Universidade de Aveiro Departamento de Economia, Gestão, Engenharia Industrial e Turismo
2018

José Eduardo F. T. Palhares

Nexo entre o desempenho dos bancos e a eficiência do Capital Intelectual

Banking Firms´ Performance and Intellectual Capital Efficiency Nexus

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Dissertação apresentada à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Mestre em Gestão, realizada sob a orientação científica do Doutor Victor Manuel Ferreira Moutinho, Professor Auxiliar do Departamento de Economia, Gestão, Engenharia Industrial, e Turismo da Universidade de Aveiro, e coorientação científica do Doutor José António Fernandes Lopes Oliveira Vale, Professor Adjunto convidado do Instituto Superior de Contabilidade e Administração do Porto.

Dedico este trabalho à minha mãe por todo o amor, apoio, carinho e dedicação incondicionais.

o júri

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palavras-chave

Capital Intelectual; VAIC; DEA em 2-estágios; Desempenho; Bancos; Regressão por quantis; Regressão fracionária

resumo

Este estudo tem por objetivo a avaliação do desempenho de 58 bancos Ibéricos e a sua relação com a eficiência do Capital Intelectual. Por conseguinte, uma análise de dois estágios foi aplicada de forma a responder às questões de investigação propostas relacionadas com a banca Ibérica (Portuguesa e Espanhola) no geral, e com cada país em particular, durante o período compreendido entre 2013 e 2016. Num primeiro estágio, foi feita uma avaliação e respetiva classificação do desempenho dos bancos selecionados, através da estimação dos seus resultados de eficiência, i.e. aplicando os modelos *Constant* e *Variable Returns to Scale* (CRS e VRS) e de Super-Eficiência do *Data Envelopment Analysis* (DEA). Num segundo estágio, e de modo a aferir a relação entre o desempenho global dos bancos e a eficiência do seu Capital Intelectual, foram aplicados modelos de regressão por quantis e fracionários. Recorreu-se ainda, ao método *Value Added Intellectual Coefficient* (VAIC™), considerando-se as suas componentes como variáveis independentes, para além das variáveis Endividamento, e Dimensão. Os resultados obtidos sugerem que os bancos Portugueses apresentam melhores resultados médios de *technical*, *pure technical*, e *scale efficiency* (i.e. TE, PTE e SE), durante o período de estudo, comparativamente aos bancos espanhóis. Para além disso, os resultados demonstram um aumento das médias dos resultados obtidos (para ambos os modelos, CRS e VRS), durante o período de quatro anos estudado. Finalmente, os resultados obtidos durante a análise de segundo-estágio sugerem uma relação positiva e significativa entre a eficiência do capital humano (HCE) e o desempenho dos bancos selecionados. Contrariamente, os resultados sugerem um impacto negativo e significativo de ambos os componentes, eficiência do capital estrutural e do capital aplicado (SCE e CEE), no desempenho dos bancos que constituem a amostra. Esta poderá ser uma indicação do papel preponderante das práticas aplicadas pela Gestão de Recursos Humanos (HRM), e no impacto que a aplicação das "melhores práticas" poderá ter no desempenho do sector bancário Ibérico no geral, e também no desempenho dos bancos Portugueses e Espanhóis em particular.

keywords

Intelletual Capital; VAIC; 2-stages DEA; Performance; Banks; Quantile regression; Fractional regression

abstract

This study aims to assess 58 Iberian banks´ performance and its relationship with Intellectual Capital efficiency. Therefore, a two-stage analysis was conducted in order to address several proposed research questions related to Iberian (Portuguese and Spanish) banks in general, and each country, individually, during the period from 2013 to 2016. In a first-stage, sampled banks´ performance and respective rankings were assessed, through the measurement of their efficiency scores, i.e. using DEA´s (Data Envelopment Analysis) Constant and Variable Returns to Scale (CRS and VRS) and Super efficiency models, and in second-stage, both quantile and fractional regression models were applied as way of inferring about the impact of selected independent variables, i.e. Value Added Intellectual Coefficient (VAIC™) components, Leverage and Size, on the DEA scores of Iberian banks´. Findings suggest that Portuguese banks have constantly better average Technical, Pure Technical, and Scale Efficiency (i.e. TE, PTE, and SE) scores throughout the studied period, in comparison to Spanish banks. Also, findings show an increase on average efficiency scores (for both CRS and VRS), over the studied four-year period, for all sampled Iberian banks. Finally, second-stage analysis findings suggest a positive and significant relationship between Human Capital Efficiency (HCE) and sampled banks´ performance. Conversely, results suggest a negative and significant impact of both Structural and Employed Capital Efficiency (i.e. SCE and CEE) on sampled banks´ performance. This may be an indication of 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, and also on Portuguese and Spanish banks´ performance in particular.

Table of contents

List of tables

List of figures

Abbreviations & Acronyms

BV – Book Value

CEE – Capital Employed Efficiency

CRS – Constant Returns to Scale

DEA – Data Envelopment Analysis

DUM – Decision Making Unit

EPS – Earnings Per Share

HC – Human Capital

HCE – Human Capital Efficiency

IA – Intellectual Asset

IC – Intellectual Capital

ICE – Intellectual Capital Efficiency

IL – Intellectual Liability

MV- Market Value

MVAIC – Modified Value Added Intellectual Coefficient

OECD – Organisation for Economic Co-operation and Development

PTE – Pure Technical Efficiency

RC – Relational Capital

RCE - Relational Capital Efficiency

ROA – Return on Assets

ROE – Return on Equity

SC – Structural Capital

SCE – Structural Capital Efficiency

SE – Scale Efficiency

TE – Technical Efficiency

VA – Value Added

VAIC™ - Value Added Intellectual Coefficient

VRS – Variable Returns to Scale

Chapter 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) (Alhassan & Asare, 2016; M. Cabrita, Ribeiro da Silva, Gomes Rodrigues, & Muñoz Dueñas, 2017; Tiwari & Vidyarthi, 2018; Vale, Branco, & Ribeiro, 2016). Nowadays, IC seems to be built upon the same three-dimensional model followed by earlier conceptualisations (Inkinen, 2015; Inkinen, Kianto, Vanhala, & Ritala, 2017), namely Human Capital (HC), Structural Capital (SC), and Relational Capital (RC). These dimensions constitute IC, representing knowledge, experience, intellectual property, innovation potential, culture, external relationships, and information (Andreeva & Garanina, 2017; Kianto, Sáenz, & Aramburu, 2017; Tiwari & Vidyarthi, 2018), and are now seen as a vital input for improving performance, and thereby sustain a competitive advantage (Venugopal, Nambi, & M., 2018). This has been reflecting in the exponential increase of capital investment in immaterial resources (Intangibles Assets), in detriment of the more traditional 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).

Organisations have been using various measurement tools for assessing and evaluating their respective tangible (TA), and intangible assets (IA), such as IC (Pablos, 2003). VAIC™ seems to be one of the most attractive and suggested IC measurement tools (Zéghal & Maaloul, 2010) for analysing IC efficiency (Nazari & Herremans, 2007), which is used transversely in a panoply of countries and in different methodology contexts. This is due to the fact that the VAIC™ method, despite of its limitations, provides consistent and objective measurements, "which are applicable to any industry because they are designed to evaluate efficient usage of resources" (Xu et al., 2017, p. 1059).

The importance of IC transcends any specific sector particularities, beside all the intrinsic aspects that may exist, e.g. culture and inherent sectoral differences. Nevertheless, those differences may consubstantiate in the fact that some sectors are more knowledge-intensive than others. This is the case for institutions pertaining to the banking sector, which use knowledge as their main source and product in the input-output process (M. Cabrita et al., 2017).

The banking sector is entirely different from other sectors in the economy (Danisman, 2018), due to the pivotal socio-economic role it plays regionally, nationally and internationally, as 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 & Carrales, 2018). After the 1970s, the liberalisation and deregulation process resulted in increased competition in the sector and has led banks to shift their focus from gathering deposits and providing loans to conducting a wider array of activities (Danisman, 2018).Therefore, banks are nowadays amongst the most important agents in the financial system by actively contributing to the efficient reallocation of resources in the market, funding enterprise projects, promoting economic growth, maintaining long-term relationships with organisations, reducing information asymmetry and share risk, hence mitigating economic fluctuation (Novickytė & Droždz, 2018).

On the other hand, in the same way, banks face great financial risks, and can become responsible for economic collapse, when in the epicentre of a potential systemic crisis by disseminating financial contagion through the interaction with other participants pertaining to the financial system (Danisman, 2018), as was the case in the subprime mortgage crisis of 2009 (Diallo, 2018). Consequently, nowadays banks comply to more stringent regulations, their financial reports are under constant scrutiny, and their performance is being continuously monitored, as a "prophylactic" approach that identifies poor performance indicators that may eventually lead to substantial financial, economic and social undesirable consequences (Ouenniche & Carrales, 2018). It is up to the regulatory and supervisory entities to properly monitor banking risks and to prevent such situations from occurring, which is not always the case due to information asymmetry (Bos & Kool, 2006).

Financial sector´s development should be seen as an essential strategy for achieving extensive sustainable economic growth in the long term (Novickytė & Droždz, 2018). Hence, it is of great importance to safeguard an effective operation of banking firms through the implementation of methods and tools that allow for 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 for 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 one, is the Data Envelopment Analysis (DEA) method (C.-H. Tsai, Wu, Chen, Chen, & Ye, 2017). DEA is 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). Therefore, DEA is often suggested as the method of choice for compiling bank ratings (i.e. reference points for comparison), which takes efficiency as a key concept and is determined by comparing the related input and output variables (Ponomarenko, Kolodiziev, & Chmutova, 2017).

This study´s purpose consists in analysing both banks´ performance (through efficiency assessment) and IC efficiency (through VAIC™), as well as, their respective relationship (regression analysis). Taking into account the presented subject and framework, this study aims to analyse:

1. The evolution of Iberian banking industry´s efficiency in general, and also of both Portuguese and Spanish banking industry individually, during a recent time period, more specifically, in a post-crisis recovery period, i.e. 2013 to 2016.

2. The effect of the chosen IC-related efficiency variables on sampled banks´ performance.

Hence, to pursue the aforementioned objectives, it is important to raise a set of research questions, such as: (1) Which Iberian banks achieved maximum efficiency? (2) How are IC efficiency components related to sampled banks´ performance? (3) How do Portuguese and Spanish banks differ regarding both performance and IC efficiency?

This study applies a two-stage analysis as 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 regression models (i.e. quantile and fractional) in order to infer about the effect of IC efficiency (using VAIC™ components) on performance (as measured by banks´ efficiency scores).

There seems to be a lack of studies that simultaneously encompass parametric (i.e. DEA) and non-parametric (i.e. regression analysis) methods for evaluating efficiency and its IC-related determinants, using a two-step analysis logic. Additionally, the existence of a study that includes data from these two EU countries, i.e. aggregating both Portugal and Spain, while applying the aforesaid methodology for inferring about the relationship of IC efficiency on performance, is unknown to date.

Some contributions resulted from this study, namely:

1. The presentation of an efficiency analysis of sampled banks operating in the Iberian Peninsula, during the period from 2013 to 2016 (post-crisis).

2. Analysis of changes in efficiency and consequent relative positioning, including banks with maximum efficiency (i.e. efficient banks), through the application of the DEA-Super-efficiency;

3. Analysis of the determinants of banks´ performance (assessed through efficiency scores), more precisely, the components that allow for the assessment of IC efficiency (i.e. pertaining to the VAIC™ model), and also, the components of risk (i.e. Leverage ratios) and dimension (i.e. Size variable), during the proposed four-year period, through the application of both quantile and fractional regression models.

This dissertation is organised in five main chapters: In Chapter 1, an introduction to the subject is made, in which, the purpose, main objectives, and proposed research questions are outlined. In Chapter 2, a brief introduction will be made through an extensive literature review, including all theoretical and empirical evidence that sustains the subject of organisational performance and its nexus with intellectual capital efficiency. In Chapter 3, contextual setting, data collection and research methodology are described, as well as the applied variables in the first- (i.e. DEA) and second-stage (i.e. quantile and fractional regression models) analysis. Then, in Chapter 4, results are analysed and discussed, with a clear goal of identifying the existence or absence of similarities in the behaviour of bank´s performance explanatory variables, at the Iberian level (total sample of 58 Portuguese and Spanish banks), but also, at each country individual level (sample with 42 banks operating in Spain and sample with 16 banks operating in Portugal). Finally, conclusions and cues for future research are offered in Chapter 5.

