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A Two-Stage DEA Model to Evaluate the Performance of Iberian Banks

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Abstract: This paper's goal is twofold: it aims to assess the performance of 58 Iberian banks and explore the relationship between such performance and the banks' Intellectual Capital (IC) efficiency during a post-crisis period. As long as the authors are aware, there is a gap in the literature in exploring the relationship between banks' global performance and IC efficiency. First, the Data Envelopment Analysis model was adopted to measure the efficiency of Iberian banks and rank them according to their performance. Data were collected digitally, specifically by using the Bankscope database provided by Bureau van Dijk. Results show that by improving their resources management practices, banks can significantly increase their efficiency. Then, fractional regressions were used to infer the relationship between IC's efficiency and the scores obtained in the first stage. Results suggest that Iberian banks' global performance is mainly determined by their human capital efficiency. Finally, this study stresses the importance of IC measurement to support more efficient decision-making by bank managers.

Keywords: Intellectual Capital; VAIC; banking efficiency; two-stage efficiency; data envelopment analysis; fractional regressions

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1. Introduction

In the present global economy, a knowledge-based one, Intellectual Capital (IC) is progressively being recognised as the dominating resource and driver of organisational performance, efficiency, productivity, and value creation (or destruction) (Cabrita et al. 2017; Tiwari and Vidyarthi 2018; Vale et al. 2016). Nowadays, there is some consensus regarding the dimensions composing IC (Inkinen 2015; Inkinen et al. 2017). The so-called "traditional taxonomy" encompasses three dimensions: Human Capital (HC), Structural Capital (SC), and Relational Capital (RC). Therefore, IC represents knowledge, experience, intellectual property, innovation potential, culture, external relationships, and information (Kianto et al. 2017; Tiwari and Vidyarthi 2018), being seen as a vital input for improving performance, and thereby sustain a competitive advantage (Venugopal et al. 2018). This has been reflecting in the exponential increase of capital investment in Intangible Assets, to the detriment of physical resources (Tangible Assets). Hence, exploring the impact of IC efficiency on organisational performance has become a central issue in both academic and commercial fields worldwide (Inkinen 2015; Xu et al. 2017).

The importance of IC transcends any specific sector particularities, besides all the intrinsic aspects that may exist, such as organisational culture or sectoral differences. Nevertheless, those differences may consubstantiate in the fact that some sectors are more knowledge-intensive than others. This is the case of institutions pertaining to the banking sector, which use knowledge as their primary source and product in the input-output process (Cabrita et al. 2017). The banking sector is entirely different from other sectors in the economy due to the pivotal socio-economic role it plays regionally, nationally, and internationally. Banks act as financial intermediaries at the core of financial systems by borrowing money, accepting deposits, issuing debt securities, and lending money both directly to their customers and indirectly by investing in debt securities through capital markets (Ouenniche and Carrales 2018).

Such a role was empashied by the subprime mortgage crisis of 2007, which created significant macroeconomic problems in several Eurozone economies. This crisis had adverse effects on the banking sector of most European economies, and in particular on the Portuguese and Spanish, which were amongst the most affected. Although between 2010 and 2015, the Eurozone economies and its banking systems were in a recovering trajectory, several Iberian banks have not followed their European counterparts, exhibiting worse indicators (see Portuguese Association of Banks 2016 (Banco de Portugal 2020)). More specifically, when compared with the whole Eurozone, the Iberian bank sector showed:

(a) lower total assets to GDP ratio;
(b) an higher customer credit to total assets ratio;
(c) a higher individual' credits stocks to country's GDP;
(d) a higher non-financial firms' credits to the country's GDP;
(e) an higher credit risk to total credit ratio (namely regarding Portugal);
(f) a higher dependence on customer deposits (Banco de Portugal 2020).

Therefore, this paper focuses on the banks about two of the economies which suffered most from the 2007 crisis and whose bank sector had more difficulty recovering. Furthermore, "because at an international and sometimes European level, given the geographical proximity, commercial and cultural relations, these markets are understood as one" (Neves et al. 2020, p. 2).

Hence, it is of great importance to safeguarding an effective operation of banking firms through the implementation of methods and tools that allow the correct monitoring over the efficiency and effectiveness of management, as well as for the comparison with the best practices being followed by leaders in relevant market segments (i.e., benchmarking). Benchmarking allows the assessment of banks' strengths and weaknesses and, by comparison with the more efficient banks (top performers), the realisation of the desirable level of efficiency, as well as the necessary adjustments to increase competitiveness.

One of the leading methods for efficiency evaluation and benchmarking, being applied to real-world problems in an array of sectors, such as the banking sector, is the Data Envelopment Analysis (DEA) method (Tsai et al. 2017). DEA is a non-parametric method, which does not require a particular functional form, nor a specific structure of the shape of the efficiency frontier, thus resulting in a better method for the estimation of individual Decision-Making Units (DMUs) than a parametric one (Diallo 2018). Several studies have already been conducted with the aim of assessing the relationship between IC and business performance in the banking sector by using the DEA. For example, Yalama and Coskun (2007) analysed all the banks listed on Istanbul Stock Exchange for the period 1995–2004. They found that efficiency values were not stable annually, also stressing the importance of IC towards tangible resources. Likewise, Vidyarthi (2018) analysed 38 listed Indian banks during the period 2005–2016, suggesting that IC has a low impact on efficiency.

The literature on Two-stage DEA in banks presents by Henriques et al. (2020) has made it possible to identify several gaps. In fact, there is a gap in the Two-stage DEA analysis of production and profitability efficiency for Iberian Banks considering in a post-crisis recovery period, i.e., 2013 to 2016. In fact, there are no studies using a DEA 2nd stage, not only to assess banks efficiency, but also the influence of IC (at the level of the stochastic boundaries) in banks' efficiency. Hence, this study applies a two-stage DEA analysis. In the first stage, the DEA was used to analyse the bank's efficiency on production and profitability, and measures, considering constant and variable returns to scale (technical efficiency). In the second stage, the attained efficiency's scores were used as the dependent variable in the

FRM to analyse the role played by the main determinants, i.e., the IC dimensions (using the VAIC™ components). By employing the FRM it is possible to endogenize some factors and to estimate their implications for banking activity efficiency. FRM can be considered as the most natural way of modelling bounded and proportional response variables, such as the DEA scores of the Iberian Banks. In addition, tests for assessing the correct specification of each alternative model can also be made (see Ramalho et al. 2010).

To the best of our knowledge, there are no studies that examine the efficiency of countries' baking industry by using FRMs for second stage DEA efficiency approaches, something which can potentially contribute to the literature of two-stage DEA in banks.

This study's purpose consists in assessing banks' performance (through efficiency assessment) and their IC efficiency (using the Value Added Intellectual Coefficient—VAIC™), as well as their respective relationship (through a regression analysis), in a post-crisis recovery period, i.e., 2013 to 2016. This study applies a two-stage analysis as a way to, in a first-stage, rank Iberian banks' according to their efficiency (i.e., performance) scores, and in a second-stage, conduct the selected fractional regression models in order to infer the effect of IC efficiency (using VAIC™ components) on performance (as measured by banks' efficiency scores). In fact, there is a lack of studies that simultaneously encompass non-parametric (i.e., DEA) and parametric (i.e., regression analysis) methods for evaluating the efficiency and its IC-related determinants, using a two-stage analysis logic. Furthermore, as long as the authors are aware, there is no evidence of any study applying the aforesaid methodology for inferring the relationship of IC efficiency on the performance of Iberian banks.

The following section is devoted to the review of relevant literature. In Section 3, data collection and research methodology are described, as well as the applied variables in the first- (i.e., DEA) and second-stage (i.e., fractional regression models) analysis. Then, in Section 4, results are analysed and discussed. Finally, some concluding remarks and cues for further research are offered in Section 5.

2. Literature Review

2.1. Intellectual Capital and Its measurement

The term Intellectual Capital (IC) is not a new one. Although Galbraith was not a pioneer in the use of the term IC, he was the first scholar to conceptualise and study it within the context of knowledge-intensive industries and to relate it with the concept of capital. IC was, then, described as the knowledge that generates profit or helps in the creation of other values (Dyakona 2015). It is a fact that IC definitions have been evolving over the years with the blooming of new IC literature. Nevertheless, there is no commonly accepted definition for it (Ozkan et al. 2017; Zéghal and Maaloul 2010). One of the reasons for this lack of convergence (to some extent) has to do with the confusion raised by the application of diverse terminology and taxonomies (e.g., IC, Intangible Assets (IA), Intangible Liabilities (IL), Intellectual Property, Knowledge-based Assets, etc.), in some cases interchangeably, drawn from several fields of study (Anifowose et al. 2017; Garcia-Parra et al. 2009; Joshi et al. 2013; Xu et al. 2017). In this paper, we define IC as a set of immaterial resources, not touchable by its nature (intangibles), such as knowledge, experience, intellectual property, innovation potential, culture, external relationships, and information (Kianto et al. 2017; Vidyarthi 2018), which may be leveraged, and over time (Giuliani 2015) result in "a value-added (VA) for the company" (Zéghal and Maaloul 2010, p. 41), or in a deteriorated one (Vale et al. 2016; Vale et al. 2017).

