primary sectors (total value of deals in millions of euros: 2007–2020).

	Cluster 1	Cluster 2	Cluster 3
Banking, insurance and financial services/other Banking, insurance and financial services	130	136	45
Communications	5.290	290	0
Computer hardware and software	245	671	0

Overall, the results provide evidence that banking groups in cluster 2 have adopted a more aggressive patent investment strategy in relation to patent quantity and have attained wider legal and geographical protection to minimize any kind of litigation risk. In addition, the most efficient banking groups (cluster 1) have patents with the highest technical quality and with a higher potential of application in many different fields.

Observing the patent mean value and the number of inventions reveals the greater investment effort by banking groups in cluster 2 but observing the number of high-tech patents in the banks' portfolios (obtained as the difference between the number of patents acquired and sold) between 2016 and 2020, it is evident that the greatest investment is seen in the banking groups in cluster 1, followed by banks in cluster 2, and then those in cluster 3.

Table 4 presents the total value of acquisitions of targets operating in primary sectors[p] that could provide innovation in the financial industry. Banking groups in cluster 1 focused mainly on acquisitions of companies operating in communication services. Banking groups in cluster 2 (medium efficiency) seem to focus on the acquisition of computer hardware and software firms (i.e. businesses typically related to information systems and information technology). The banking groups in cluster 3 focused exclusively on acquiring companies that provide financial services.

Table 5 presents the number and the values of the high-tech companies' acquisition deals in the period 2009–2020. Observing the acquisition data related to the broader definition of high-tech company (i.e. high-tech manufacturing and KIS), it seems clear that companies in cluster 2 concluded more acquisitions, and that they spent, on average, double the amount of money than did the banks in cluster 1. Overall, the same evidence is found for all three high-tech subsets presented in Table 5.

An interesting result is found in observing cluster 3. It seems that in the past 12 years, these banking groups acquired exclusively knowledge-intensive financial services companies. Conversely, banks in cluster 2 acquired 174 (=534–360) companies that provide high-tech manufacturing. This result suggests that the banking groups in cluster 2 operated a different acquisition investment strategy because they diversified their high-tech investments to the high-tech manufacturing sector

[p] These are according to the classification provided by Bureau van Dijk and are therefore referred to as the 'BvD primary sector'.

Table 5. Acquisition in high-tech industries and KIS between 2009 and 2020.

		Cluster 1	Cluster 2	Cluster 3
High-tech manufacturing and KIS	Number of acquisitions	271	534	13
	Average deal value (in euro millions)	2.558	4.981	847
	Total deal value (in euro millions)	18.251	49.701	1.382
(of which):				
High-tech KIS and financial services	Number of acquisitions	212	360	13
	Average deal value (in euro millions)	3.434	7.088	847
	Total deal value (in euro millions)	18.173	48.502	1.382
(of which):				
Knowledge-intensive financial services	Number of acquisitions	163	180	13
	Average deal value (in euro millions)	4.525	7.889	846
	Total deal value (in euro millions)	17.820	47.578	1.382

(i.e. hardware or software components) and did not focus only on sectors directly related to financial services (as did the banking groups in cluster 3). Considering that 50% of cluster 3 is large banking groups, our results confirm that large banks usually have the advantage of economies of scale and are more able to bear the cost of adopting fintech (Wheelock & Wilson 2012). Arundel (2001) and Cohen *et al.* (2000) found that patent propensity increases significantly with firm size because larger firms can spread fixed costs of patent applications over many patents. In addition, small firms may have difficulty in enforcing their patent rights because of the significant legal costs.

The average deal values demonstrate that knowledge-intensive financial services seem to be more expensive than high-tech manufacturing and KIS. In fact, examining the banking groups in cluster 2 reveals that almost 4% (=(49701–47578)/49701) of their investments is focused on high-tech manufacturing companies. This could suggest that the direct acquisition of financial services companies that use high-tech knowledge is more expensive than the acquisition of high-tech companies that are engaged in manufacturing or KIS in other sectors.

Tables 6 and 7 provide evidence of the relationship (measured via connection [k-square, Cramer's V] and correlation [Bravais–Pearson's r] indices) that emerged,

Table 6. Relationships between banking group efficiency and total IP quality in each cluster (p-values in parentheses).

	Cluster 1	Cluster 2	Cluster 3
Pearson's χ^2	132 (0.233)	132 (0.233)	132 (0.233)
Cramer's V	1 (0.233)	1 (0.233)	1 (0.233)
Contingency coefficient	0.957 (0.233)	0.957 (0.233)	0.957 (0.233)
Bravais–Pearson's r	−0.657 (0.02)	−0.584 (0.046)	−0.597 (0.04)

Table 7. Relationships between banking group efficiency and acquisitions in high-tech manufacturing and KIS companies (total deal value) (p-values in parentheses).