Chapter 2 Literature review

2.1 Performance conceptualisation and measurement

One of the most intensively studied topics, at the management level, is entrepreneurial performance. Nevertheless, several scholars believe that there is an obvious necessity to deepen that study, and rethink the concept and measurement of performance, which is rarely defined with precision (e.g. Choong, 2014; Folan, Browne, & Jagdev, 2007; Franco-santos et al., 2007; Lebas & Euske, 2011; Neely, Gregory, & Platts, 2005)

The difficulty in defining performance resides also in its multidisciplinary character, in its multiple coexisting dimensions, not always consistent with each other, since it is possible to appreciate performance through a myriad of perspectives, e.g. accounting, economy, human resources management, marketing, operational management, psychology, and sociology (Choong, 2014; Lebas & Euske, 2011; A. Neely et al., 2005).

Neely et al. (2005), defined performance measurement as the process of quantifying efficiency and effectiveness of a company´s equity through metrics that capture each share´s efficiency and effectiveness. Effectiveness refers to the satisfaction of clients´ necessities, while efficiency corresponds to the way an organisation´s resources are applied with the purpose of satisfying those necessities.

According to Lebas & Euske (2011), the term performance can be used while referring to an action or the result of that action, as well as to the success of that action´s result comparing to some particular reference. As for the concept, in general and empiric terms, this study delves into the term performance and relates it to the efficiency and profitability meanings.

Over the years, several methods or tools have been developed for measuring organisations´ performance. Until the 80s, performance was basically analysed through economic-financial indicators, such as: profit, sales volume, sales profitability, sales per employee, ROI, ROA, Equity profitability (e.g. ROE), appreciated either in simple form as in additive models or Dupont multiplicative, or the EVA (Economic Value Added). For many scholars these metrics were limited, because they only focused in the past and on the internal perspective of organisations, essentially only focusing in them and in their own processes (Chenhall & Langfield-Smith, 2007; Tezza, Bornia, & Vey, 2010). Therefore, these metrics do not take in account, nor measure all the critical factors necessary for achieving organisational success (Gomes, 2005).

Since the 80s, pointed criticism to financial metrics allied with occurring changes in the corporate scenario (Melnyk, Bititci, Platts, Tobias, & Andersen, 2014), led to the development of more sophisticated tools, which incorporate both financial and non-financial indicators, e.g. the Strategic Measurement and Reporting Technique (SMART pyramid) from Cross & Lynch (1988); the performance Measurement Matrix from Keegan, Eiler, & Jones (1989); the Results-Determinants Framework from Brignall, Fitzgerald, Johnston, Silvestro, & Voss (1991); the Balanced Scorecard (BSC) from Kaplan & Norton (1992); the Input Process-Output-Outcome Framework from Brown (1996); and the Performance Prism (PP) from Neely & Adams (2001).

These tools measure performance in a multidimensional perspective, but they do not present a global performance index for comparing or benchmarking amongst organisations. This multidimensionality is captured through multiple indicators, which incurs in a risk of dispersing managers' attention and in loss of focus (Neves & Lourenço, 2009). Eventually, one could summarise in a measure of performance, all the subjective weighted averages from the various analysed dimensions, as suggested by Kaplan & Norton (1996) with the BSC. This implies a previous attribution of subjective weights for analysing each variable, in each of the performance measuring methods, which has been generating a lot of controversy, and that may skew comparisons between firms (Neves & Lourenço, 2009).

2.1.1 Measuring firms´ performance through efficiency (DEA)

The abovementioned limitations to the traditional performance measurement have led to a rise in the use of frontier methods, which present a global performance index, and whose calculation requires the estimation of an efficiency frontier and the measurement of each unity´s deviation from that same frontier. Although several performance measurement methods have been developed, in the last decades, based on the frontier concept, the most popular seem to be the Stochastic Frontier Analysis (SFA) and the Data Envelopment Analysis (DEA) (Coelli, Rao, O'Donnell, & Battese, 2005).

The SFA is a parametric methodology that allows for error measurement, but that requires the previous definition of the functional form for the production function, i.e. the specification and estimation of an equation, which represents the transformation process of resources (inputs) in goods or services (outputs). On the other hand, the DEA is a non-parametric methodology, which is built upon an empirical model based on linear programming, therefore not requiring the previous specification of the production function, 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). DEA is often suggested as the method of choice for compiling bank ratings (Ponomarenko et al., 2017), by taking both efficiency and effectiveness as key concepts for assessing productivity, and thus, measure performance.

Although sometimes used interchangeably, the terms efficiency, effectiveness, and productivity, have in fact distinctive semantic value. Both Efficiency and effectiveness compose productivity, which refers to the reason between outcomes (outputs) and applied resources (inputs). Efficiency (assessed by applying an input-oriented DEA) measures the efficient application of resources (doing things right), while effectiveness (assessed by applying an output-oriented DEA) measures the degree to which something is successful in producing a desired result (doing the right things) (Carvalho, 2004).

Given the DEA methodology´s flexibility and following the example of several authors (see also Appendix 3), such as (Barman, Adhikari, & Dey, 2015; Diallo, 2018; Kumar, Charles, & Mishra, 2016; Novickytė & Droždz, 2018; Ouenniche & Carrales, 2018; Ponomarenko et al., 2017; Rusydiana & Firmansyah, 2017; Said, Zouari-Hadiji, & Bouri, 2017; Sumantyo & Tresna, 2017; Vidyarthi, 2018), hence the DEA was the chosen method for the purpose of analysing the performance of the sampled Iberian banks. This is one of the leading methodologies for efficiency evaluation and benchmarking, being applied to real world problems in a multitude of sectors, such as the banking one (Cook, Tone, & Zhu, 2014; C.-H. Tsai et al., 2017). The two-stage analysis methodology applied in this study will be more thoroughly explained in Chapter 3.

Basílio, Pires, & Reis (2016), studied 24 Iberian (10 PT and 14 ES) banks´ efficiency in a first-stage (applying DEA) and its determinants in a second-stage (Generalised Linear Model with a fractional response model), from 2008 to 2013 (6 years). For the DEA an intermediation approach was followed, in which, personal expenses and deposits were chosen as the inputs, while Loans was the chosen output. These authors found Spanish banks to be slightly more efficient than their Portuguese counterparts, and positive and significant effect of liquidity on overall efficiency, and positive and negative (significant) impacts of the capitalisation variable on PT and ES banks´ overall efficiency, respectively. Also, Ghaeli (2017), studied the efficiency of 26 US banks (DMUs) in 2016, using Total Assets and Number of Employees as inputs, and Net Revenue as output for the DEA. The authors found “Santander” to be the most efficient bank operating in the US followed by “SunTrust” and “HSBC”, and that the other banks preserved lower efficiency in comparison. Liu (2018), studied the efficiency of 29 foreign commercial banks in Taiwan (DMUs), from 2011 to 2014 (4 years), using

Operating Resources (inputs), Interest and Non-Interest Revenue (outputs) for the DEA (3-stage model). The authors found that most foreign banks need to reduce more inputs in the third stage than in first stage to achieve relative efficiency, and that using a three-stage DEA approach can result in a more specific and precise set of criteria for true managerial efficiency. Novickytė & Droždz (2018), studied the performance efficiency of 6 commercial banks in Lithuania, from 2012 to 2016 (5 years), using Deposits, Labour expenses, Debts to banks and other financial institutions (inputs), Operating Profit, Loans, Profit before tax, and Net interest income (outputs) for the DEA (5 alternative models with different input-output combinations). The authors found that local banks show better efficiency results on the VRS assumption, while the CRS assumption shows that banks owned by the Nordic parent group and branches, have higher pure efficiency and success at working at the right scale than local banks. Ouenniche & Carrales (2018), studied the efficiency of 109 commercial banks in the UK, from 1987 to 2015 (29 years), using Resources, Costs (inputs), and the ability to provide both financial services and generate revenue (outputs) for the DEA (regression-based feedback mechanism, and models without explicit inputs (WEI) or outputs (WEO)). The author found that, on average, commercial banks in the UK (domestic or foreign) are yet to achieve acceptable levels of overall TE, PTE and SE, and also, that a linear regression-based feedback mechanism proves effective at improving discrimination in DEA unless the initial choice of inputs and outputs is well informed. Martins (2018), studied the efficiency of 26 Portuguese banks, from 2005 to 2010 (6 years), using two-stage models for obtaining efficiency scores for both production and intermediation approaches. For the production approach, these authors chose Equity, Nº of employees, and Nº of branches as inputs, while selecting deposits as the only output. In the intermediation approach, the deposits variable was chosen as the only input, while Loans, Gross Value Added, and Shareholder value creation, were chosen as the outputs. Furthermore, the author applied a fractional regression model for inferring about the effect of the selected 18 independent variables (classified into five categories, namely, competition, human resources, dynamics, finance, and characteristics). The author found that the average efficiency level was of 69,7%, and the internationalisation and dimension variables appear to have a major positive influence on overall efficiency.

2.2 Intellectual Capital

The term Intellectual Capital (IC) is not a new one. In fact, its use dates back to the 19th century, when the economist Nassau William Senior applied the term in his 1836´s book "An Outline of the Science of Politic Economy" (Marr, 2007). However, due to the scope and substance of its application, some authors also give a great relevance to the seminal use of the term by John Kenneth Galbraith in his 1967´s and 1969´s publications (Chang & Hsieh, 2011; Dyakona, 2015; Garcia-Parra, Simo, Sallan, & Mundet, 2009; Hsu & Fang, 2009; Xu et al., 2017). 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 the term with the concept of capital, describing IC as knowledge that generates profit or helps in the creation of other values (Dyakona, 2015).

Nowadays, this conceptualisation can be considered incomplete, ambiguous and even inadequate, however it captured some of the essence of IC, and is somewhat aligned with the connection of thought followed by contemporary definitions. According to Marr (2007), there are no right or wrong definitions of IC, only adequate or inadequate ones. This author claimed that a least adequate definition results from failing to concisely construct IC, leaving it open to different possible interpretations from the readers. As to be expected, these definitions have been evolving over the years with the blooming of new IC literature. Nevertheless, authors like Ozkan, Cakan, & Kayacan, (2017), W.-K. Wang, Lu, Kweh, & Cheng (2014), and Zéghal & Maaloul (2010), claimed there was no commonly accepted definition for the construct of IC at the time, and that premise still applies today.

One of the reasons for this lack of convergence (to some extent) regarding the construct of IC 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, Rashid, & Annuar, 2017; Garcia-Parra et al., 2009; Joshi, Cahill, Sidhu, & Kansal, 2013; Xu et al., 2017), e.g. Economy, Strategic Management, Finance, Accounting, Human Resources, Marketing, etc., which restricts the potential for generalisation and comparability (Marr, 2007). This incongruity between definitions and taxonomies, and the resulting proliferation of diverse classifications and measurement techniques, indicates methodological and practical difficulties (OECD, 2008).

Chronologically speaking, IC research can be said to have been developed in two major phases (Inkinen, 2015). The first phase occurred in 1990s with the publishing of the more theoretical papers made by seminal authors like Bontis (1999), Kaplan & Norton (1992), Pulic (1998), Edvinsson (1997), Saint-Onge (1996), Sveiby (1997), which gave the IC subject some momentum (Tiwari & Vidyarthi, 2018) and publicity, therefore attracting more attention, and making it a more thoroughly studied topic (Cheng, Lin, Hsiao, & Lin, 2011; Joshi et al., 2013; Martín-de-Castro, Delgado-Verde, López-Sáez, & Navas-López, 2011; Zéghal & Maaloul, 2010). Consequently, a second phase succeeded in the early 2000s (i.e. everything post-seminal), which has been focusing on the IC measurement methods and new levels of analysis (Inkinen, 2015). Before delving into those methods and other aspects of IC, one should try to define the term based on the revised literature. Table 1 contains a chronological-summary of a few selected IC definitions.