Although there is still a lot of work to be done for achieving a standard definition of IC, there seems to be a joint base, grounded on seminal literature, suggesting a three-dimensional conceptualization of IC (Inkinen 2015; Inkinen et al. 2017), although some authors seem to use slightly altered terminologies, and/or add other subdivisions (Alipour 2012; Inkinen et al. 2017). Furthermore, Social Capital seems to be gaining more supporters and has emerged as the fourth dimension of IC (Ferenhof et al. 2015). In this study, the traditional taxonomy is also used, whereby IC is composed of three interrelated dimensions: Human Capital (HC), Structural Capital (SC), and Relational Capital (RC).

HC is composed by knowledge (explicit and tacit) generated and controlled by an organisation's employees (Martín-de-Castro et al. 2011) and their idiosyncrasies such as loyalty, versatility, or flexibility (Cabrita et al. 2017). It represents a source of innovation and strategic renewal (Ahangar 2011; Bontis 2001; Kianto et al. 2017). It is the sum of all individual and collective innovation knowledge, which combines intelligence, skills, and expertise (Bontis 2001) gathered by personnel within an organisation with the purpose of creating value. Structural Capital (SC) can be seen as the supportive infrastructure (Ahangar 2011), which comprises all non-human intangible resources owned by the organisation. In other words it can be said that these resources stay within the organisation when employees go back home (Ahangar 2011). It encompasses the information systems, routines, procedures, strategies, organisational charts, databases, managerial philosophies, organisational culture, patents, copy rights, trademarks, and anything whose material value is lower than the value to the organisation (Cabrita and Bontis 2008; Chen 2008). Relational Capital (RC) is a transitional type of IC (Anifowose et al. 2017) encompassing the knowledge embedded in all the interactions an organisation develops (Nazari and Herremans 2007). RC is the most challenging dimension to establish since it is the most external to the organisation's core, thus the most difficult to codify. It can only be measured through a function of longevity, which relates to the dynamic process of value creation or destruction that evolves (Giuliani 2015; Vale et al. 2016).

Organisations have been using various measuring tools to value their respective tangible and intangible assets, such as IC. Sveiby and Lloyd (2010) suggests that different methods for measuring IC can be allocated into four different categories: Direct (DIC), Scorecard (SCM), Market Capitalisation, and Return on Assets (ROA) methods. Without delving too much into the pros and cons of each category, there is one particular decision factor that stands out, which is the availability of the data required for the application of the chosen method. The SCM and DIC methods require non-public and, therefore, less accessible data, whilst the ROA methods (e.g., VAIC™), usually apply financial indicators to measure IC based on audited reports, thus making these methods the most widely used amongst practitioners (Xu et al. 2017). In this paper, the VAIC™ model was chosen as the IC measuring method.

2.2. Relating Firms' IC and Performance

Assessing an organisation's performance has been considered of extreme importance in the present globalised and technically advanced economy (Alipour 2012), and consequently, so the accurate measurement of IC and its efficient application as a determining factor for achieving optimal effectiveness and efficiency. Hence, several scholars have been applying some of the abovementioned methods and tools for measuring both IC and performance and by relating them through different approaches. The more common approach consists of using parametric methods (e.g., regression analysis) for measuring the average performance for a given population (Shewell and Migiro 2016). Several scholars have been trying to apply the VAIC™ model and to correlate it with other financial indicators, such as Asset Turnover (ATO), Earning Per Share (EPS), Return on Assets (ROA), or Return on Equity (ROE).

Alipour (2012) studied 39 Iranian insurance firms between 2005 and 2007, having found a positive and significant relationship between VAIC™ (and all its components) and performance (measured through ROA). Wang (2011) studied several Taiwanese companies, finding a positive relationship between VAIC™ and performance (measured through ROA) and market capitalisation. Maditinos et al. (2011) studied 96 Greek companies from 4 sectors for a three-year period, having found a positive relationship between Human Capital Efficiency (HCE) and performance (measured through ROE). Tan et al. (2007) studied 150 Singapore-listed companies for a two-year period. He found a correlation between IC and performance, and also that the contribution of IC to performance will differ across industries. Veltri and Silvestri (2011) studied all the financial sector firms listed in the Italian stock exchange between 2006 and 2008, having found a positive relationship between Book value (BV) and market value (MV) on the one hand, and IC components (VAIC) and MV on the other. Maji and Goswami (2016) studied 100 listed Indian companies between 1999 and 2012, having found a positive and significant relationship between VAIC™ and performance (measured through ROA). This author also found that the impact of IC efficiency on ROA was more significant in knowledge-based sectors than in traditional ones.

Nevertheless, results are far from unanimous, as other studies presented mixed, contrary, or inconclusive results. Kujansivu and Lönnqvist (2007) studied Finnish companies from 11 industry sectors between 2001 and 2003, and they were not able to clarify the existence of a relationship between value and the efficiency of IC. Firer and Williams (2003) studied 75 publicly traded firms in South Africa from knowledge-intensive sectors, and they were not able to support the existence of a relationship between IC and performance, founding a negative relation between HCE and Productivity (ATO) and MB. However, they found a positive relation between structural capital efficiency (SCE) and ROA. Joshi et al. (2013) studied the top 40 financial companies listed in the Australian Securities Exchange for a 3-year period, having found a positive and significant relationship between capital employed efficiency (CEE) and performance (measured through ROA), but no evidence about VAIC™ impacting performance.

Tsai et al. (2017) used DEA for measuring the efficiency of 21 listed Taiwanese corporations (Decision Making Units—DMUs) pertaining to the semiconductor industry in 2009, having applied both IC and Corporate Governance (CG) as inputs and Operating Income, ROA, and Tobin's Q as outputs. The authors found inefficiency issues regarding resource allocation of semiconductor corporations. Long Long Kweh et al. (2013) studied the efficiency of 25 Malaysian public-listed software companies (DMUs) in 2010, using VAIC™ components (i.e., HCE, SCE, and CEE) as inputs, and Tobin's Q and ROE as outputs for the DEA method. The authors found "Eduspec" to be the most efficient company and that IC played an essential role in value creation and overall performance. Venugopal et al. (2018) studied an Indian Company (Titan), for 20 years (1997 to 2016), having used VAIC™ and its components as inputs, and ROA, ROE, EPS, and Market Capitalisation as outputs for the application of the DEA. They found that there were only 6 best performing years out of the 20 studied, and that some of the less efficient ones showed very poor use of IC.