	Cluster 1	Cluster 2
Pearson's χ^2	132 (0.233)	132 (0.233)
Cramer's V	1 (0.233)	1 (0.233)
Contingency coefficient	0.957 (0.233)	0.957 (0.233)
Bravais–Pearson's r	−0.543 (0.068)	0.446 (0.146)

Note: Cluster 3 does not present data in all the years, therefore, the relationship with banking group efficiency cannot be estimated.

over time, between the average level of efficiency achieved by banking groups and the values assumed by specific high-tech investment indicators (total IP quality and acquisition in high-tech manufacturing and KIS companies). Table 7 presents results only for clusters 1 and 2 because there were too few observations available for cluster 3 to obtain a significant result.

The first three indices exhibit a high value and a quite high p-value; this result confirms our expectations of the existence of an important relationship between the efficiency and high-tech investment. Moreover, Bravais–Pearson's r shows that this relationship is significant and negative, as also expected (except in the case of cluster 2 in Table 7, where the r-index is positive, which will be discussed below).

The presence of a Bravais–Pearson's correlation index negative sign (Table 6) probably relates to the fact that high-tech investments are different from other kinds of real investments because they require not only a large initial effort, in relation to costs, but they also imply repeated expenditures over time to ensure that all the technologies are up-to-date. This means that a longer period is required for investments to become profitable.

Table 7 presents opposite signs for the correlation indices for clusters 1 and 2. As stated, cluster 2 comprises the banking groups that attempted to exploit the benefits of diversification because they implemented much more high-tech acquisitions, although for a lower average value each. So, the positive sign could be explained as arising from a higher level of diversification.

However, the banking groups in cluster 1, as seen in Table 6, exhibit a lower level of overall expenditure, but concentrated only on few operations that need a great deal more time to produce positive cash flows.

4. Conclusions

The paper has investigated the relationship between the level of efficiency achieved by Euro Area banking groups and their high-tech investment activity in the period between 2009 and 2020. We expected to find a relationship between high-tech banks' activity (in relation to patent portfolio quality, dimension and high-tech specialization and in relation to high-tech companies' acquisitions) and bank efficiency, we expected that this relationship would currently be negative (i.e. an indirect relationship).

The analysis must be considered as a preliminary empirical investigation of high-tech investments in the banking sector developed for the purpose of providing insight into a topic that could be important for banking efficiency.

Despite extensive and ongoing innovation processes in the banking industry, we found that banking groups are accelerating their investments in high technology through increasing their patent portfolios (especially focused on high-tech innovations) and acquiring high-tech companies.

Analyzing the patent portfolio quality indicators, we reported a decreasing total IP quality value moving from the most efficient banks (cluster 1) to the least efficient banks (cluster 3). We reported the same decreasing trend through observing the number of transactions in high-tech patents in the past five years. Moreover, we found evidence that banking groups in cluster 2 (i.e. the medium efficiency banks) have either adopted a more aggressive patent investment strategy or have concluded a higher number of high-tech acquisitions and are more diversified. Conversely, in the past 12 years, the least efficient banking groups (cluster 3), have acquired exclusively knowledge-intensive financial services companies, which we demonstrated are more expensive than high-tech manufacturing and KIS in other sectors.

As we expected, using some connection measures applied to the efficiency values and to values of different high-tech investment indicators, we found a stable and overall significant relationship between these values. Only the medium efficiency banking groups, which adopted a more diversified investment acquisition strategy, have a positive relationship with high-tech investment; otherwise, the relationship between banking group efficiency and high-tech investment indicators seems to be negative.

There are several possible explanations for this difference in the sign of the correlation between banking group efficiency and high-tech investment aptitude. First, high-tech investments require a huge amount of capital and constant effort over time, while the benefits need more time to be cashed out. Second, as suggested by Cipher (2018), patent litigation among banks increased in the last few years and given that the litigation is slow, expensive, and inefficient, banking groups might have adopted a more stringent protection guarantee for their IP. Third, integrating IP in banking processes requires high maintenance costs because patents expire and because competition and technological innovation cause a rapid reduction in the life cycle of technology, and thus require continuous patent renovation. Four, in relation to the previous point, the high obsolescence rate of patents sometimes means their expected value is partially realized. Five, the acquisition of high-tech companies is motivated not only by the desire to acquire complementary knowledge, but also sometimes by the desire to reduce the benefits that competitors might receive from partnership with or acquisition of such companies.

Although banking groups are clearly fostering their high-tech investments to appear more innovative and to keep up with fintech and techfin, their high-tech investment strategies are implemented in the context of great competition in the technology sector that is populated by firms whose value is very difficult to evaluate, which leads to the possibility that some acquisitions are achieved at prices higher than the real fair value.

We conjecture those new entrants to the banking market (e.g. fintech and techfin companies) that are more specialized in the production of patents and high-tech instruments can benefit from lower production costs compared with incumbent financial firms. For this reason, we suggest further research to investigate the differences between investments in high-tech internal divisions or companies and acquisitions of high-tech companies.

Open banking regulation aimed to increase competition in the banking sector to reduce customers' costs (Thakor 2020). However, our paper reveals that to compete with new entrants (fintech and fintech), banking groups are investing in resources that, on average, have not yet generated a positive effect on efficiency. Regulators should be aware of this acceleration in the enhancement of high technology either because it can reduce the stability of banking groups or because an increase of intangibles assets (such as patents) could also be motivated by an interest rather than by an earnings management strategy.

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