***Table 1** – Chronologically-ordered Intellectual Capital definitions*

Author	Definition
	1st Phase (Seminal)
(Saint-Onge, 1996), p. 10)	"Includes (…) the capabilities of the individuals required to provide solutions to customers" (Human Capital), "the depth (penetration), width (coverage), attachment (loyalty), and profitability of customers" (Customer Capital), and "the capabilities of the organization to meet market needs" (Structural Capital)
(Edvinsson, 1997, p. 368)	"the possession of knowledge, applied experience, organisational technology, customer relationships, and professional skills that provides (…) a competitive edge in the market"
(Sveiby, 1997, p. 76)	"the invisible part of the balance sheet" that "can be classified as a family of three": Employee competence; Internal Structure; and External Structure
(Bontis, 1999, p. 436)	"comprises intangible resources: people and their expertise, business processes and market assets such as customer loyalty, repeat business, reputation, and so forth"
	2nd Phase (Post-seminal)
(Pablos, 2003, p. 63-64)	"A broad definition (…) difference between the company's market value and its book value. Knowledge-based resources (…) not registered in the financial accounts"
(Kannan, 2004, p. 389)	"intellectual material such as knowledge, information, intellectual property and experience that can be used to create wealth. "
(Youndt, 2004, p. 337)	"the sum of all knowledge an organization is able to leverage in the process of conducting business to gain competitive advantage."
(Kujansivu, 2008, p. 26)	"immaterial sources of value related to employees' capabilities, the organisation's resources and processes and relationships with its stakeholders"

(Zéghal & Maaloul, 2010, p. 41)	"the sum of all knowledge a company is able to use in the process of conducting business to create value – a VA for the company".
(Alipour, 2012, p. 54)	"group of knowledge assets that are owned and/or controlled by an organization and most significantly drive organization value creation mechanisms for targeted company key stakeholders"
(Dyakona, 2015, p. 70)	"the aggregate of human, structural, consumer, organizational, process, innovative and cultural qualities of society, which are acquired through learning, skills and experience, applied in intellectual activity by each member of society individually or collectively and increase work efficiency."
(Andreeva & Garanina, 2017, p. 32),	Defined IA as: "Knowledge, know-how, innovation potential, licence agreements, management culture, and other resources of company growth."
(Cabrita et al., 2017, p. 3)	"Skilled employees as well as sound infrastructures, networking systems, information systems, innovativeness, brand name, trademarks and knowledge bases (…) needed to facilitate the delivery of high value-added products and services".
(Vidyarthi, 2018, p. 2)	"knowledge, experience, intellectual property and information", which enhances "productivity, efficiency, and profitability".

As may be seen from the aforementioned definitions (Table 1), initial investigation on IC was mostly based on the fact that financial accounting could not explain the existing discrepancy between MV and BV (Anifowose et al., 2017; Appuhami, 2007; Kujansivu & Lönnqvist, 2007). Therefore, prior studies defined IC as the hidden value in traditional financial statements, which traditional reporting frameworks failed to identify (Brennan & Connell, 2000; Edvinsson, 1997; Pablos, 2003; Sveiby, 1997). Those definitions seem inadequate by today's standards, nevertheless they touched some pertaining aspects about IC conceptualization, measurement, and reporting.

Bontis (1999), alleged that the hidden value in organisations financial reports could be partly explained by the traditional focus on reporting tangible assets in the annual reports, which could be explicitly calculated. Conversely, knowledge is mostly tacit and therefore difficult to measure, evaluate and report (Guthrie, Ferrier, & Wells, 1999). Guthrie et al. (1999), claimed that accounting practice did not provide for correct measure and evaluation of the intangibles such as staff competencies, customer relationships and models, nor even for the more traditional intangibles such as brand equity, patents, and goodwill, which not long ago, had also been omitted from the financial reports.

Therefore, this “hidden value theory” was preponderant for establishing the bases for future literature and spurred further investigation on the topic. Since then, other scholars have come along with their own idiosyncratic definitions of IC, which are normally linked to different disciplinary assumptions. Although this inter-disciplinary approach to the conceptualisation of IC seems a major source of divergence amongst the myriad of IC definitions, it is also a way for the “under-developed” perspectives of IC (e.g. Marketing, HR, Accounting) to improve their conceptualisation, measuring, and reporting approach, based on “more developed” ones, e.g. the economist and strategy perspectives (Marr, 2007).

Vale et al. (2016) claimed that IC conceptualizations tend to focus only on future benefits (e.g. competitive advantage, improved efficiency and productivity, and value creation) that IC investments (i.e. Intellectual Assets - IAs), may present, while future losses (e.g. bad application of IC investments, deterioration/destruction of IAs) from those investments (i.e. Intellectual Liabilities – ILs) seem to be relegated. This approach is based on two perspectives over ILs, i.e. a strategic and an accounting one (Garcia-Parra et al., 2009), which explains the potential causes for organisational deterioration.

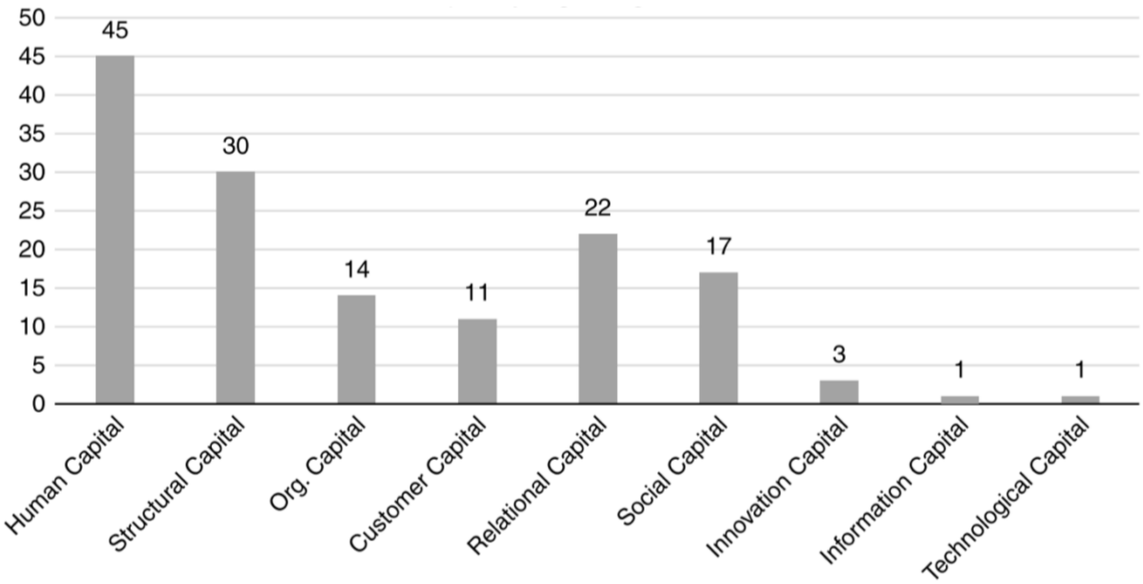
Based on Table 1 and other revised literature, we can try to define IC as a set of immaterial resources, not touchable by its nature (intangibles), such as knowledge, experience, intellectual property, innovation potential, culture, external relationships and information (Andreeva & Garanina, 2017; Kianto et al., 2017; Vidyarthi, 2018), which may be leveraged, and over time (Giuliani, 2015) result in “a Value added (VA) for the company”(Zéghal & Maaloul, 2010, p. 41), or in a deteriorated one (Vale et al., 2016; Vale, Ribeiro, & Branco, 2017).

2.2.1 IC and its dimensions

As can be seen from the aforementioned concepts and descriptions, there is still a lot of work to be done for achieving a standard definition of IC. Nevertheless, there seems to be a common base, grounded on seminal literature, suggesting a three-dimensional conceptualisation of IC (Anifowose et al., 2017; Bontis, Chua, Keow, & Richardson, 2000; M. do R. Cabrita & Bontis, 2008; M. Cabrita et al., 2017; Cavicchi & Vagnoni, 2017; Costa, 2012; Javornik, Tekavcic, & Marc, 2012; Özer, Ergun, & Yılmaz, 2015).

Nowadays, most scholars seem to support, or build upon the same three-dimensional IC model followed by earlier conceptualisations (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; Javornik et al., 2012). Figure 1 results from the tracking of varied IC dimensions applied in the revised literature by Inkinen (2015). This author claims that highly cited publications from seminal authors have indeed "shaped the empirical state of the field" of research, which "is rarely conducted without incorporating human and structural/organisational capital within the measurement model", (e.g. VAIC™), and also, "relational/customer capital as the third dimension", p. 528.

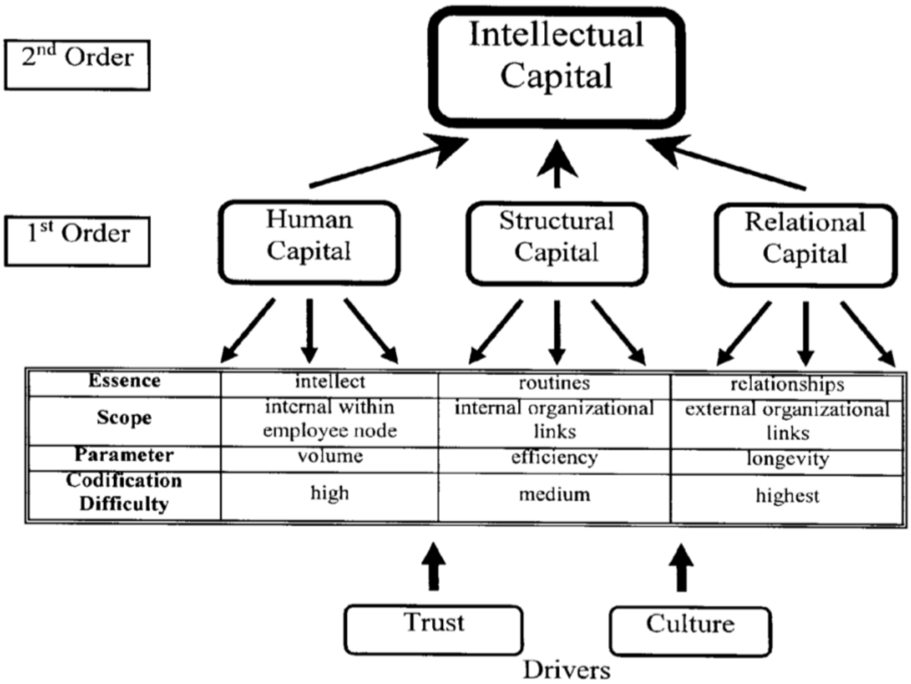
Figure 1 *- Publication frequency regarding different IC Dimensions*



Source: (Inkinen, 2015)

Social Capital seems to be gaining more supporters (Figure 1) and has emerged as a fourth dimension of IC. However, this dissertation will be focusing on the three most commonly cited dimensions of IC (Figure 1 and 2), i.e. Human Capital (HC); Structural Capital (SC); and Relational Capital (RC), which are more related to the chosen VAIC™ method.

Figure 2 - *Conceptualisation of Intellectual Capital*



Source: (Bontis, 1999)

2.2.1.1. Human Capital

According to Ahangar (2011), p. 89, Human Capital (HC) is the most studied dimension of IC, and recognized as an organisation´s "largest and most important" intellectual asset. Kianto et al., (2017), referred to HC as "the most significant element of IC, because a firm can accomplish nothing (including innovation) without it", p. 12. Yang & Lin (2009), p. 1968, defined HC as the "core asset of an organisation", that sustains a competitive advantage; "the greatest and most powerful asset", which is composed by "knowledge, skills, experience, competence, attitude, commitment, and individual personal characteristics.".

In essence, HC is the basic component for the IC process (Chahal & Bakshi, 2014), constituted by knowledge (explicit and tacit) generated and controlled by an organisation´s employees (Martín-de-Castro et al., 2011) and their idiosyncrasies, e.g. loyalty, versatility or flexibility (M. Cabrita et al., 2017), which represents a source of innovation and strategic renewal (Ahangar, 2011; Bontis, 1999; Kianto et al., 2017; C.-H. Liu, 2017a). Therefore, HC is not an asset owned by an organisation (Bontis et al., 2000), but the sum of all individual and collective innovation knowledge, which combines intelligence, skills, and expertise (Bontis, 1999), gathered by personnel within an organisation with the purpose of creating value. This presupposes an IA perspective over HC, however an IA may as well turn into an IL, and therefore value may disappear if not properly managed (Dumay, 2016), by getting deteriorated or destroyed (Vale et al., 2016, 2017).

Martín-de-Castro et al. (2011) considered three main dimensions for categorizing the nature of HC, such as: Knowledge (i.e. formal education, specific training, experience, and personal development), Abilities (i.e. individual learning, collaboration-team work, communication and leadership), and Behaviours (i.e. felling of belonging and commitment, self-motivation, job-satisfaction, friendship, flexibility, and creativity).

As "knowledge generation and transfer is an essential source of firm´s sustainable competitive advantage" that "entirely depends on individuals´ willingness" (Cabrita & Vaz, 2005, p. 12), hence HC has been drawing more attention and investment from the organisations. Therefore, Human Resources Management (HRM) practices (i.e. recruiting and selection, health and safety, performance and appraisal, and training and development) have been seen as a crucial investment, since it can have a significant impact (positive or negative) in HC, and consequently, in innovation (Kianto et al., 2017), sustainable development (Cavicchi & Vagnoni, 2017), value creation (Yang & Lin, 2009), and in the overall company success (Inkinen, 2015). Again, this can work both ways, which means that a bad HRM practices implementation, may actually deteriorate HC, and thus negatively impact an organisation's performance (Vale et al., 2016, 2017).