2.3. IC and Performance in the Banking Sector: Prior Studies

As it can be seen by the abovementioned literature, it is clear that VAIC™ is a popular IC measurement tool, which is used transversely by a panoply of countries in diverse sectors, and applied in different methodological contexts. This method seems to be even more popular when the object of study pertains to the financial services sector, more specifically to the banking industry. Meles et al. (2016) studied 5.749 US commercial banks from 2005 to 2012, having used an econometric approach to relate VAIC™ and its components (independent variables) with ROA and ROE. The authors found a significant positive relationship between VAIC™ in general and HCE in particular, with both ROA and ROE. Nawaz and Haniffa (2017) studied 64 Islamic financial institutions operating in 18 countries from 2007 to 2011, having used an econometric approach to analyse VAIC™ and its components (independent variables) and ROA. The authors found HCE to be the main value driver, as well as a significant positive relationship between VAIC™, HCE, and CEE with ROA, and conversely, a significant negative relationship between Risk (control variable) and ROA. Irawanto et al. (2017) studied 33 Indonesian banks from 2013 to 2014, having used an econometric approach to analyse VAIC™ and its components, Corporate Governance (CG) indicators (independent variables), and ROA (dependent variable). The authors found a significant positive relationship between HCE, SCE and CG with ROA, a significant positive relationship between CG with HCE and SCE, and also that HCE particularly had a positive effect on financial performance. Also, Al-Musali and Ismail (2014) suggest, in their study of 11 commercial banks listed in Saudi Stock Exchange, that the capability of the examined banks to create value is mainly dependent on HCE. A positive and significant relationship between CEE and ROE was also found. In fact, according to Iqbal and Zaib's (2017) study of listed banks in the Pakistanis Stock Exchange, CEE is the most effective component of IC, contributing to financial performance. These authors also found a positive and significant relationship between Size and ROA (and ROE) when referring to commercial banks, while suggesting a negative relationship between Size and Tobin's q when referring to Microfinance and investment banks. Regarding Leverage, they found a negative relationship between this variable and ROA (and ROE). In fact, the importance of HC is also stressed by Jafarnezhad and Tabari (2016) in their study of 11 banks listed in the Tehran Stock Exchange. They also found a positive and significant relationship between CEE and ROA. In a study of 16 Islamic banks in Malaysia during a three-year period, Ousama and Fatima (2015) found a positive and significant relationship between VAIC (and all its components) and (namely) ROE. They found that HCE was higher than SCE and CEE. However, CEE seemed to contribute more to profitability. There we no conclusive result regarding the effect of leverage on the dependent variables (ROA and ROE). Similar results were obtained by Ozkan et al. (2017) in their study of 44 Turkish banks during a ten-year period, considering the relationship between VAIC, HCE, CEE, and ROA. However, in this case, results also suggested negative relationships between SCE and ROA, as well as leverage and ROA. It was also found that components of VAIC are better at explaining profitability than VAIC alone. Thakur (2017) studied 40 public and private banks in India from 2013 to 2015, having used an econometric approach to analyse VAIC™ and its components (independent variables), ROA, and ROE (dependent variables). The authors found a significant positive relationship between VAIC™, HCE, and CEE with both ROA and ROE, and that CEE had a stronger impact on ROA and ROE, rather than HCE and SCE. Yalama and Coskun (2007) studied the efficient transformation of IC in the profitability of all the banks listed on the Istanbul Stock Exchange, from 1995 to 2004 (except the year 2001), using both VAIC™ and DEA methods. The authors used three alternative portfolios for the inputs (i.e., VAIC, CEE, and MV/BV per share), and ROA, ROE, LDR (Loans to Deposits Ratio) for the outputs, having found that, among others, IC seems to be a more important factor than physical capital in the profitability of banks. Vidyarthi (2018) studied the performance efficiency of 38 listed Indian banks, from 2005 to 2016, using Total non-interest and Total interest expenses (inputs), Deposits, Loans and Advances, and Investments (Outputs) for the DEA. This author also resorted to an econometric approach for assessing about the existence of a possible relationship between VAIC™, MVAIC (modified VAIC), and its respective components (independent variables) with the previously obtained DEA variables, i.e., Technical (TE), Pure Technical (PTE), and Scale Efficiency (SE) coefficients (dependent variables). The author found a significant positive relationship between VAIC™, MVAIC, and Size (control variable) with TE, PTE, and SE, and more generally, that IC had low but positive impact on efficiency. He also found a negative relationship between Leverage and TE, PTE and Scale Efficiency.

Although there are several studies applying both VAIC™ and DEA methods throughout other sectors in an effort to solve the IC and Performance nexus conundrum, there seems to be a gap regarding the application of these two methods simultaneously in the banking sector, which constitutes one of the contributions from this study.

3. Methodology

3.1. Contextualisation of the Banking Sector and Period of Analysis

The 2007 crisis led to several macroeconomic problems in the different Eurozone economies, including both Portugal (PT) and Spain (ES), which were amongst the most affected EU economies, along with their banking sectors. Since then, legal restrictions have led banks to increase their capital ratios, and consequently, to decrease their operational risk. Over time, banking activity slowly recovered. This paper focuses on the banking systems pertaining to these two cross-border countries. Players in the global market as well as the press, have been considering these Iberian markets as a whole (Neves et al.

2020). The 2007 crisis led to an economic recession, and consequently, to the subjection to austerity programs in the following years. More specifically, there was the need to greatly recapitalise Portuguese Banking with the intervention of the so-called "Troika" in May 2011, something which lasted for three years. At this point, it is important to stress that Portugal's banking system found its main capital sources in Spain (Neves et al. 2020). Likewise, in 2012, a more "soft" intervention was also needed in Spain (Kickert and Ysa 2014). That is why it is the aim of this paper to assess the period ranging from 2013 to 2016. More specifically, this paper aims to determine the period in which Eurozone economies, and namely PT and ES, seemed to be exhibiting signs of recovery. Therefore, it not intends to assess the behavior of the Iberian banking system during the early stages of the crisis, nor its effects in any particular bank. Although during the period under analysis (2013–2016), Portugal and Spain were already recovering from the abovementioned crisis, their banks were still presenting several indicators below the Eurozone ones.

According to the overview report of the Portuguese banking system, developed by the Portuguese Association of Banks (Banco de Portugal 2020)[1], the resizing of the European banking sector during the period from 2010 to 2015 is noticeable when comparing the total assets to GDP ratio. However, when comparing Portugal and Spain with the Eurozone, this ratio presented a general decrease from 2010 to 2015, mainly due to the severe reduction of total assets (although GDP as also decreased in the same period), with a variance of −19.6%, −18.5%, and −4.3%, for PT, ES, and Eurozone banking industries, respectively. Despite the aforesaid reduction, customer credit still composed half of the total assets of PT and ES banking industries, with a customer credit to total assets ratio (as of June 2016) of around 49% for each country, which compares with a value of 37.5% for the Eurozone.

Moreover, the level of banking indebtedness of the Spanish and Portuguese economies has also been declining, closing the gap to the rest of Europe. Despite the decrease of the customer credit to GDP ratio during those years, at the end of 2015, this ratio still presented values of 131% and 123% for the ES and PT banking sectors, respectively, while the average for the Eurozone was 113%, (see Overview of the Portuguese banking system, 2016). Also, individuals' credit stock to the country's GDP was 66.3% for Spain and 67% for Portugal, while the rest of the Eurozone average was 51.1%. The credit to non-financial firms to the country's GDP ratio was 49.2% for Spain and 46.3% for Portugal, whereas the Eurozone average was 41%. Furthermore, the volume of credit risk to total credit ratio has increased in the post-crisis aftermath for the Eurozone countries, emphasizing peripherical countries, such as Portugal and Spain. Regarding the financing structure, PT and ES banking sector seemed to have a higher dependency on customer deposits, whose proportion, as of June 2016, was of 53% and 50%, respectively, when comparing with the Eurozone average (38%). Finally, wholesale funding had a less relevant position, with values of 24%, 26%, and 30%, for Spain, Portugal and the Eurozone, respectively (see Overview of the Portuguese banking system, 2016).

3.2. Data Collection and the Data Envelopment Analysis (DEA) Model

Data was collected using the Bankscope database, which can be accessed through digital means, i.e., by using the webpage provided by Bureau van Dijk. The initial sample was composed by all the 314 Iberian banks available in the Bankscope database regarding the period 2013–2016. Then, the consolidation code was used as an exclusion criteria, i.e., banks with unconsolidated data were excluded, something which reduced the sample to 90 banks. Finally, the sample was filtered according to (1) the availability of variables needed for the study and; (2) the banks that have been operating for the whole of the aforementioned time period. Thus, the final sample encompassed 58 Iberian banks—16 Portuguese and 42 Spanish—over a four-time period (2013–2016), which translates into 232 observations.

To assess Iberian banks' performance and their IC efficiency, as well as their relationship, a two-stage DEA model was adopted. The two-stage DEA model allows surpassing the black box problem. An important limitation of traditional DEA models "is that they treat the production process like a black box, in which the input variables are transformed within this box to give the output variables" (Henriques et al. 2020, p. 3). Hence, highly complex sectors, such as banking, need a more structured model (Henriques et al. 2020). In this study, while the first stage aimed at measuring banks' efficiency and ranking them according to their performance, in the second stage, a fractional regression model (FRM) was applied to infer the potential relationship between IC efficiency and such performance. In this stage, IC's components are used as independent variables, while the first stage DEA scores are used as dependent ones. The FRM, developed by Papke and Wooldridge (1996), requires the assumption of a functional form whose dependent variables (i.e., the first-stage DEA scores) are limited to the interval [0, 1].

The DEA model is a non-parametric method (Charnes et al. 1978), which can be used in performance measurement and analysis (Shewell and Migiro 2016). Being a non-parametric method does not require a particular functional form, nor a specific structure of the shape of the efficiency frontier, thus resulting in a better way for the estimation of the efficiency level of a set of peer entities, i.e., individual Decision-Making Units (DMUs), than a parametric one (Diallo 2018). In this particular study, DMUs are Iberian banking firms. Based on determining inputs and outputs, DEA measures the relative efficiency of each sampled bank by establishing an empiric production function and applying linear programming to build a technological production frontier, also known as efficiency frontier, which encompasses all efficient banks.

Banks with maximum efficiency will be situated in the efficiency frontier, therefore retaining a value of 1 and serving as an example for being the best "practitioners". In contrast, all the other banks are considered inefficient with a value between 0 and 1 (Barman et al. 2015). From this comparison between efficient and inefficient banks, it is then possible to determine the necessary changes, in terms of inputs and/or outputs (reduction or increase), for inefficient banks to "catch up" with efficient ones (i.e., join the efficiency frontier).