2.2.1.2 Structural Capital

Structural Capital (SC) can be seen as a supportive infrastructure (Ahangar, 2011), which comprises all non-human assets (M. do R. Cabrita & Bontis, 2008; Rehman, Rehman, & Zahid, 2011) owned by, and that therefore, stay within the organisation when employees go back home (Ahangar, 2011). Conversely to HC, SC "is an intangible asset that can be traded, reproduced and shared within the firm (Mehralian, Rasekh, Akhavan, & Ghatari, 2013), and as such, can be protected by law as intellectual property (Martín-de-Castro et al., 2011).

One may describe SC as the skeleton and the glue of an organisation, as it provides the tools for retaining, packaging, and moving knowledge, generated by HC, along the value chain, and therefore, may constitute a strategic asset, which embodies 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 (Bontis et al., 2000; M. do R. Cabrita & Bontis, 2008; Y.-S. Chen, 2008), thus necessary for the transformation of HC into business intellect (Nazari & Herremans, 2007). Organisation´s SC may be used to "inspire employees to question the prevailing learning culture norms and initiate new ways of thinking", (Liu, 2017, p. 15), therefore fostering innovation "by providing a (collective) infrastructure for knowledge development activities within an organization." (Kianto et al., 2017, p. 12).

One important constituent of SC is organisational culture, which composes the beliefs, core values, traditions and pervasive mind-sets within an organization, and "results in a language, symbols, and habits of behaviour and thought" (Bontis, 1999, p. 450). According to Bratianu et al. (2011), culture is a powerful integrator as it acts on individual intelligence and individual core values, contributing to the development of IC with potential for innovation.

Structural Capital seems to be the most applied term within the existing nomenclature for this class of IC (Appuhami, 2007; Bontis et al., 2000; M. Cabrita et al., 2017; Dyakona, 2015; Inkinen, 2015). However, other scholars have divided SC into other subcategories, such as Customer Capital and Organisational Capital (Edvinsson, 1997; C.-H. Liu, 2017b), and some have gone even further by also subcategorizing Organisational Capital into Process Capital and Innovation Capital (Nazari & Herremans, 2007). Anifowose et al. (2017), claimed that there was some ambiguity regarding the conceptualisation of SC and its taxonomies, therefore the author pertinently proposed a tripartite categorisation: (1) Innovation Capital (i.e. direct consequence of an organisation´s culture), (2) Protected Capital (i.e. IAs covered by legal protection - Intellectual Property), and (3) Process Capital (i.e. workflow, operation processes, specific methods, business development plans, information technology systems, cooperative culture, etc. (Hsu & Fang, 2009).

2.2.1.3 Relational Capital

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 & Herremans, 2007), whether it is of market channels, customer and supplier relationships, as well as a profound understanding of governmental or industry association influences, representing the potential an organisation has to externalize its intangibles (Bontis, 1999). Hence, when talking about RC one should focus on the way organisations absorb, exploit and explore new knowledge from its environment (e.g. business ties) to obtain and sustain a competitive advantage (Martín-de-Castro et al., 2011), which, e.g., allows them to "identify new market niches and gain market advantages over competitors" (Liu, 2017b, p. 555).

According to Bontis (1999), RC is the most difficult of the three dimensions to develop since it is the most external to the organisation´s core, thus the most difficult to codify, and that can only be measured through a function of longevity, which relates to the dynamic process of value creation or destruction that evolves over time view of IC (Giuliani, 2015; Vale et al., 2016). Some of the knowledge composing RC can be considered proprietary, but merely within a temporal perspective and not with a great degree of confidence (Guthrie et al., 1999).

Although some researchers have been using distinct terminology for this class o IC (Inkinen, 2015), such as Social Capital (C.-H. Liu, 2017a, 2017b; W. Tsai & Ghoshal, 1998), Customer Capital (C.-H. Liu, 2017b; Saint-Onge, 1996) and External Structure (Sveiby, 1997), nowadays, the vast majority of scholars seem to adopt the term RC (Hassan, Mei, & Johari, 2017; Inkinen et al., 2017; Tiwari & Vidyarthi, 2018; Vidyarthi, 2018; Xu et al., 2017), as it is more relatable to the concepts proposed by sociologists (Youndt et al., 2004).

Youndt et al. (2004), referred that an organization might have the ability to develop each dimension of IC independently. However, these authors also indicated that many of the theoretical foundations of IC developed by literature across organisational learning and knowledge management, seem to confirm the existence of a significant positive interdependency between the aforementioned three dimensions (Table 2). Liu (2017a) and (2017b), also seems to confirm this interconnection by suggesting that Social Capital (i.e. RC) and Organisational Capital (i.e. SC) can increase the effects of innovation behaviour that can result from the development of HC, via connecting internal and external resources. Kianto et al. (2017), also corroborated this interconnection by suggesting that knowledge-based HRM could partially impact SC and RC through HC, and that, on the other hand, HC could impact innovation through SC and RC.

Table 2 *– Factorial summary of each IC dimension*

Human Capital (HC)	Structural Capital (SC)	Relational Capital (RC)
• Employee social capital • Technical knowledge and ability capital • Motivation capital • Innovation/adaptation	• Organisational culture • Knowledge technologies • Organisational image • Management philosophy • R&D and innovation • Process • Intellectual ownership	• Customer capital • Supplier capital • Network relations • Investor/shareholder relations • Public relations

Source: Adapted from Özer et al. (2015)

2.2.2. IC measuring methods and tools

Organisations have been using various measuring tools to value their respective tangible, and intangible assets, such as IC (Pablos, 2003). According to the existent literature, the suggested methods for IC measuring could be decomposed in four main categories (Table 3), namely Direct, Scorecard, Market Capitalisation, and Return on Assets methods (Sveiby, 2010).

***Table 3** – IC measuring methods categories*

Method	Definition
Direct Intellectual Capital (DIC)	Estimate the monetary value of intangible assets by identifying its various micro-components. Once identified, these components can be directly evaluated, individually or as an aggregated coefficient (e.g. Dynamic Monetary Model and The Value explorer™).
Scorecard Methods (SCM)	Similarly to the DIC approach, but without determining monetary value, the various micro-components of intangible assets are identified. Indicators and indices generated are then reported in scorecards or charts (e.g. Balanced Score card, Intangible Asset Monitor and Skandia Navigator™)
Market Capitalisation Methods (MCM)	Calculate a monetary amount for IC by determining the difference between a company´s market capitalisation and its stockholders' equity (e.g. Tobin´s q and The Invisible Balance Sheet).
Return on Assets (ROA)	Uses average pre-tax earnings and divides them by the average tangible assets of the company for a period of time. This results in an indicator (ROA) that is then compared with its industry average. The difference from these two indicators (company´s and industry´s average) is then multiplied by the company´s average tangible assets, reflecting the average annual earnings from the intangibles. Dividing the above-average earnings by the company´s average cost of capital or an interest rate provides an estimate for the value of its IC (e.g. Knowledge Capital Earnings, Economic Value Added, VAIC™).

Source: Adapted from Sveiby (2010)

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&ROE methods (e.g. VAIC™), normally apply financial indicators to measure IC based on audited reports, thus making these methods the most widely used amongst practitioners (Xu et al., 2017).

There are several measuring methods that fit into each of those four categories. In fact, Sveiby (2010), discriminated at least forty-two methods for measuring IC. The Skandia Navigator (Edvinsson, 1997) is one the most frequently cited seminal methods, since it gave a crucial contribute and ignited the debate and promotion for further research regarding the IC measurement conundrum. Other frequently cited methods are, e.g., the Balanced Scorecard (Kaplan & Norton, 1992), the Intangible Asset Monitor (Sveiby, 1997), and the Value Added Intellectual Coefficient - VAIC™ (Pulic, 1998). This dissertation will focus on the VAIC™ model, since it is the IC measuring method of choice for this study.

2.2.2.1 Measuring IC and its efficiency: The VAIC™ model

The Value Added Intellectual Coefficient (VAIC™) method was introduced by Pulic, partially based on the Skandia Navigator (Pulic, 1998, 2004), as a value creation efficiency analysis, which uses data collected from audited financial reports to identify efficiency of IC (Nazari & Herremans, 2007). In fact, the VAIC™ method works for the assessment of both value creation or destruction, as IC efficiency may indicate that value is being destroyed and not created (Pulic, 2004).

The VAIC™ method provides consistent and objective measurements, "which are applicable to any industry because they are designed to evaluate efficient usage of resources" (Xu et al., 2017, p. 1059). That is one of the reasons why this method remains one of the most attractive and suggested methods to measure IC (Zéghal & Maaloul, 2010) amongst both academic and commercial fields (Xu et al., 2017).

In the VAIC™ method, after calculating the added value (i.e. VA) generated by the organisation, then the created value-added coefficient is calculated according to the different types of resources involved, (Xu et al., 2017), whether its financial capital (physical, i.e. Capital Employed - CE) or IC (intangible). In other words, VAIC™ measures the value added created per monetary unit invested in each type of resource (i.e. VAIC™ components: Human Capital Efficiency – HCE; Structural Capital Efficiency – SCE; and Capital Employed Efficiency – CEE) (Ozkan et al., 2017).

This method has been applied for measuring organisation´s IC efficiency with good results, in particular when correlated with profitability indicators, such as Price-to-Earnings ratio (PER), Return on Assets (ROA), Return on Investment (ROI) and Return on Equity (ROE) (Joshi et al., 2013; Maditinos, Chatzoudes, Tsairidis, & Theriou, 2011; Phusavat, Comepa, Sitko-lutek, & Ooi, 2011; Rehman et al., 2011). Other popular approaches consist in combining the components of the VAIC™ with frontier methods, such as the Data Envelopment Analysis (DEA), which allows for the assessment of the efficient application of multiple Inputs (e.g. VAIC and components) and their effective transformation into outputs (e.g. performance variables), or the application of the VAIC™ as a mean of obtaining the necessary independent variables for relating IC and Performance through the regression models applied in the two-stage analysis, which is adopted for this study and explained further ahead in Chapter 3.

In Table 4 it can be seen a summary of the VAIC™ method advantages and limitations. Although, the method presents some downsides, there is no perfect method currently available (Joshi et al., 2013), hence one should select a suitable method, according to the purpose, situation and audience (Sveiby, 2010). That is probably one of reasons for the recurring adoption of the VAIC™ method for studying bank performance (Ozkan et al., 2017; Xu et al., 2017).

Therefore, this method was chosen taking in account its advantages, as they make it an appropriate measure for the purpose of this study. The process followed in the calculation of the VAIC™ method will be more thoroughly explained in the methodology section, in 3.3.3 (see also appendix 6).

Table 4 – *Summary of VAIC model advantages and limitations*

Value Added Intellectual Coefficient (VAIC™)	
Advantages	**Limitations/Critiques**
• Easy to apply and calculate; • Produces consistent, standardised, quantifiable and objective measurements; • Needed data is publicly disclosed and can be found in organisation´s audited reports (reliability); • Verifiability of the data gathered; • Comparability (e.g. traditional financial indicators; benchmarking); • Provides indicators that are relevant, useful and informative to all stakeholders; • Treats HC as the most important source of IC, which corroborates all major IC definitions found in the literature (Though, HC calculation is based on labour costs only, which is criticised); • In addition to Pulic´s work, has more than 30 published studies in the past decade;	• The method uses overlapping variables (e.g. variables are pure financial parameters; indicates the efficiency of labour and capital investments); • Components are calculated from organisation accounts; thus, one may consider that the method only measures operating efficiency, but has no actual connection to IC (e.g. HC is merely based on human resources costs); • The derivation of SC appears as one of the weakest points of the model, lacking economic explanation (SC = VA – HC, which equals Operational Profit); • SCE results as SC divided by VA, which resembles VA efficiency rather than SCE; • R&D expenditure and advertising expenses, which are generally considered the drive for technological advancements and growth (should be treated as asset-like investments), are expensed as incurred (accounting standards), thus subtracted from the calculation of VA (i.e. omitted from the VAIC™ model). • Does not generate valuable analysis in organisations whose Input surpasses Output (i.e. organisations with negative BV or OP); • Does not take organisation risk into account (important factor for determining the value of an organisation and its IC; • Does not deal with RC (Although, there are other Modified variants that do (e.g. MVAIC);

Source: (Chan, 2009a; Javornik et al., 2012; Kehelwalatenna, 2016; Kujansivu & Lönnqvist, 2007; Maditinos et al., 2011; Ming-Chin, Shu-Ju, & Yuhchang, 2005; Nadeem, Dumay, & Massaro, 2017; Pulic, 2004; Ståhle, Ståhle, & Aho, 2011)

2.2.2.2 Modifying the original VAIC™: developing the formula

Several scholars have been working on new altered versions (e.g. MVAIC or M-VAIC, and Extend VAIC), which try to suppress the abovementioned critiques to the original VAIC™ model (Nadeem et al., 2017; Nazari & Herremans, 2007; Tiwari & Vidyarthi, 2018; Vidyarthi, 2018). These variations consist in adding new components to the formula, e.g. measuring Relational Capital Efficiency (RCE) via marketing expenses, and/or proposing new variables for calculating some of the other components, e.g. measuring SC through R&D expenses, and also adding back this expenses to the calculation formula of VA thus considering R&D as an investment rather than a cost (Nadeem et al., 2017).