There are two DEA models based on measuring the radial distance that can be used to evaluate banks' efficiency, namely the CCR model, which stands for Charnes et al. (1978), and the BCC model, which stands for Banker et al. (1984). The essential difference between these two modes lies in the fact that CCR is based on constant returns to scale (CRS) and measures technical efficiency (TE), while the BCC is based upon the assumption of variable returns to scale (VRS) measuring pure technical efficiency (PTE) (Barman et al. 2015). In another perspective, the difference between CRS (i.e., CCR) and VRS (i.e., BCC) is that the first assumes that any variation in the inputs will produce a proportionate variation in the outputs (constant: same direction), while the latter takes a disproportionate relation between inputs and outputs (variable: lower, regular, or higher). Scale Efficiency (SE), which represents the potential productivity gain achieved from the optimal size of a DMU (Raheli et al. 2017), can be derived from the TE to PTE ratio. The problem above translates in the maximisation ratio (i.e., Technical efficiency—TE) of the weighted sum of the chosen outputs in relation to the weighted sum of the selected inputs (Liu 2017), whereas weights are defined by the DEA-CCR model for each DMU.

Input and Output Variables

There are different approaches in the banking theory literature, which help to explain the selection of inputs and outputs variables necessary for the bank performance evaluation in DEA. On the one hand, some authors consider three main approaches: the production, profitability, and intermediation approaches (e.g., Paradi et al. 2011; Tsolas et al. 2020; Novickytė and Droždz 2018). On the other hand, others, such as Ahn and Le (2014), consider the existence of four approaches: the production, the intermediary, the user cost, and the value-added approaches. The production approach contemplates banks as producers of services for account holders, assuming that banks use Capital and other resources to produce services (e.g., loans and deposits) (Said et al. 2017). The profitability approach considers banks as profit-seekers, thus, aiming for the minimisation of costs (e.g., interest and non-interest expenses) and the maximisation of income (e.g., interest and non-interest income) (Novickytė and Droždz 2018). The intermediation approach contemplates banks as intermediaries by using labor, operational costs, and capital (i.e., collected funds) to provide loans and other assets (investments) (Ouenniche and Carrales 2018). The user cost approach, which is grounded in the concept of opportunity cost, considers banks as "producers of financial services with the aim to minimize the user costs of liabilities and assets or maximize the economic return" (Ahn and Le 2014, p. 13). Finally, the value-added approach aims to maximise the value-added of banks' activities to get long-term competitive viability (Ahn and Le 2014). In this study, the choice of the inputs and outputs being used for the application of the DEA models is driven by the abovementioned production and profitability approaches. These two approaches are selected according to the findings depicted in the bibliometric analysis developed by Henriques et al. (2020). In fact, they claims that few studies used the production approach (five studies) and the profit approach (five studies), while eighteen studies followed the intermediation approach. Moreover, on the one hand, according to this bibliometric analysis, authors such as Wanke et al. (2016), Luo (2003), Wanke and Barros (2016), Chen et al. (2018) or Wanke et al. (2017) followed the production approach. On the other hand, authors such as Xu (2018), Aggelopoulos and Georgopoulos (2017), Du et al. (2018) or Fernandes et al. (2018) adopted the profit approach.

The variables were selected based on the combination of the two aforementioned approaches, the availability of the data, and by following the example of other studies, such as Barman et al. (2015), Liu (2017), Ouenniche and Carrales (2018), Said et al. (2017) or Vidyarthi (2018). In fact, according to Paradi et al. (2011, p. 101), "the production approach measures how a branch produces transaction services (outputs) based on the use of capital and labor (inputs)" while "the profitability approach has been used to measure a branch's profitability based on expenses as inputs and revenues as outputs." Similarly, Tsolas et al. (2020, p. 12) claims that the profitability approach considers the bank "as a producer of profit components, such as interest and fee income (outputs), generated through the use of inputs, such as operating expenses and the quality of the loan portfolio, i.e., cost components."

Classification of inputs and outputs throughout the banking literature is typically based on resources, costs, or financial burden for the inputs, while the outputs are generally based on banks' ability to provide services, generate revenue, and acquire more assets (Ouenniche and Carrales 2018; Vidyarthi 2018). Thus, this study applies a similar logic, in which chosen inputs are based on resources (i.e., number of employees; and fixed assets) and on costs (i.e., total operating expenses), whereas outputs are based on financial services (i.e., total net loans and advances and total deposits) and on generated revenue (i.e., net interest income) (see Table 1).

Table 1. Selected output and input variables for the application of the first-stage DEA.

Outputs	Inputs
• Total net loans and advances (costumers + banks) • Total Deposits (costumers + banks) • Net interest income	• Total operating expenses • Number of employees • Fixed assets

The selected inputs and outputs were grounded in different studies. Following the production approach, Chiu et al. (2013) suggest the following inputs: number of employees and total assets. Chen et al. (2018) consider as inputs the operational costs, personnel expenses, number of employees, and as outputs the total assets, gross loans, customer deposits, and net interest income. Also, Wanke et al. (2016) suggest total deposits and income before tax as outputs. Following the profit approach, Aggelopoulos and Georgopoulos (2017) consider operational expenses as input and income as output. Du et al. (2018) suggest non-interest expenses as input and aggregate net income as output. Fernandes et al. (2018) use operating expenses as input and total income as output.

3.3. Econometric Analysis

In the second stage of the applied methodology, fractional regressions are used for inferring the impact of IC (i.e., VAIC™ components) on the performance (i.e., score efficiencies obtained through DEA in the first-stage) of Iberian banks.

The choice of the appropriate regression model for the second-stage DEA is not a meagre econometric problem, since the traditional approaches of using either traditional linear or Tobit regression models have been criticised (in second-stage DEA context) by their limitations of efficiency scores at the unit (Raheli et al. 2017; Ramalho et al. 2010). Given the bounded nature of DEA methodology applied in the first stage, Papke and Wooldridge (1996) fractional regression model (FRM) was chosen for the correlation of IC and performance variables in the second-stage DEA.

3.3.1. Fractional Regression Model (FRM)

The FRM avoids the problems associated with the application of the linear and tobit models in the DEA context, requiring the assumption of a functional form whose dependent variables (i.e., first-stage DEA scores) are limited to the interval [0, 1]. This functional form for y that enforces the desired constraints on the conditional mean of the dependent variable, $E(y\,|\,x) = G(x\theta)$ is, therefore, bounded to that same interval, where $G(.)$ represents a non-linear function satisfying the condition: $0 \leq G(.) \leq 1$ (Ramalho et al. 2010).

Papke and Wooldridge (1996) proposed the estimation of FRMs by using the quasi-maximum likelihood (QML), based on the Bernoulli log-likelihood function, which is given by:

$$LL_i(\theta) = y_i \log\ \Phi[G(x_i\theta)] + (1 - y_i) + \log[1 - G(x_i\theta)]$$

Papke and Wooldridge (1996) suggested as possible specifications for the $G(.)$ function any cumulative distribution function, such as the already applied to model binary data. The most widely used ones are logit and probit functional forms. However, there are other alternatives, such as the loglog and the complementary loglog, namely (cloglog), following Raheli et al. (2017) and Ramalho et al. (2010).

Partial effects associated to each of the abovementioned fractional regression model alternatives are given by $(\partial E(y\,|\,x))/(\partial x\_j) = \theta\_j\ g(x\theta)$, where $g(x\theta) = (\partial G(x\theta))/\partial x\theta$. Similarly to the Tobit model, the direction and significance of partial effects in the aforesaid models are observed from significance analysis and from θ_j signal, since g($x\theta$) is strictly positive.

Ramalho et al. (2010) proposed two generalised models as an alternative to the aforementioned standard models, which use an additional parameter, α, thus, resulting in the first and second generalisations, where $\alpha > 0$ such that $0 < E(y\,|\,x) < 1$. Furthermore, there also the two part-models, which should be used when the probability of observing a DEA score of unity is relatively large, leading to the suspection that sources of DMU efficiency may differ from those of DEA inefficiency (Ramalho et al. 2010). The first part of such model encompasses a standard binary choice model, which manages the probability of observing an efficient DMU, where: z is a binary indicator that takes the values of 0 (i.e., $0 < y < 1$) and 1 (i.e., $y = 1$) for inefficient and efficient DMUs, respectively. The conditional probability of observing an efficient DMU (estimated through maximum likelihood of the whole sample) is given by $Pr(z{=}1\,|\,x) = E(z\,|\,x) = F(x\beta\_1P)$, where β_1P is a vector of variable coefficients and F(.) is a cumulative distribution function. The second part of the two-part model is estimated through the use of the sub-sample inefficient DMUs only, thus allowing for the assessment of the DEA scores on the interval]0, 1[and $(y\,|\,x{,}y \in\ ]0{,}1[) = M(x\beta\_2P)$, where $M(.)$ may be any of the considered for $E(y\,|\,x)$, and β_2P is another vector of coefficients, (see more details in Ramalho et al. 2010).

3.3.2. Dependent, Independent, and Control Variables

As previously mentioned, the second-stage DEA consists in applying the FRM, for inferring about the existence of a relationship between IC efficiency and performance. The choice for the dependent, independent, and control variables applied on these regressions is based on the revised literature.

The VAIC™ method is based on the premise that value-added (VA) derives from two main resource bases: physical capital resources and IC resources (Kujansivu and Lönnqvist 2007). Therefore, this method provides information about the value creation efficiency of both tangible (i.e., capital employed) and intangible assets in an organisation (Maditinos et al. 2011). It allows for the efficiency measurement of three types of inputs: Financial Capital (monetary and physical); Human Capital, and Structural Capital. In essence, the mathematical formula for the calculation of VAIC™ results from the sum of those three inputs efficiency: Capital Employed Efficiency (CEE); Human Capital Efficiency (HCE); and Structural Capital Efficiency (SCE). The expression can be put as follows (Alipour 2012; Chen 2008; Pulic 2004):

$$\text{VAIC} = \text{CEE}\ (\frac{VA}{CE}) + \text{HCE}\ (\frac{VA}{HC}) + \text{SCE}\ (\frac{SC}{VA})$$

where: VA = Value Added; CE = Capital employed; HC = Human Capital; SC = Structural Capital; and: CE = Net assets (Total assets − Total liabilities); HC = Labour expenses; $SC = VA - HC$.

The aforesaid VAIC™ components (i.e., HCE, SCE, and CEE) were chosen as independent variables for the regression models. Furthermore, based on the revised literature, four control variables were selected for the regression models conducted in this study, namely Size and three types of leverage ratios: Lev1 (total debt to total assets), Lev2 (Equity to total assets), and Lev3 (i.e., total liabilities to shareholder's equity).

4. Results and Discussion

4.1. Banks' Efficiency Analysis

The results presented in the correlation matrix (see Table 2) allow to assess the presence of collinearity. When the correlation coefficient overpasses 0.8, it reveals potential collinearity, something which may rise some concerns. The correlation matrix shows that, for the estimation of the first-stage DEA, inputs variables (Total Operating expenses, Number of Employees, and fixed assets) and outputs variables (Net Loans and advances, Total deposits, and net interest income) are positively and highly correlated, which means that an increase in any of those variables will most likely increase the others. However, when the non-parametric DEA is used in the first stage of the two-stage DEA models, the existence of collinearity is not problematic. In such case, inputs and outputs can be simultaneously used in the objective function. The correlation between each variable (input or output) with the other variables (inputs or outputs) can, potentially, allow for more significant efficiency scores.

Table 2. Correlation matrix of the selected outputs-inputs for the application of the first-stage DEA.

	Total NLA	Total Deposits	Net II	Total OE	Nr. Employees	Fixed Assets
Total NLA	1					
Total deposits	0.9967 *	1				
	0.0000					
Net II	0.9794 *	0.9693 *	1			
	0.0000	0.0000				
Total OE	0.9893 *	0.9832 *	0.9901 *	1		
	0.0000	0.0000	0.0000			
Nr. Employees	0.9773 *	0.9718 *	0.9869 *	0.9925 *	1	
	0.0000	0.0000	0.0000	0.0000		
Fixed Assets	0.9722 *	0.9678 *	0.9754 *	0.9714 *	0.9579 *	1
	0.0000	0.0000	0.0000	0.0000	0.0000	

Where: Total NLA = Total Net Loan and Advances; Net II = Net Interest Income; and Total OE = Total Operating Expenses; the fixed * represents a significance level of 1%.

Subsequently, banks' technical, pure technical, and associated Scale Efficiency indicators (i.e., TE, PTE, and SE) result from the input-oriented first-stage DEA, as shown in Table 3. The mean efficiency score of the sampled 58 Iberian banks from 2013 to 2016, considering the CRS model, is 0.409. These findings suggest that Iberian banks, on average, could reduce their application of resources (inputs) by at least 59.1% for achieving the same amount of outcome (outputs) by improving their resources management practices.

The mean efficiency score of the 58 Iberian banks, during the period 2013 to 2016, under the VRS model, is 70.7% (not considering super efficiency). Once more, findings suggest that Iberian banks, on average, could reduce their application of resources (inputs) by at least 29.3% for achieving the same amount of outcome (outputs) by improving their resources management practices (see Table 3):

The average efficiency scores appear to be higher when applying the VRS model, i.e., 0.623, 0.6, 0.645, and 0.653 (for Iberian banks), contrasting with the CRS model, i.e., 0.409, 0.412, 0.446, and 0.498, in 2013, 2014, 2015, and 2016, respectively.

On the one hand, the number of efficient Iberian banks, considering technical efficiency (TE), seems to be constant over the analysed period, with four efficient banks in 2013 (Deustche Bank SAE; BNP Paribas España, SA; EBN Banco de Negocios, SA; Finantipar S.G.P.S., SA), four efficient banks in 2014 (BNP Paribas España, SA; Banco Caixa Geral, SA; Banco Cooperativo Espanol; Finantipar S.G.P.S., SA), three efficient banks in 2015 (BNP Paribas España, SA; Banco Caixa Geral, SA; Finantipar S.G.P.S., SA) and six efficient banks in 2016 (BBVA PT, Banco Finantia, BNP Paribas España, SA; Banco Caixa Geral, SA; Banco Santander, SA; Finantia S.G.P.S., SA). On the other hand, the number of efficient Iberian banks, considering pure technical efficiency (PTE), appears to be increasing over time.

The average PTE is higher than the average SE for each of the 4-year period, considering Iberian banks in general (i.e., in line with the fact that the average TE is constantly < than PTE), which suggests that Iberian banks are not operating at an optimal scale of operations.

Table 3. Annual TE, PTE, and SE of Iberian banks during the period 2013–2016.