While these new variants seem to fix some of the original model´s limitations, they also seem to require more sensible, and therefore, less accessible data (e.g. R&D, selling and marketing expenses), which turns what used to be an advantage in a downside for the model. Furthermore, previous work based on these new altered versions of the VAIC™ method does not appear to demonstrate any significant effect, since it has been producing divergent results (Nadeem et al., 2017).Nevertheless, these modified variants may represent a step in the right direction for improving the original model. The table presented in appendix 5, highlights the major differences between original VAIC™ and variants equation formulas, as well as the necessary variables for their respective calculation.

2.3 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 (i.e. obtain the best outcome applying less intellectual and non-intellectual resources). 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 in using parametric methods (e.g. regression analysis) for measuring the average performance for a given population (Shewell, 2016). Thus, several scholars have been trying to apply the VAIC™ model (Appendix 1, 2 and 3) and to correlate it with other financial indicators (Nadeem et al., 2017), e.g. ATO, Earning Per Share (EPS), ROA and 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 (ROA). M. Wang (2011) studied several Taiwanese companies, having found a positive relationship between VAIC™ and performance (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 HCE and performance (ROE). Tan, Plowman, & Hancock (2007) studied 150 Singapore listed companies for a two-year period, having found a correlation between IC and performance, and also that the contribution of IC to performance will differ across industries. Veltri & Silvestri (2011) studied all financial sector firms listed in the Italian stock exchange between 2006 and 2008, having found positive relationship between BV and MV on the one hand, and IC components (VAIC) and MV on the other. Goswami & Maji (2016) studied 100 listed Indian companies between 1999 and 2012, having found a positive and significant relationship between VAIC™ and performance (ROA). This author also found that the impact of IC efficiency on ROA was greater on knowledge-based sectors than in traditional ones.

Nevertheless, results are far from being unanimous, as other studies presented mixed, contrary, or inconclusive results. Kujansivu & Lönnqvist (2007) studied Finnish companies from 11 industry sectors between 2001 and 2003, and were not able to clarify the existence of a relationship between value and efficiency of IC. Firer & Williams (2003) studied 75 publicly traded firms in South Africa from knowledge intensive sectors, and 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, but a positive relation between 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 CEE and performance (ROA), but no evidence about VAIC™ impacting performance.

More recently, however, other approaches consist in applying efficiency analysis methods for assessing organisational performance. One such method, the DEA, has been adopted by several scholars for assessing efficiency and effectiveness (i.e. productivity) of Decision Making Units (DMUs), and as a way to rank them accordingly (benchmarking).

Tsai et al. (2017), used DEA for measuring the performance efficiency of 21 listed Taiwanese corporations (Decision Making Units – DMUs) from 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 (see Appendix 3). The authors found inefficiency issues regarding resource allocation of semiconductor corporations. Long Kweh, Chuann Chan, & Wei Kiong Ting (2013), studied the performance 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 important role in value creation and overall performance. Venugopal et al. (2018), studied an Indian Company (Titan), for 20 years (1997 to 2016 - DMUs), having used VAIC™ and its components as inputs, and ROA, ROE, EPS, and Market Capitalisation as outputs for the application of the DEA. The authors 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 utilisation of IC.

2.3.1. IC and performance in the banking sector: prior studies

As 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 methodology 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. (See appendix 2 and 3).

Meles, Porzio, Sampagnaro, & Verdoliva (2016), studied 5.749 US commercial banks, from 2005 to 2012 (8 years), 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 & Haniffa (2016), studied 64 Islamic financial institutions operating in 18 countries, from 2007 to 2011 (5 years), 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, a significant positive relationship between VAIC™, HCE, and CEE with ROA, and conversely, a significant negative relationship between Risk (control variable) and ROA. Irawanto, Gondomono, & Hussein (2017) Irawanto (2017), studied 33 Indonesian banks, from 2013 to 2014 (2 years), having used an econometric approach to analyse VAIC™ and its components, 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. Thakur (2017), studied 40 public and private banks in India, from 2013 to 2015 (3 years), 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.

It seems clear that the econometric approach (correlation and regression analysis) is a very common one amongst the revised literature, as a mean for inferring about the relation between IC and performance in the banking industry. Other approach, the Data Envelopment Analysis (DEA) method, which is commonly used for performance measurement across multiple sectors, also appears to be frequently applied in the banking sector (see Appendix 3). On the other hand, there seems to be a lack of studies applying both methods (VAIC™ and DEA) for the assessment of the efficient transformation of IC into profitability in the banking sector. In fact, results from the prior conducted research for the elaboration of this study, showed that only 2 papers have previously used the mentioned methods simultaneously for evaluating banks´ IC and performance.

Yalama & Coskun (2007), studied the efficient transformation of IC in profitability of all the banks listed on Istanbul Stock Exchange (ISE), from 1995 to 2004 (except year 2001: 9 years), using both VAIC™ and DEA methods. The authors used 3 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 efficiency values are not stable annually, that different efficiency level ranking is observed amongst banks for every year, that the ratio of transforming IC into profitability is calculated as 61.3

percent for the sampled banks, that Portfolio 1 (based on IC) seems to have the highest annually return, and finally, that 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 (12 years), 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, 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.

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.

Chapter 3 Data collection and methodology

This chapter consists in four main sub-chapters. The first sub-chapter (3.1) gives a contextualisation of the Iberian banking sector, which is composed by both Portuguese and Spanish banks. The second sub-chapter (3.2), explains the specifics of the sample data and its respective source, followed by an explanation of the applied DEA methodology and of respective variables chosen for assessing banks´ efficiency (3.3). The fourth sub-chapter (3.4) presents the econometric models (fractional and quantile regressions, plus dependent, independent, and control variables) applied for estimating the impact of IC on the performance of Iberian banks over a 4-year period (2013 – 2016).

3.1 Contextual setting of the Iberian banking sector

The subprime mortgage crisis of 2007 originated a number of macroeconomic problems in several Euro area economies, including both Portugal (PT) and Spain (ES). These two neighbouring countries, were amongst the most affected EU economies, with their respective banking sectors suffering the impact of a systemic crisis. Since then, legal restrictions on bank activity and minimum capital requirements led banks to increase their capital ratios by reducing their activity, and thereby, to the reduction of the risk inherent to the carried-out operations. As a result, there was a widespread decrease in granted credit, mostly to companies, which can be justified by the greater effectiveness that this type of measure confers, taking into account a slowdown of banking activity in the short-term. At the moment, there is a gradual retake of banking activity, which privileges the solvency and liquidity necessary to ensure the stability of the financial system, so as not to compromise again its future sustainability.

According to the overview report of the Portuguese banking system, elaborated by the Portuguese Association of Banks (2016), the resizing of the European banking sector, during the period from 2010 to 2015, is noticeable when comparing the total assets to GDP ratio in both Portugal (PT) and Spain (ES), but also in most countries pertaining to the Euro area. This ratio presented a general decrease when comparing the values of 2015 to 2010, which is 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 Euro area banking industries, respectively. Despite the aforesaid reduction, customer credit still composes half of the total assets of PT and ES banking industries, with a customer credit to total assets ratio (as June 2016) of around 49% for each country, which compares with a value of 37.5% for the Euro area.

Moreover, the level of banking indebtedness of the Spanish and Portuguese economies has been declining, closing the gap to the rest of Europe. Despite the decrease of the customer credit to GDP ratio during recent 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 Euro area was of 113%, (see Overview of the Portuguese banking system, 2016). Another significant evidence pointed out in this same report is that individuals´ credit stock to country´s GDP is of 66.3% for Spain and 67% for Portugal, while the rest of Euro area average is of 51.1%. On the other hand, the report indicates that the credit to non-financial firms to country´s GDP ratio is of 49.2% for Spain and 46.3% for Portugal, whereas the rest of the Euro area average is of 41%. Furthermore, the volume of credit risk to total credit ratio has increased in the post-crisis aftermath, for the Euro area countries, with more emphasis on peripherical countries, such as Portugal and Spain, although a slight improvement seems to be taking place in recent years Hence, for the years 2012, 2013, 2014, and 2015, respectively, this ratio registered values of 7.5%, 9.4%, 8.5%, and 7% for Spain, and of 9.8%, 10.6%, 11.9% and 12% for Portugal, whereas the average values registered for the Euro area were of 7.5%, 7.9%, 6.8% and 6.7%.

Regarding the financing structure, PT and ES banking sector seem to have a higher dependency on customer deposits, whose proportion, as of June 2016, was of 53% and 50%, respectively, which compares to the 38% of the Euro area average. On the other hand, comparatively to customer deposits, wholesale funding takes on a less relevant position, with values of 24%, 26%, and 30%, for Spain, Portugal and the Euro area, respectively (see Overview of the Portuguese banking system, 2016).

In essence, PT and ES banking sectors appear to share similar characteristics, probably due to their geographic proximity and cultural commonalities. These two countries´ economies suffered a great impact caused by the systemic financial crisis originated in USA in 2007, which lead to economic recession, and consequently, to the subjection to austerity programmes in the following years. More recently, Euro area economies, including PT and ES, seem to be exhibiting signs of recovery, which consequently, should reflect on their respective banking sectors´ activities.

3.2 Data collection

The Bankscope database, provided by Bureau van Dijk, was employed in this study´s empirical investigation for the extraction of the relevant annual information (see appendix 6) of the 16

Portuguese and 42 Spanish sampled banks, over a period of 4 years (2013-2016). Initial retrieved dataset was composed by a total of 314 Iberian banks (i.e. all the data available in Bankscope concerning Portuguese and Spanish banks). Subsequently, data was filtered according to the consolidation code (i.e. excluded banks with unconsolidated data: U1), which reduced the sample to a total of 90 banks. Finally, the sample was filtered according to the availability of variables needed for the application of this study´s methodology, and to the Nº of DMUs–period maximisation perspective, which resulted in the final selected sample and period. Thus, this study´s dataset includes a total of 58 Iberian banks (i.e. DMUs) consisting in a total number of 232 bank-year observations.

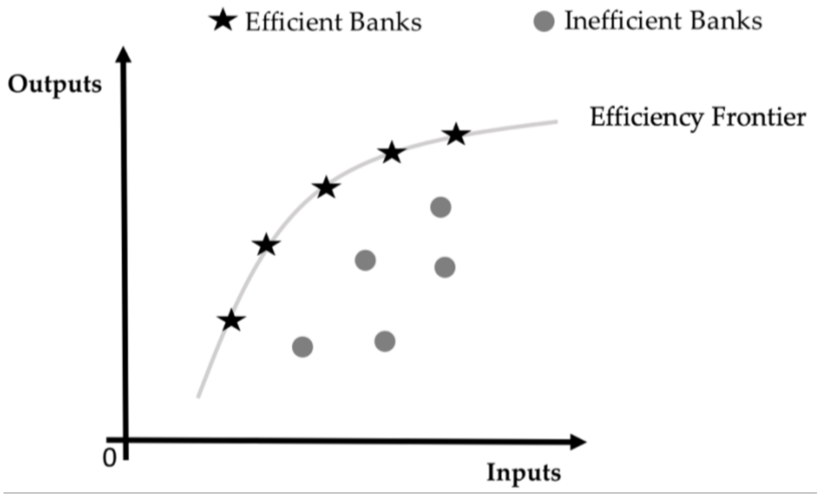
3.3 The Data Envelopment Analysis (DEA) model

The DEA model was chosen, in the first stage of the applied methodology for this study, for measuring the efficiency of Iberian banks, and to rank them accordingly to their performance. The DEA model is a non-parametric method (Charnes, Cooper and Rhodes, 1978), based on a mathematical linear programming tool, which can be used in performance measurement and analysis (Shewell & Migiro, 2016). Being a non-parametric method, results in it does not requiring 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 the efficiency level of a set of peer entities, i.e. individual Decision-Making Units (DMUs), than a parametric one (Diallo, 2018).

DMUs are comparable units responsible for converting a determined number of resources (inputs) into a determined number of outcomes (outputs). Thus, DEA can assess effectiveness, by measuring the degree to which analysed DMUs have produced more outputs using the same fixed amount of inputs (output-orientation), and also efficiency, by following the inverse logic (input-orientation), that consists in fixing the amount of output while trying to minimise the level of input (Barman et al., 2015; Said et al., 2017).

In this particular study, DMUs are Iberian sampled banking firms. Thus, based on determined inputs and outputs (see 3.3.1), DEA will be measuring the relative efficiency of each sampled bank, by establishing an empiric production function and applying linear programming to build a technological production frontier (see figure 3), also known as efficiency frontier, which encompasses all efficient banks.

Figure 3 -*DEA efficiency frontier*



Source: Adapted from Gerek, Erdis, Mistikoglu, & Usmen (2014)

Banks with maximum efficiency will be situated in the efficiency frontier (Figure 3), therefore retaining a value of 1 and serving as example for being the best "practitioners" (benchmarking), whereas 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 to the 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 radial distance that can be used to evaluate banks´ efficiency, namely the CCR model, which stands for Charnes-Cooper-Rhodes (Charnes et al., 1978), and the BCC model, which stands for Banker-Charnes-Cooper (Cooper, Seiford, & Tone, 2007). Both methods can be applied using an input-or-output orientation, depending on the goals and sample of the particular study (i.e. minimising inputs and fixing the outputs, or fixing the inputs and maximising the outputs) (Rebelo, 2017; Said et al., 2017).

The essential difference between these two modes lies on 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; Novickytė & Droždz, 2018). In another perspective, the difference between CRS (i.e. CCR) and VRS (i.e. BCC), is the first assumes that any variation in the inputs will produce a proportionate variation in the outputs (constant: same direction), while the later assumes a disproportionate relation between inputs and outputs (variable: lower, constant, or higher). The main advantage of considering VRS is that it allows for heterogeneity capture amongst countries (Moutinho, Madaleno, & Robaina, 2017). Scale Efficiency (SE), which represents the potential productivity gain achieved from optimal size of a DMU (Raheli, Rezaei, Jadidi, & Mobtaker, 2017), can be derived from the TE to PTE ratio (Liu, 2018), resulting as follows:

$SE = \frac{TE}{PTE}$, which means that $TE = PTE \times SE$, is also true.

Therefore, e.g. when a particular DMU does not obtain a SE equal to 1 (i.e. maximum scale efficiency), it means that PTE is higher than TE. Following this logic can help to sort the nature of DMUs´ inefficiencies (Madaleno, Moutinho, & Robaina, 2016; Rebelo, 2017). Thus, as a way of maximising the relative efficiency of a j_0 DMU, it is necessary to adopt the most favourable set of weights for each DMU. If a DMU employs m inputs to produce s outputs, the Relative Efficiency (RE) score of the j_0 DMU can be achieved by solving the following linear programming problem:

$$RE_{j_0} = max \frac{\sum_{p=1}^{s} v_p y_{pj_0}}{\sum_{q=1}^{m} w_q x_{pj_0}} \quad (1)$$

Subject to:

$$\frac{\sum_{p=1}^{s} v_p y_{pj}}{\sum_{q=1}^{m} w_q x_{pj}} \leq 1, \qquad j = 1, \dots, n$$

$$v_p \ \geq \ \varepsilon, \qquad p \ = \ 1, 2, 3, \dots, s$$

$$w_q \ \geq \ \varepsilon, \qquad q \ = \ 1, 2, 3, \dots, m$$

The problem above translates in the maximisation ratio (i.e. Technical efficiency - TE) of the weighted sum of chosen outputs in relation to the weighted sum of the selected inputs (H.-H. Liu, 2018), whereas weights are defined by the DEA-CCR model for each DMU. In other words, RE_{j_0} represents the relative efficiency score of DMU j_0. Describing the rest of the nomenclature: n represents the number of DMUs composing this study´s dataset, ε represents an infinitesimal positive number, x and y represent inputs and outputs and v and w their respective weights, while p and q represent respectively, the number of outputs ($p \ = \ 1, 2, 3, \dots, s$) and the number of inputs ($q \ = \ 1, 2, 3, \dots, m$).

Table 5 -Expressions for the Input-or-Output orientations using DEA-CCR (multiplier and envelopment models)

Input orientation	**Output orientation**
Linear or multiplier models (CCR)	
$RE_{j0} = max \sum_{p=1}^{s} v_p y_{pj0}$ (2) Subject to: $\sum_{q=1}^{m} w_q x_{pj0} = 1$ $\sum_{p=1}^{s} v_p y_{pj} - \sum_{q=1}^{m} w_q x_{pj} \leq 0 \quad j = 1, \dots, \mathrm{n}$ $v_p \geq \varepsilon, \quad p = 1, 2, 3, \dots, s$ $w_q \geq \varepsilon, \quad q = 1, 2, 3, \dots, m$	$RE_{j0} = min \sum_{q=1}^{m} w_q x_{pj0}$ (3) Subject to: $\sum_{p=1}^{s} v_p y_{pj0} = 1$ $\sum_{p=1}^{s} v_p y_{pj} - \sum_{q=1}^{m} w_q x_{pj} \leq 0 \quad j = 1, \dots, \mathrm{n}$ $v_p \geq \varepsilon, \quad p = 1, 2, 3, \dots, s$ $w_q \geq \varepsilon, \quad q = 1, 2, 3, \dots, m$
Dual linear or envelopment models (converted from the above)	
$minRE_{j0} = \theta - \varepsilon[\sum_{q=1}^{m} s_q^- + \sum_{p=1}^{s} s_p^+]$ (2.1) Subject to: $y_{po} = \sum_{j=1}^{n} y_{pj}\, \lambda j - s_p^+ \quad p = 1, 2, 3, \dots, s$ $\theta x_{qo} - \sum_{j=1}^{n} x_{qj}\, \lambda j - s_q^- = 0 \quad q = 1, 2, 3, \dots, m$ $\lambda j, s_p^+, s_q^- \geq 0 \quad j = 1, \dots, \mathrm{n}$	$maxRE_{j0} = \theta + \varepsilon[\sum_{q=1}^{m} s_q^- + \sum_{p=1}^{s} s_p^+]$ (3.1) Subject to: $x_{qo} = \sum_{j=1}^{n} x_{qj}\, \lambda j + s_q^- \quad q = 1, 2, 3, \dots, m$ $\theta y_{po} - \sum_{j=1}^{n} y_{pj}\, \lambda j + s_p^+ = 0 \quad p = 1, 2, 3, \dots, s$ $\lambda j, s_q^-, s_p^+ \geq 0 \quad j = 1, \dots, \mathrm{n}$

Source: (Cooper et al., 2007)

DMUs efficiency can be assessed using a DEA-CCR (Table 5) or a DEA-BCC (Table 6) model, and by selecting between an Output or Input orientation for each one. When following an input orientation, it is necessary to maximise the numerator and to equal the denominator to 1 for the linearization of the expression (1), resulting in the expression (2) and (4), which will indicate the necessary changes on the applied inputs in order for DMUs to achieve 100% efficiency (i.e. for $RE_{j0} = 1$). On the other hand, if following an output orientation, it is necessary to minimise the denominator, while the numerator has to be equalled to 1 for the linearization of the expression (1), thus resulting in the expression (3) and (5), which will show the necessary changes on the produced outputs in order for DMUs to achieve maximum efficiency (i.e. for $RE_{j0} = 1$).

Table 6 - *Expressions for the Input and Output orientations using DEA-BCC (linear or multiplier model)*

Input orientation	Output orientation
Linear or multiplier models (BCC)	
$RE_{j0} = max \sum_{p=1}^{s} v_p y_{pj0} - v^*$ (4) Subject to: $\sum_{q=1}^{m} w_q x_{pj0} = 1$ $\sum_{p=1}^{s} v_p y_{pj} - \sum_{q=1}^{m} w_q x_{pj} - v^* \le 0 \quad j = 1, \dots, \text{n}$ $v_p \ge \varepsilon, \quad p = 1, 2, 3, \dots, s$ $w_q \ge \varepsilon, \quad q = 1, 2, 3, \dots, m$ $v^* - Without\ restritions$	$RE_{j0} = min \sum_{q=1}^{m} w_q x_{pj0} - w^*$ (5) Subject to: $\sum_{p=1}^{s} v_p y_{pj0} = 1$ $\sum_{q=1}^{m} w_q x_{pj} - \sum_{p=1}^{s} v_p y_{pj} - w^* \ge 0 \quad j = 1, \dots, \text{n}$ $v_p \ge \varepsilon, \quad p = 1, 2, 3, \dots, s$ $w_q \ge \varepsilon, \quad q = 1, 2, 3, \dots, m$ $w^* - Without\ restrictions$
Dual linear or envelopment models (converted from the above)	
$minRE_{j0} = \theta - \varepsilon[\sum_{q=1}^{m} s_q^- + \sum_{p=1}^{s} s_p^+]$ (4.1) Subject to: $y_{po} = \sum_{j=1}^{n} y_{pj}\, \lambda j - s_p^+ \quad p = 1, 2, 3, \dots, s$ $\theta x_{qo} - \sum_{j=1}^{n} x_{qj}\, \lambda j - s_q^- = 0 \quad q = 1, 2, 3, \dots, m$ $\sum_{j=1}^{n} \lambda j = 1$ $\lambda j, s_p^+, s_q^- \ge 0 \quad j = 1, \dots, \text{n}$	$maxRE_{j0} = \theta + \varepsilon[\sum_{q=1}^{m} s_q^- + \sum_{p=1}^{s} s_p^+]$ (5.1) Subject to: $x_{qo} = \sum_{j=1}^{n} x_{qj}\, \lambda j + s_q^- \quad q = 1, 2, 3, \dots, m$ $\theta y_{po} - \sum_{j=1}^{n} y_{pj}\, \lambda j + s_p^+ = 0 \quad p = 1, 2, 3, \dots, s$ $\sum_{j=1}^{n} \lambda j = 1$ $\lambda j, s_q^-, s_p^+ \ge 0 \quad j = 1, \dots, \text{n}$

Source: (Cooper et al., 2007)

Considering the dual linear programming theory in both CCR and BCC models (Table 5 and 6), the multiplier model expressions (2), (3), (4) and (5) are then converted into envelopment model ones (Cooper et al., 2007), as seen (2.1), (3.1), (4.1) and (5.1). Explaining the nomenclature used in the later expressions, θ represents the efficiency score for DMU_0 (i.e. reflecting the radial distance from DMU_0 to the estimated efficiency frontier), s_q^- represents the slack of input q (i.e. amount of input q that needs to be reduced for achieving 100% efficiency), s_p^+ represents the slack of output p (i.e. amount of output p that needs to be increased for achieving 100% efficiency), and λj represents the contribution or weight of DMU_j in the formation of target values that need to be met so that DMU_0 can achieve efficiency (peer weight).

The envelopment expressions (2.1), (3.1), (4.1) and (5.1) are solved using a two-phase process, which allows for the measurement of the efficiency score (θ) of each DMU (first phase), and identification of possible existing slacks (s_p^+, s_q^-) at input-or-output level that may be hindering a DMU from achieving strong efficiency, i.e. with no slacks (second phase). In order for achieving strong efficiency (i.e. $s_p^+, s_q^- = 0$ and $\theta = 1$) it is necessary to eliminate existing slacks, and to radially reduce inputs (if input oriented) or to radially increase outputs (if output oriented), by applying the equations in Table 7.