Country	DMU	Bank	TE					PTE					SE				
			2013	*2014*	*2015*	*2016*	*Mean*	*2013*	*2014*	*2015*	*2016*	*Mean*	*2013*	*2014*	*2015*	*2016*	*Mean*
PT	1	Banco L. J. Carregosa, S.A.	0.423	0.253	0.372	0.287	0.334	1.000	1.000	1.000	1.000	1.000	0.423	0.253	0.372	0.287	0.334
ES	2	Caixabank, S.A.	0.231	0.274	0.307	0.398	0.303	0.779	0.945	0.971	1.000	0.924	0.296	0.290	0.317	0.398	0.325
ES	3	BFA Tenedora de Acciones	0.387	0.500	0.437	0.437	0.440	1.000	1.000	0.881	0.883	0.941	0.387	0.500	0.496	0.495	0.469
ES	4	Liberbank SA	0.209	0.227	0.259	0.360	0.264	0.473	0.434	0.483	0.641	0.508	0.441	0.524	0.536	0.562	0.516
ES	5	Renta 4 Banco, S.A.	0.055	0.046	0.053	0.124	0.069	0.208	0.214	0.211	0.246	0.220	0.265	0.214	0.251	0.503	0.308
ES	6	Ibercaja Banco SA	0.219	0.228	0.171	0.381	0.250	0.540	0.482	0.359	0.615	0.499	0.405	0.473	0.475	0.619	0.493
ES	7	Abanca C. B. SA	0.213	0.235	0.190	0.424	0.265	0.436	0.468	0.551	0.644	0.525	0.488	0.502	0.345	0.658	0.498
ES	8	Kutxabank SA	0.176	0.176	0.234	0.447	0.258	0.496	0.548	0.558	0.650	0.563	0.355	0.321	0.420	0.688	0.446
ES	9	Banco Caminos SA	0.384	0.311	0.477	0.549	0.430	0.512	0.402	0.502	0.615	0.508	0.749	0.775	0.949	0.893	0.841
ES	10	Banco Inversis SA	0.575	0.572	0.385	0.354	0.471	0.728	0.797	0.744	0.880	0.787	0.790	0.718	0.517	0.402	0.607
ES	11	CIMD Group	0.219	0.052	0.033	0.049	0.088	0.637	0.441	0.404	0.521	0.501	0.344	0.117	0.082	0.093	0.159
PT	12	Santander Totta SGPS	0.338	0.341	0.387	0.547	0.403	0.711	0.671	0.808	0.818	0.752	0.475	0.507	0.479	0.669	0.533
PT	13	Montepio Geral	0.273	0.460	0.323	0.374	0.357	0.323	0.607	0.568	0.495	0.498	0.843	0.758	0.569	0.755	0.732
PT	14	Caixa Geral de Depositos	0.118	0.155	0.212	0.456	0.235	0.912	0.848	0.878	0.995	0.908	0.130	0.183	0.241	0.458	0.253
PT	15	Millennium BCP	0.212	0.289	0.436	0.536	0.368	0.660	0.675	0.700	0.960	0.749	0.321	0.428	0.622	0.559	0.482
PT	16	BBVA	0.212	0.344	0.457	1.000	0.503	0.225	0.354	0.491	1.000	0.517	0.943	0.971	0.930	1.000	0.961
PT	17	Banco de Investimento SA	0.452	0.471	0.598	0.473	0.498	0.582	0.656	0.763	0.763	0.691	0.777	0.718	0.784	0.619	0.724
ES	18	BBVA	0.385	0.378	0.446	0.449	0.414	0.876	1.000	1.000	1.000	0.969	0.439	0.378	0.446	0.449	0.428
ES	19	Bankia, SA	0.357	0.440	0.520	0.560	0.469	0.974	0.944	1.000	1.000	0.979	0.367	0.466	0.520	0.560	0.478
ES	20	Bankinter SA	0.298	0.336	0.450	0.542	0.406	0.813	0.838	0.847	0.931	0.857	0.366	0.401	0.531	0.582	0.470
ES	21	Banco Popular Espanol SA	0.482	0.492	0.547	0.424	0.486	1.000	1.000	1.000	0.960	0.990	0.482	0.492	0.547	0.442	0.491
ES	22	Caixa d'Estalvis de Pollensa	0.426	0.411	0.674	0.496	0.502	1.000	1.000	1.000	0.945	0.986	0.426	0.411	0.674	0.525	0.509
ES	23	Caja de Ahorros: Ontinyent	0.430	0.666	0.659	0.529	0.571	0.559	0.916	0.759	0.690	0.731	0.769	0.726	0.869	0.766	0.783
ES	24	Cajas de Ahorros—CECA	0.356	0.270	0.212	0.398	0.309	0.412	0.274	0.225	0.456	0.342	0.864	0.983	0.942	0.872	0.915
ES	25	Banco Mediolanum SA	0.568	0.514	0.434	0.382	0.474	0.694	0.677	0.619	0.697	0.672	0.818	0.759	0.700	0.548	0.707
ES	26	Banca March SA	0.194	0.211	0.192	0.235	0.208	0.287	0.343	0.229	0.306	0.291	0.677	0.614	0.839	0.767	0.724
ES	27	Caixa Estalvis	0.203	0.236	0.290	0.347	0.269	0.751	0.866	0.945	0.878	0.860	0.271	0.273	0.307	0.395	0.312
ES	28	Banco de Sabadell SA	0.246	0.313	0.456	0.466	0.370	0.809	0.790	1.000	1.000	0.900	0.304	0.396	0.456	0.466	0.406
ES	29	Caja Rural de Almendralejo.	0.611	0.527	0.652	0.638	0.607	0.743	0.647	0.684	0.720	0.698	0.823	0.815	0.954	0.885	0.869
PT	30	Haitong Bank SA	0.456	0.373	0.283	0.336	0.362	0.458	0.381	0.320	0.385	0.386	0.996	0.981	0.882	0.872	0.933
PT	31	Banco Finantia SA	0.992	1.000	0.912	1.000	0.976	0.995	1.000	0.992	1.000	0.997	0.997	1.000	0.919	1.000	0.979
PT	32	Banco Santander Totta SA	0.331	0.332	0.365	0.500	0.382	0.703	0.643	0.728	0.799	0.718	0.471	0.516	0.501	0.625	0.528
ES	33	Deutsche Bank SAE	1.000	0.931	0.790	0.776	0.874	1.000	1.000	1.000	1.000	1.000	1.000	0.931	0.790	0.776	0.874
PT	34	CCCAM	0.232	0.199	0.313	0.329	0.268	0.340	0.299	0.353	0.446	0.359	0.683	0.666	0.888	0.737	0.743
ES	35	Bankoa SA	0.280	0.264	0.445	0.760	0.437	0.414	0.409	0.523	0.886	0.558	0.675	0.646	0.851	0.858	0.757

Table 3. *Cont.*

Country	DMU	Bank	TE					PTE					SE				
			2013	***2014***	***2015***	***2016***	***Mean***	***2013***	***2014***	***2015***	***2016***	***Mean***	***2013***	***2014***	***2015***	***2016***	***Mean***
ES	*36*	*Santander Consumer F.*	*0.828*	*0.853*	*0.834*	*0.931*	*0.862*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*0.828*	*0.853*	*0.834*	*0.931*	*0.862*
ES	*37*	*Crédito de Los Ingenieros*	*0.286*	*0.384*	*0.393*	*0.490*	*0.388*	*0.318*	*0.447*	*0.440*	*0.567*	*0.443*	*0.897*	*0.858*	*0.894*	*0.863*	*0.878*
ES	*38*	*Caja Rural de Jaen,*	*0.374*	*0.390*	*0.508*	*0.539*	*0.452*	*0.409*	*0.430*	*0.516*	*0.576*	*0.483*	*0.913*	*0.906*	*0.984*	*0.935*	*0.934*
ES	*39*	*Caja Rural de Navarra*	*0.178*	*0.161*	*0.180*	*0.168*	*0.172*	*0.218*	*0.221*	*0.190*	*0.197*	*0.206*	*0.815*	*0.729*	*0.950*	*0.849*	*0.836*
ES	*40*	*Caja Rural de Soria*	*0.335*	*0.334*	*0.444*	*0.653*	*0.441*	*0.446*	*0.503*	*0.587*	*0.856*	*0.598*	*0.751*	*0.663*	*0.756*	*0.763*	*0.733*
ES	*41*	*Caja Rural de Zamora*	*0.467*	*0.414*	*0.496*	*0.601*	*0.494*	*0.533*	*0.522*	*0.529*	*0.734*	*0.580*	*0.875*	*0.792*	*0.937*	*0.819*	*0.856*
ES	*42*	*Banco Cooperativo Espanol*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*
ES	*43*	*Banco Alcala*	*0.269*	*0.200*	*0.154*	*0.184*	*0.202*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*0.269*	*0.200*	*0.154*	*0.184*	*0.202*
ES	*44*	*Banco Caixa Geral SA*	*0.807*	*1.000*	*1.000*	*1.000*	*0.952*	*0.810*	*1.000*	*1.000*	*1.000*	*0.953*	*0.995*	*1.000*	*1.000*	*1.000*	*0.999*
ES	*45*	*BNP Paribas España SA*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*
ES	*46*	*EBN Banco de Negocios SA*	*1.000*	*0.791*	*0.927*	*0.175*	*0.723*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*0.791*	*0.927*	*0.175*	*0.723*
PT	*47*	*Banco BPI SA*	*0.335*	*0.344*	*0.427*	*0.821*	*0.482*	*0.644*	*0.698*	*0.804*	*1.000*	*0.786*	*0.520*	*0.493*	*0.532*	*0.821*	*0.591*
ES	*48*	*Allfunds Bank SA*	*0.355*	*0.255*	*0.263*	*0.144*	*0.254*	*0.636*	*0.537*	*0.456*	*0.411*	*0.510*	*0.558*	*0.475*	*0.576*	*0.349*	*0.489*
ES	*49*	*Banco Santander SA*	*0.428*	*0.359*	*0.457*	*0.456*	*0.425*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*0.428*	*0.359*	*0.457*	*0.456*	*0.425*
PT	*50*	*BIG*	*0.469*	*0.395*	*0.354*	*0.434*	*0.413*	*0.584*	*0.566*	*0.519*	*0.584*	*0.563*	*0.802*	*0.698*	*0.681*	*0.744*	*0.731*
PT	*51*	*Banco Invest SA*	*0.695*	*0.809*	*0.662*	*0.543*	*0.677*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*0.695*	*0.809*	*0.662*	*0.543*	*0.677*
ES	*52*	*Cajamar Caja Rural, S.C.C.*	*0.235*	*0.214*	*0.287*	*0.319*	*0.264*	*0.510*	*0.494*	*0.511*	*0.468*	*0.496*	*0.460*	*0.434*	*0.562*	*0.682*	*0.534*
ES	*53*	*Criteria CaixaHolding SA*	*0.011*	*0.241*	*0.291*	*0.375*	*0.229*	*0.031*	*0.886*	*0.978*	*0.964*	*0.715*	*0.343*	*0.271*	*0.298*	*0.389*	*0.325*
ES	*54*	*Caja Laboral Popular*	*0.257*	*0.266*	*0.337*	*0.409*	*0.317*	*0.403*	*0.463*	*0.468*	*0.592*	*0.481*	*0.638*	*0.575*	*0.720*	*0.690*	*0.656*
ES	*55*	*Unicaja Banco SA*	*0.308*	*0.213*	*0.249*	*0.338*	*0.277*	*0.528*	*0.494*	*0.586*	*0.587*	*0.549*	*0.582*	*0.431*	*0.425*	*0.576*	*0.503*
ES	*56*	*Banco De Credito Social*	*0.227*	*0.214*	*0.260*	*0.316*	*0.254*	*0.492*	*0.494*	*0.464*	*0.465*	*0.479*	*0.460*	*0.434*	*0.562*	*0.679*	*0.534*
PT	*57*	*Atlântico Europa, Sgps, S.A*	*0.321*	*0.224*	*0.393*	*0.626*	*0.391*	*0.684*	*0.660*	*0.756*	*1.000*	*0.775*	*0.470*	*0.340*	*0.519*	*0.626*	*0.489*
PT	*58*	*Finantipar—S.G.P.S., S.A.*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*
		Mean	*0.409*	*0.412*	*0.446*	*0.498*	*0.441*	*0.660*	*0.689*	*0.705*	*0.773*	*0.707*	*0.623*	*0.600*	*0.645*	*0.653*	*0.630*

4.2. IC and Performance Nexus Analysis

This section starts with a correlation matrix of the applied variables applied in the second-stage analysis (i.e., econometric analysis), as shown in Table 4. Subsequently, the results obtained from the application of the Fractional regression models are presented in Tables 5 and 6.

Table 4. Correlation matrix of the applied variables for the second-stage analysis (Iberian sample).

	PTE	TE	HCE	SCE	CEE	SIZE	Lev1	Lev2	Lev3
PTE	1								
TE	0.8921 *	1							
	0.0000								
HCE	0.2064 *	0.3426 *	1						
	0.0017	0.0000							
SCE	0.0134 *	0.0924	0.5348 *	1					
	0.8403	0.1642	0.0000						
CEE	−0.0517	−0.0685	0.1845 *	0.1112	1				
	0.4371	0.3030	0.0052	0.0940					
SIZE	−0.0528	−0.0399	−0.0720	0.1039	−0.2405 *	1			
	0.4279	0.5490	0.2792	0.1177	0.0002				
Lev1	0.0912	0.1201	−0.1144	−0.2944 *	−0.1272	0.3711 *	1		
	0.1698	0.0702	0.0847	0.0000	0.0551	0.0000			
Lev2	−0.0911	−0.1195	0.1149	0.2942 *	0.1274	−0.3746 *	−0.9999 *	1	
	0.1702	0.0716	0.0834	0.0000	0.0548	0.0000	0.0000		
Lev3	0.4248 *	0.5638 *	0.0250	−0.0340	−0.0902	0.4522 *	0.5913 *	−0.0902 *	1
	0.0000	0.0000	0.7068	0.6096	0.1749	0.0000	0.0000	0.0000	

Notes * VRS and CRS based on Super efficiency scores. The * denotes statistical significance at 1% level.

Table 5. Estimation results for the fractional regression models One part Models (Iberian sample).

	One-Part Models				One-Part Models 1st Part			
	Logit		Cloglog		Logit		Cloglog	
	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
HCE	0.54653	0.3964	0.36	0.2371	0.688	0.449	0.625	0.3601
	(0.00) ***	(0.00) ***	(0.00) ***	(0.00) ***	(0.00) ***	(0.001) ***	(0.00) ***	(0.00) ***
SCE	−0.64	−0.5856	−0.34	−0.2867	−0.799	−0.34	−0.659	−0.23613
	(0.021) **	(0.166)	(0.041) **	(0.080) *	(0.266)	(0.560)	(0.314)	(0.628)
CEE	−2.64	−1.01	−2.23	−0.7058	−7.21	−2414	−7.31	−2037
	(0.00) ***	(0.059) *	(0.00) ***	(0.035) **	(0.036) **	(0.094) *	(0.019) **	(0.095) *
SIZE	−0.2864	0.048	−0.22	0.0505	−1.28	−0.16023	−1.18	−0.1545
	(0.00) ***	(0.645)	(0.00) ***	(0.489)	(0.008) ***	(0.420)	(0.010) ***	(0.363)
Lev1	−14.35	−358.5	−4434	−155.4	482.8	−48.74	470	−44.19
	(0.697)	(0.001) ***	(0.892)	(0.00) ***	(0.835)	(0.814)	(0.829)	(0.807)
Lev2	−18.5	−359.17	−7.3	−156.07	486.3	−49.09	473.5	−444,281
	(0.616)	(0.001) ***	(0.823)	(0.00) ***	(0.833)	(0.813)	(0.827)	(0.806)
Lev3	0.00589	0.013	0.0081	0.0075	0.119	0.0133	0.11	0.0181
	(0.627)	(0.447)	(0.284)	(0.401)	(0.068) *	(0.663)	(0.048) **	(0.388)
Constant	16.9	358.32	6.03	154.8	−474.62	48.82	−462.62	44,038
	(0.649)	(0.001) ***	(0.854)	(0.00) ***	(0.837)	(0.814)	(0.831)	(0.808)
Observation	232	232	232	232	232	232	232	232
R^2	0.35626	0.13281	0.367	0.1367	0.3594	0.0874	0.375	0.09399

Notes: ***, ** and * denotes statistical significance at 1%, 5% and 10% level, respectively.

Table 6. Estimation results for the fractional regression Two-Part Models—2nd part (Iberian sample).

	Two-Part Models—2nd part							
	Logit		**Probit**		**Loglog**		**Cloglog**	
	CRS	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**
HCE	0.442 (0.00) ***	0.3216 (0.00) ***	0.261 (0.00) ***	0.2006 (0.000) ***	0.265 (0.000) ***	0.236 (0.00) ***	0.31 (0.00) ***	0.2264 (0.00) ***
SCE	−0.405 (0.107)	−0.4436 (0.078) *	−0.237 (0.137)	−0.2791 (0.062) *	−0.24 (0.142)	−0.331 (0.079) *	−0.251 (0.215)	−0.3 (0.043) **
CEE	−2012 (0.00) ***	−0.132 (0.776)	−1175 (0.00) ***	−0.0853 (0.762)	−1.06 (0.000) ***	−0.0319 (0.918)	−1.69 (0.00) ***	−0.20673 (0.559)
SIZE	−0.14341 (0.037) **	0.20535 (0.070) *	−0.086 (0.042) **	0.1319 (0.061) *	−0.0865 (0.034)**	0.1376 (0.099) *	-0.11 (0.073) *	0.1635 (0.039) **
Lev1	−3.42 (0.913)	−336.41 (0.001) ***	−0.5204 (0.978)	−187.13 (0.00) ***	0.965 (0.959)	−304,014 (0.001) ***	0.54 (0.984)	−152.5 (0.00) ***
Lev2	−8.63 (0.782)	−336.92 (0.001) ***	−3.43 (0.857)	−187.43 (0.00) ***	−1.4 (0.941)	−304.1 (0.001) ***	−3,643 (0.892)	−153 (0.00) ***
Lev3	−0.0146 (0.366)	0.024 (0.329)	−0.0082 (0.399)	0.0145 (0.316)	−0.0063 (0.485)	0.02103 (0.269)	−0.01216 (0.385)	0.0142 (0.324)
Constant	4.73 (0.881)	333.95 (0.001) ***	1.27 (0.948)	185.56 (0.00) ***	0.025 (0.999)	302.63 (0.001) ***	0.177 (0.995)	150.3 (0.001) ***
Observations	232	232	232	232	232	232	232	232
R^2	0.296	0.22583	0.294	0.2269	0.286	0.2212	0.2955	0.2337

Notes: ***, ** and * denotes statistical significance at 1%, 5% and 10% level, respectively.

The correlation matrix (Table 4), retrieved from Stata 14, for all the selected variables for the second-stage analysis (Iberian sample), shows Lev3 and HCE to be the variables with the highest correlation (significant) with the chosen dependent variables (i.e., TE and PTE). Thus, HCE appears to be the IC-related variable with the highest correlation with banks' performance (i.e., DEA scores). In the second-stage analysis, an econometric analysis was conducted by employing the selected aforementioned variables for the application of the regression models (i.e., fractional).

The selected fractional regression estimates are shown considering both CRS and VRS efficiency scores (i.e., TE and PTE) as dependent variables. Our results indicate a positive and significant effect of HCE on TE and PTE for all fractional regression models.

Also, results show a negative and significant impact of SCE on Iberians banks' efficiency, in the one-part models, according to Table 5 (CRS only), and in one-part cloglog and all second-part of the two-part models, according to Table 6 (VRS only). Moreover, results indicate a negative and significant impact of CEE on Iberians banks' efficiency for all models, except for second part models while considering VRS. The SIZE control variable appears to have a negative and significant impact on Iberian banks' TE in all the models (i.e., one- and two-part models). Conversely, results show a positive and significant effect of SIZE on the PTE of Iberian banks in the second part of the two-part models (see Table 6). Furthermore, the financial risk variables, Lev1 and Lev2, do not show any significant effect on TE in all models. On the other hand, results indicate a negative and significant effect of Lev1 and Lev2 on PTE in the one-part and in the second part of the two-part models (i.e., excludes first-part models). Also, results indicate a positive and significant impact of Lev3 variable on TE, only in the first part of the two part-models.