Table 7 *–Second phase envelopment equations*

Input orientation	**Output orientation**
2nd phase envelopment equations	
$\hat{x}_{q0} = \theta x_{q0} - s_q^{-*} = \sum_{j=1}^{n} x_{qj} \lambda_j^* \quad q = 1, 2, 3, \ldots, m$	$\hat{y}_{p0} = \theta y_{p0} + s_p^{+*} = \sum_{j=1}^{n} y_{pj} \lambda_j^* \quad p = 1, 2, 3, \ldots, s$
$\hat{y}_{p0} = y_{p0} + s_p^{+*} = \sum_{j=1}^{n} y_{pj} \lambda_j^* \quad p = 1, 2, 3, \ldots, s$	$\hat{x}_{q0} = x_{q0} - s_q^{-*} = \sum_{j=1}^{n} x_{qj} \lambda_j^* \quad q = 1, 2, 3, \ldots, m$
Where: θ, λ_j^*, s_q^{-*}, s_p^{+*} are the respective weights and slacks for the optimal solution	

Source: (Cooper et al., 2007)

Additionally, there are other DEA variants rather than the more basic models mentioned (i.e. CCR and BCC). One of them is the Super-efficiency DEA model, originally proposed by Andersen and Petersen (Andersen & Petersen, 1993). The Super-Efficiency model was meant to increase the discriminatory power of the CCR and BCC models, and thus assist in the ranking process of DMUs. The increase in the discriminatory power is due to exclusion of the DMUs under evaluation from the reference set. In essence, this means that the efficiency frontier drawn by the CCR and BCC models is not altered, therefore the θ from inefficient DMUs remains the same, only altering the θ from efficient DMUs (i.e. looking for top performers amongst the efficient DMUs: $\theta \geq 1$). Thus, Super-Efficiency allows for the identification of the possible amount of increases in inputs or reductions in outputs, that efficient DMUs may suffer without losing their efficiency status (Bongo, Ocampo, Magallano, Manaban, & Ramos, 2018; Cooper et al., 2007). In Table 8, it can be seen the expression, using both linear and envelopment perspectives, for the Super-Efficiency model based on CCR and following an input orientation.

***Table 8** – Expression for the CCR based Super-Efficiency model (Input-orientation)*

Linear or multiplier model	Dual linear or envelopment model
$$SE_{j0} = max \sum_{p=1}^{s} v_p y_{pj0}$$ Subject to: $$\sum_{q=1}^{m} w_q x_{pj0} = 1$$ $$\sum_{p=1}^{s} v_p y_{pj} - \sum_{q=1}^{m} w_q x_{pj} \leq 0, \quad \forall j, \quad j \neq 0$$ $$v_p \geq \varepsilon, \quad p = 1, 2, 3, \dots, s$$ $$w_q \geq \varepsilon, \quad q = 1, 2, 3, \dots, m$$	$$\theta^* = \min_{\theta,\lambda,s^-,s^+} \theta - \varepsilon e s^+$$ Subject to: $$\theta x_0 = \sum_{j=1,\neq 0}^{n} \lambda_j x_j + s^-$$ $$y_0 = \sum_{j=1,\neq 0}^{n} \lambda_j y_j - s^+$$ Where: $\boldsymbol{\lambda}, \boldsymbol{s}^-$, $\boldsymbol{s}^+$ are constrained to be non-negative, $\boldsymbol{\varepsilon} > 0$, and $\boldsymbol{e}$ is the row vector with unity for all elements

Source: (Cooper et al., 2007)

The main difference between the basic DEA-CCR model and the Super-Efficiency one, is in the second constraint, where the DMU j_0 is excluded, thus resulting that Super-Efficiency does not empirically limit the value of the θ (Bongo et al., 2018).

For the purpose of this study, CRS, VRS and Super-efficiency models, were applied for the first-stage DEA, following an input-orientation, as way of identifying top performing Iberian banks, when it comes to the efficient management of their resources. Nevertheless, choosing between an input-or-output orientation using the CCR model is indifferent, since both orientations produce similar results (efficiency scores) for this particular model (Cooper et al., 2007).

3.3.1 Input and Output variables

There are three main 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, namely the production, profitability, and intermediation approaches (Novickytė & Droždz, 2018). 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, as the name implies, 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 & Droždz, 2018). The intermediation approach, contemplates banks as intermediaries by using labour, operational costs, and capital (i.e. collected funds) to provide loans and other assets (investments) (Ouenniche & Carrales, 2018). 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, by the availability of the data, and by following the example of other studies, such as (Barman et al., 2015; Kumar et al., 2016; H.-H. Liu, 2018; Ouenniche & Carrales, 2018; Pham, Nguyen, Nghiem, Roca, & Sharma, 2016; Rusydiana & Firmansyah, 2017; Said et al., 2017; Vidyarthi, 2018).

Table 9 *- Selected output and input variables for the application of the first-stage DEA*

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

Classification of inputs and outputs throughout the banking literature (see appendix 3), is typically based on resources, costs or financial burden for the inputs, while the outputs are normally based on banks´ ability to provide services, generate revenue, and acquire more assets (Ouenniche & 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).

3.4 Econometric Analysis

In the second-stage of the applied methodology for this study, both fractional and quantile regressions will be used for inferring about 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 unit (Raheli et al., 2017; Ramalho, Ramalho, & Henriques, 2010). Given the bounded nature of DEA methodology applied in the first-stage, both Papke and wooldridge´s (1996) fractional regression model (FRM), and Koenker & Bassett's (1978) quantile regression model (QRS) were chosen for the correlation of IC and performance variables in the second-stage DEA.

3.4.1 Quantile regression model (QRM)

Koenker & Bassett (1978) introduced quantile regression as a robust alternative to the Ordinary least squares (OLS) estimation. QRM has robust properties, even in the absence of normality, which allow the capacity of describing the relationship in the conditional outcome distribution (Y) at different points (Moutinho et al., 2017), being particularly useful in the case of heteroscedasticity and when trying to rank the extremes (i.e. top and bottom efficient DMUs), such as in the case of benchmarking (Roth & Rajagopal, 2018). Moreover, QRM can be applied to more eclectic types of datasets, since it can deal with abnormal residuals or constant variance, which is not the case for OLS.

The variable Y can be depicted by its distribution function (Behr, 2010):

$$F(y) = \Pr(Y \leq y)$$

For any $0 < \tau < 1$ the τth quantile of Y is defined as:

$$F^{-1}(\tau) = \inf\{y : F(y) \geq \tau\}$$

Quantiles estimation can be made by solving a minimisation problem, using a loss function (Behr, 2010):

$$p_\tau(u) = u(\tau - I(u < 0)) = u\tau I(u \geq 0) - u(1-\tau)I(u < 0)$$

$$E[p_\tau(Y-\hat{y})] = (\tau - 1)\int_{-\infty}^{\hat{y}} (y-\hat{y})dF(y) + \tau \int_{\hat{y}}^{\infty} (y-\hat{y})dF(y)$$

The value that minimises the expected loss is $\hat{y}$, which gives the solution to the minimisation problem above through $F(\hat{y}) = \tau$. Thus, each element of $\{y : F(y) = \tau\}$ minimises the expected loss. Replacing the theoretical by the empirical distribution results in function bellow, with $\hat{y}$ being chosen for the minimisation of the expected loss, what leads to the sample τth quantile (Behr, 2010):

$$F_n(y) = \mathrm{n}^{-1}\sum_{i=1}^{n} I(Y_i \leq \mathrm{y})$$

$$\int_{-\infty}^{\infty} p_\tau(y-\hat{y})dF(y) = \mathrm{n}^{-1}\sum_{i=1}^{n} p_\tau(Y_i \leq \hat{y})$$

The conditional τth quantile of Y can be found given a covariate vector x' and by specifying the conditional quantile function formula in logarithms as (Behr, 2010):

$$Q_{lny}(\tau|X) = \beta(\tau)\ln \mathrm{x}'$$

$\hat{\beta}(\tau)$ represents the solution for the following minimisation problem:

$$\min_{\beta \in R^p} \sum_{i=1}^{n} p_\tau\,(\ln \mathrm{y}_i - \beta(\tau)\ln \mathrm{x}'_i)$$

A linear regression, with identical and distributed errors υ, between $\ln \mathrm{x}$ and $\ln \mathrm{y}$, is assumed, where the conditional quantile is a vertical shifted linear function $\beta_0 + \beta_1 \ln \mathrm{x}_i$ by the quantile of the error term distribution $F_\upsilon^{-1}(\tau)$ (Behr, 2010). In this case, besides QR functions being vertically shifted, they can also have changing slope parameters for multiple values of τ.

$$\ln \mathrm{y}_i = \beta_0 + \beta_1 \ln \mathrm{x}_i + \upsilon_i$$

$$Q_{lny}(\tau|X) = \beta_0 + \beta_1 \ln \mathrm{x}_i + F_\upsilon^{-1}(\tau) = [\beta_0 + F_\upsilon^{-1}(\tau)] + \beta_1 \ln \mathrm{x}_i$$

Explaining some of nomenclature applied in the aforesaid functions: τ (tau) represents the sample quantile, and can take a value between 0 and 1, where a τ = 0.5 corresponds to the median (e.g. τ = 0.95 corresponds to the top 5 percent limit, whereas a τ = 0.05 corresponds to the bottom 5 percent limit); N represents the total number of data points; y_i is the target variable; x'_i is the vector of covariates; and β_τ is the produced vector of coefficients for the given τ value.

3.4.2 Fractional regression model (FRM)

The FRM avoids the problems associated with the application of the linear and tobit models in the DEA context. The FRM, developed by Papke and wooldridge´s (1996), requires 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 (Ramalho, 2010), $E\ (y|x) = G(x\theta)$, is therefore, bounded to that same interval, where $G(.)$ represents a non-linear function satisfying the condition: $0 \leq G(.) \leq 1$.

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

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

As the Bernoulli distribution pertains to the linear exponential family, the θ QML estimator, defined by $\hat{\theta} \equiv \arg\max_{\theta} \sum_{i=1}^{N} LL_i\,(\theta)$, is consistent and asymptotically normal, regardless of the true distribution of y conditional on x, as long as abovementioned $E\ (y|x)$ is correctly specified (Ramalho, 2010). Moreover, the asymptotic of the QML estimator is given by $\sqrt{N}\big(\hat{\theta} - \theta_0\big) \xrightarrow{d} \mathcal{N}(0, V)$, where: $V = A^{-1}BA^{-1}$, with $A = E[-\nabla_{\theta\theta'}LL(\theta)]$ and $B = E[\nabla_\theta LL(\theta)\nabla_{\theta'}LL(\theta)]$. Consistent estimators for A and B are given by $\hat{A} = N^{-1}\sum_{i=1}^{N} \hat{g}_i^2 x'_i\, x_i\, [\hat{G}_i(1 - \hat{G}_i]^{-1}$ and $\hat{B} = N^{-1}\sum_{i=1}^{N} \hat{u}_i^2 \hat{g}_i^2 x'_i x_i\, [\hat{G}_i(1 - \hat{G}_i]^{-2}$, respectively, where $\hat{G}_i \equiv G\big(x_i\hat{\theta}\big), g(x_i\theta) = \frac{\partial G(x_i\theta)}{\partial(x_i\theta)}, \hat{g}_i \equiv g(x_i\hat{\theta})$ and $\hat{u}_i = y_i - \hat{G}_i$.

Papke and wooldridge´s (1996) suggested as possible specifications for the $G(.)$ function any cumulative distribution function, such as the already applied to model binary data, as seen in Table 10. The most widely used ones are logit and probit functional forms, although there are other alternatives, such as the loglog and the complementary loglog (cloglog) (Raheli et al., 2017; Ramalho et al., 2010).

Table 10 – Fractional regression: standard models

Logit	Probit	Loglog	Cloglog
$G(x\theta) = \dfrac{e^{x\theta}}{1+e^{x\theta}}$	$G(x\theta) = \phi(x\theta)$	$G(x\theta) = e^{-e^{x\theta}}$	$G(x\theta) = 1 - e^{-e^{x\theta}}$

Source: Adapted from Raheli (2017) and Ramalho (2010)

Partial effects associated to each of the abovementioned (Table 10) fractional regression model alternatives are given by $\frac{\partial E(y|x)}{\partial x_j} = \theta_j g(x\theta)$, where $g(x\theta) = \frac{\partial G(x\theta)}{\partial x\theta}$. 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 (Table 10), which use an additional parameter, α, thus, resulting in the first and second generalisations depicted in Table 11, where $\alpha > 0$ such that $0 < E\ (y|x) < 1$.

Table 11 - Fractional regression: generalised models and partial effects of a unitary change of x_j

Generalised type I model	Generalised type II model
$E\ (y|x) = G(x\theta)^{\alpha}$	$E\ (y|x) = 1 - [1 - G(x\theta)]^{\alpha}$
Partial effects of a unitary change of x_j in both models	
$\dfrac{\partial E(y|x)}{\partial x_j} = \theta_j g(x\theta)\alpha G(x\theta)^{\alpha-1}$	$\dfrac{\partial E(y|x)}{\partial x_j} = \theta_j g(x\theta)\alpha[1 - G(x\theta)]^{\alpha-1}$

Source: Adapted from Ramalho (2010)

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 (Table 10), which manages the probability of observing a 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 (as those either in Table 10 or Table 11).