Finally, r-squared results show more consistency (less variance throughout models) regarding TE (i.e., CRS) throughout the models (Table 5). However, one-part models (i.e., 0.35626 and 0.367 for Logit and Cloglog, respectively) and first-part of the two-part models (i.e., 0.3594 and 0.375 for Logit and Cloglog, respectively) appear to have the higher determination coefficients (i.e., R2). Conversely, r-squared results regarding PTE (i.e., VRS) indicate more inconsistency (more variance throughout model), which translates in much higher determination coefficients, in the second part of the two-part models (i.e., 0.22583, 0.269, 0.2212, and 0.2237 for the second-part Logit, Probit, Loglog, and Cloglog, respectively).

The results for the two-part model (Tables 5 and 6) indicate a consistently positive and significant effect of HCE on Iberian banks' TE and PTE in the first-part and second-part models, which means that, according to the results obtained for this regression, HCE is positively and significantly related to, first, DEA scores of efficient banks (i.e., first-part), and second, DEA scores of inefficient banks (i.e., second-part). Also, SIZE is, in the first-part models, negatively (not significantly) related to efficient Iberian banks' PTE (i.e., VRS), while in the second-part models, results show SIZE to have a positive and significant impact on inefficient Iberian banks' PTE. Also, R-squared results seem to be higher, considering VRS, in the second-part model, which means that the results obtained are better at determining the effects of the independent variables on the inefficient Iberian banks' PTE, rather than first-part models in determining the effects of those independent variables on the efficient Iberian banks' PTE.

5. Discussion

The results obtained in the first-stage analysis show that the averages of Iberian banks' TE and PTE, during the period from 2013 to 2016, are of 40.9% and 70.7%, respectively. In essence, findings from the first-stage DEA suggest that Iberian banks, on average, could reduce their application of resources (inputs) by at least 59.1%, considering CRS, and 29.3%, considering VRS, for achieving the same amount of outcome (outputs) by improving their resources management practices. The results obtained in the second-stage DEA indicate a positive and significant relationship between HCE and performance (i.e., TE and PTE scores), which is in line with the results presented by authors such as Meles et al. (2016), Al-Musali and Ismail (2014), Irawanto et al. (2017), Nawaz and Haniffa (2017), Ousama and Fatima (2015), Ozkan et al. (2017) or Thakur (2017). Moreover, the results indicate a negative and significant effect of SCE (i.e., the other IC-related variable, besides HCE) on TE and PTE, considering fractional regression models (not effective in all the applied regression and models—see Tables 5 and 6). These findings are in line with the results obtained by Ozkan et al. (2017). Furthermore, results show CEE (i.e., non-IC related VAIC™ component) to have a negative and significant relationship with banks' performance (i.e., TE and PTE). These findings contradict all the revised literature that related CEE and banks' performance, such as Al-Musali and Ismail (2014), Iqbal and Zaib (2017), Jafarnezhad and Tabari (2016), or Nawaz and Haniffa (2017), which found a positive and significant relationship between those variables.

These results stress the importance of IC efficiency to create value, namely in the context of developed countries such as Portugal or Spain. Mention and Bontis (2013) already considered the importance of IC, namely of HC, in their study of the banking sector of Belgium and Luxembourg.

Finally, findings suggest inconclusive results for the SIZE variable, showing a negative and significant effect of that variable on banks' efficiency, in some of the fractional models, and also, a positive and significant effect of SIZE on banks' efficiency, considering fractional regression second-part of two-part models, i.e., representing the effect on the DEA scores of inefficient banks. Other authors have found inconclusive results when trying to infer a possible relationship between a SIZE variable (i.e., representative of a bank's size, generally related to the total assets variable) and banks' performance, such as Iqbal and Zaib (2017). Similarly, findings indicate inconclusive results for the Lev1 (i.e., total debt to total assets), Lev2 (i.e., Equity to total assets), and Lev3 (i.e., total liabilities to shareholder's equity) financial risk variables, as results indicate both positive and negative effects of those variables on banks' performance. However, while seeing significant effects only, results show a negative effect of Lev1 and Lev2 on inefficient (considering fractional regression second-part of the two-part models) Iberian banks' PTE, which is in line with the results obtained by Ozkan et al. (2017) and Vidyarthi (2018). Conversely, while seeing significant effects only, results show Lev3 to have a positive and significant impact on more efficient (considering fractional regression first-part of the two-part models) Iberian banks', which contradicts the negative effect of a Lev3-like variable on bank's performance found by Iqbal and Zaib (2017), and the inconclusive results, using the same leverage variable, found by Ousama and Fatima (2015).

6. Concluding Remarks

In this study, a two-stage analysis was conducted in order to address several proposed research questions related to Iberian banks during the period from 2013 to 2016. Therefore, the main purpose of this study was, in a first-stage, to assess sampled banks' performance and respective rankings, through the measurement of their efficiency scores (i.e., using DEA's CRS and VRS models), and in a second-stage, to investigate the impact of IC efficiency and its sub-components (i.e., applying the VAIC™ method) on bank's performance, through the application of fractional (one-part and two-part models) regressions.

First-stage analysis findings show that the averages of Iberian banks' TE and PTE, during the period from 2013 to 2016, are 40.9% and 70.7%, respectively. The average efficiency score of the sampled 58 Iberian banks during the period from 2013 to 2016, considering the CRS model, is 0.409. This means that Iberian banks, on average, could reduce their application of resources (inputs) by at least 59.1% to achieve the same amount of outcome (outputs). Therefore, this paper contributes to the literature by suggesting that by improving their resources management practices, banks can be significantly more efficient. Also, second-stage analysis' findings suggest a positive and significant relationship between HCE and sampled banks' performance and, conversely, a negative and significant impact of both SCE and CEE on sampled banks' performance. At the IC-related sub-component level, only HCE has a positive and significant effect on the efficiency scores of the selected banks (i.e., TE and PTE). Consequently, another contribution to literature emerges: banks' global performance is mainly determined by their human capital efficiency, something which may indicate the pivotal importance of Human Resources Management (HRM) practices and the impact that application of the "best practices" may have on Iberian banking industry's performance in general.

Finally, this study can contribute to stimulate and develop the "IC efficiency versus global performance" theme regarding the banking sector, since it is suggested that the connection between IC components and organisational performance should address two steps to provide a more robust validation regarding the existence of different organisational performances: in a first one, by formulating the frontier function for an efficient production regarding bank products, based on the tangible resources (inputs) affected to such economic activity. A second step, aimed at developing VAIC's composition to measure IC, in order to support better or worse organisational performances. From a practical stance, this study allows stressing the importance of IC measurement as a crucial tool to support decision making. In fact, it can provide bank managers with essential directions to make better and more efficient decisions and improve their organisations' performance. More specifically, although managers should continue developing banks' human capital through different means, such as training sessions, they should also foster a knowledge-based culture as well as relationships with their stakeholders, something which can potentially have a positive impact on their reputation and efficiency. Also, banks with lower performances should follow the best practices of banks with higher ones. The latter should act as benchmarkers for the formers. Other policy implications should be emphasised, namely regarding to the regulators' activities. Regulators could be more aware about the causes of possible non-compliances from Iberian banks.

Some of this study's limitations to the adoption of the VAIC™ method and to the constrains imposed by the availability of the data. Despite using some IC components, which are encompassed in the VAIC™ method as independent variables, in the way of inferring about their impact on banks' performance, these dimensions do not represent IC as a whole, and thus, are not representative of the overall effect of IC on performance. Therefore, future research can include a modified variant of VAIC™ as a way of improving some of the limitations of the original VAIC™ method, e.g., the inclusion of other IC dimensions in the calculation formula and the reformulation of SCE's calculation parameters. Also, further efforts should be made to comprehend better exactly how and why each individual IC component may impact banks' efficiency, thus allowing for the optimisation of IC management and for a more efficient application of intangible resources.

Also, future research on this theme may adopt Benefit-of-the-Doubt Composite Indicators (BoD CI), allowing the aggregation of individual indicators to obtain an overall measure of performance. To do so, the frontier methods has to be used in order to reflect the relative performance of multidimensional concepts beyond the traditional production, intermediation and profitability approaches, involving the transformation of inputs into outputs. Finally, further research should also focus on the effects that the crisis of 2007 had on each Iberian bank.

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Note

[1] https://www.bportugal.pt/sites/default/files/anexos/pdf-boletim/overviewportuguesebankingsystem_2016q4_en_0_0.pdf, accessed in 15 January 2021.

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