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[(Ramalho et al., 2010): $E(y|x, y \in]0,1[) = M(x\beta_{2P})$, where $M(.)$ may be any of the considered for $E(y|x)$ in Table 10 and Table 11, and β_{2P} is another vector of coefficients.

Partial effects of a covariate x_j over the probability of observing an efficienct DMU and the conditional mean score for an ineficient DMU are despicted as follows (Ramalho et al., 2010): $\frac{\partial \Pr(z=1|x)}{\partial x_j} = \frac{\partial F(x\beta_{1P})}{\partial x_j} = \beta_{1P} f(x\beta_{1P})$ and $\frac{\partial E(y|x, y \in]0,1[)}{\partial x_j} = \frac{\partial M(x\beta_{2P})}{\partial x_j} = \beta_{2P} m(x\beta_{2P})$, where $f(x\beta_{1P})$ and $m(x\beta_{2P})$ are the partial deravatives of $F(.)$ and $M(.)$ respecting to $x\beta_{1P}$ and $x\beta_{2P}$, respectively.

Overall conditonal mean and partial effects of x_j on y can be described as follows (Ramalho et al., 2010): $E(y|x) = M(x\beta_{2P}) . [1 - F(x\beta_{1P})]$ and $\frac{\partial E(y|x))}{\partial x_j} = \beta_{2P} m(x\beta_{2P}) [1 - F(x\beta_{1P})] + \beta_{1P} f(x\beta_{1P}) + [1 - M(x\beta_{2P})]$.

Therefore, a total change in y can be forked in two parts, i.e. the change in the DEA scores of inefficient DMUs weighted by their observational probability, and the probability change of observing an efficient DMU weighted by one minus the expected DEA score of an inefficient DMU (Ramalho et al., 2010).

Moreover, for a correct specification of the functional form of the conditional mean $E(y|x)$ it is necessary to correctly specify the model for $G(x\theta)$ and for both $F(x\beta_{1P})$ and $M(x\beta_{2P})$ in the one- and two-part models, respectively (Ramalho et al., 2010). One way of doing this, is to apply the RESET test, which can detect general function form misspecifictions. However, this test has to be separately applied to the two components of the functional form assumed for the two-part model (i.e. $F(x\beta_{1P})$ and $M(x\beta_{2P})$).

The P test, suggested by Davidson & MacKinnon (1981), can be used for comparing nonlinear regression models, and thus, for the descrimination between alternative one-part and two-part FRMs (Ramalho et al., 2010). One may assume, as exemplified by Davidson & MacKinnon (1981), that $H(x\alpha)$ and $T(x\eta)$ are contending functional forms for $E(y|x)$. Thus, testing $H_0: H(x\alpha)$ against $H_1: T(x\eta)$ (i.e. analysing wether $H(x\alpha)$ is an appropriate specification for $E(y|x)$ in comparison to an alternative model) is similar to testing the null hypothesis $H_0: \delta_2 = 0$ using the auxiliary regression: $(y - \hat{H}) = \hat{h}x\delta_1 + \delta_2(\hat{T} - \hat{H}) + error$, where $h = \delta H(x\alpha)/\delta(x\alpha)$, δ_2 is a scalar parameter and $\hat{}$ represents evalution at the estimators $\hat{\alpha}$ or $\hat{\eta}$, resulting from the separate estimation of the models depicted by $H(.)$ and $T(.)$, respectively.

Additionally, one may also apply the GOFF- I and GOFF-II tests for inferring about the pertinency of using either Type I or Type II generalisations (Table 11), or instead, just a corresponding simpler standard FRM (Ramalho et al., 2010).

3.4.3 Dependent, Independent and control variables

As previously mentioned, the second-stage DEA consists in applying two regression models, namely, the FRM and the QRM, 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, as can be seen in Appendices 2 to 6.

The Super efficiency scores obtained by the application of the CRS and VRS models (for quantile regression models), and the traditional CRS and VRS models (for fractional regression models) adopted in the first-stage, were the chosen dependent variables for this study. Independent variables were obtained through the application of the VAIC™ method explained bellow (see also 2.1.2.1).

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 & 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; Chan, 2009b, 2009a; Pulic, 2004; Svanadze & Kowalewska, 2015):

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

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;

A higher VAIC™, resulting from the sum of the above-mentioned measures, shows that more value is generated with the same amount of resources (Pulic, 2004), suggesting a better management regarding the utilisation of an organisation´s value creation potential (M. Chen, Cheng, & Hwang, 2005)

For this study, the calculation of the VA variable was adapted from the studies conducted by Alhassan & Asare (2016) and Vidyarthi (2018) resulting from the difference:

$$VA = OUTPUT - INPUT$$

Where: OUTPUT is the bank´s operating revenues and INPUT is bank´s overall expenses excluding labour expenses (treated as investment rather than a cost).

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 three types of leverage ratios (i.e. Lev1, Lev2 and Lev3), and Size (see references and calculation parameters in appendix 6).

Chapter 4 Findings

4.1 Banks´ efficiency analysis

This section starts with the presentation of the correlation matrix and summarised statistics for the chosen outputs and inputs applied in the first-stage DEA, as mentioned in sub-chapter 3.3.1. Subsequently, banks´ technical, pure technical and associated Scale Efficiency indicators (i.e. TE, PTE, and SE) resulting from the input-oriented first-stage DEA explained in the previous chapter, are presented, as show in Table 14 and Table 15 (see also appendix 8 for banks´ efficiency rankings).

Table 12 *– Correlation matrix of the selected outputs-inputs for the application of the first-stage DEA*

	Total NLA	Total Deposits	Net II	Total OE	Nº 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			
Nº 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

Table 13 *– Summarised statistics of the selected outputs-inputs for the application of the first-stage DEA*

	Mean			Median			Maximum			Minimum			Standard deviation		
Outputs	**PT**	**Iberian**	**ES**	**PT**	**Iberian**	**ES**	**PT**	**Iberian**	**ES**	**PT**	**Iberian**	**ES**	**PT**	**Iberian**	**ES**
Total NLA	15.052	48.698	61.515	2.763	6.932	7.659	72.680	835.023	835.023	58	16	16	21.163	119.420	137.690
Total Deposits	16.460	50.535	63.515	2.827	7.725	9.046	78.155	795.657	795.657	136	14	14	22.603	116.459	133.990
Net II	258	1.368	1.791	73	94	146	1.302	32.812	32.812	4	-147	-147	327	4.382	5.086
Inputs															
Total OE	382	1.423	1.819	116	217	292	1.655	27.762	27.762	9	7	7	481	3.942	4.565
Nº Employees	3.750	10.257	12.736	730	828	1.364	19.535	193.863	193.863	66	45	45	5.408	29.439	34.137
Fixed Assets	160	836	1.094	20	56	96	755	20.770	20.770	2	0	0	216	2.479	2.871

All values in Millions of €, except for Nº of employes (unit)

Where: Total NLA = Total Net Loan and Advances; Net II = Net Interest Income; and Total OE = Total Operating Expenses

The correlation matrix presented above (Table 12), shows that all applied variables (i.e. selected outputs and inputs) for the estimation of the first-stage DEA (i.e. efficiency scores) are positively and highly correlated, which means that an increase in any of those variables will most likely result in an increase on the others. Also, in table 13, a statistical summary for the chosen outputs-inputs is presented, with a separation by location/region (i.e. PT, Iberian, and ES). Spanish banks (i.e. represented as ES) have much higher averages, medians, maximums, and standard deviations for all selected outputs-inputs than their Portuguese counterparts. High standard deviation for Spanish banks is in line with their Maximums (higher than PT´s) and Minimums (lower than PT´s) results, which means that Spanish banking industry as a much wider spectrum of types of banks (i.e. diversity) than the Portuguese one.

Table 14 *- Annual TE, PTE and SE of Iberian banks during the period from 2013 to 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 SAU	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 Corporacion Bancaria 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	Caixa Economica 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	Banco Comercial Português, SA-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	Banco Bilbao Vizcaya Argentaria (Portugal) SA	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	Caixa - 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	Banco Bilbao Vizcaya Argentaria SA-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	Colonya, 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 y Monte de Piedad de 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	Confederación Española de 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	Fundacion Bancaria Caixa Estalvis Pensions De Barcelona	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 Sociedad Cooperativa d C.	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	Caixa Central de Credito Agricola Mutuo - 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
ES	36	Santander Consumer Finance	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	Caja de 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, Barcelona y Madrid	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 Sociedad Cooperativa de Crédito	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 Sociedad Cooperativa de Crédito	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-EBN Banco	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	Banco de Investimento Global SA - 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 Coop de credito	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 Cooperativo Sa	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**

The overall top five performing Iberian banks, assuming super efficiency scores while using the CRS model, are Banco Cooperativo Espanol (ES), BNP Paribas España SA (ES), Banco Caixa Geral (ES), Finantipar SA (PT), and Banco Finantia SA (PT), with 4-year period efficiency averages of 6.47, 2.33, 1.34, 1.05, and 1.02 respectively (see also appendix 8). On the other hand, the bottom five performing

Iberian banks, assuming super efficiency scores while using the CRS model, are Renta 4 Banco SA (ES), CIMD Group (ES), Caja Rural de Navarra SCC (ES), Banco Alcala (ES), and Banca March SA (ES), with efficiency averages of 0.07, 0.09, 0.172, 0.202, and 0.208 respectively.

The mean efficiency score of the sampled 58 Iberian banks during the period from 2013 to 2016, considering the CRS model, is 0.441 (not considering super efficiency). These findings suggest that Iberian banks, on average, could reduce their application of resources (inputs) by at least 55.9% for achieving the same amount of outcome (outputs) by improving their resources management practices.

Moreover, the overall top five performing Iberian banks, assuming super efficiency scores while using the VRS model, are Banco Santander SA (ES), Banco Cooperativo Espanol (ES), BNP Paribas España (ES), Santander Consumer Finance (ES), and EBN Banco de Negocios SA (ES), with 4-year period efficiency averages of "big" (i.e. very high score, which the applied EMS software cannot define), 6.51, 5.75, 2.08, and 1.64 respectively (see appendix 8). On the other side, bottom five performing Iberian banks, assuming super efficiency scores while using the VRS model, are Caja Rural de Navarra SCC (ES), Renta 4 Banco SA (ES), Banca March SA (ES), Confederación Española de Cajas de Ahorros (ES), and Caixa Central de Credito Agricola Mutuo (PT), with efficiency averages of 0.206, 0.22, 0.29, 0.34, and 0.36 respectively.

The mean efficiency score of the sampled 58 Iberian banks during the period from 2013 to 2016, considering 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.

Nevertheless, the abovementioned improvement opportunities are based on average results from the application of CRS, VRS, and super efficiency models, which means that potential improvement opportunities vary from bank to bank (see Table 14).

Table 15 *- Average annual efficiency measures of sampled Iberian banks from 2013 to 2016*

Year	Region	Nº of banks	Nº efficient TE	PTE	SE	Average Efficiency TE	PTE	SE	Maximum value TE	PTE	SE	Minimum Value TE	PTE	SE
2013	Iberian	58	5	13	5	0,409	0,660	0,623	1	1	1	0,011	0,031	0,130
	PT	16	1	3	1	0,429	0,676	0,659	1	1	1	0,118	0,225	0,130
	ES	42	4	10	4	0,402	0,654	0,610	1	1	1	0,011	0,031	0,265
	PT*	16	7	11	7	0,879	0,952	0,920	1	1	1	0,479	0,656	0,652
	ES*	42	5	10	5	0,434	0,670	0,638	1	1	1	0,011	0,035	0,273
2014	Iberian	58	5	16	5	0,412	0,689	0,600	1	1	1	0,046	0,214	0,117
	PT	16	2	4	2	0,437	0,691	0,645	1	1	1	0,155	0,299	0,183
	ES	42	3	12	3	0,402	0,689	0,583	1	1	1	0,046	0,214	0,117
	PT*	16	4	13	4	0,801	0,944	0,847	1	1	1	0,350	0,514	0,431
	ES*	42	3	12	3	0,414	0,701	0,591	1	1	1	0,046	0,214	0,096
2015	Iberian	58	4	16	4	0,446	0,705	0,645	1	1	1	0,033	0,190	0,082
	PT	16	1	3	1	0,468	0,730	0,661	1	1	1	0,212	0,320	0,241
	ES	42	3	13	3	0,438	0,696	0,639	1	1	1	0,033	0,190	0,082
	PT*	16	4	9	4	0,843	0,920	0,915	1	1	1	0,511	0,598	0,616
	ES*	42	3	13	3	0,451	0,711	0,646	1	1	1	0,033	0,190	0,069
2016	Iberian	58	6	19	6	0,498	0,773	0,653	1	1	1	0,049	0,197	0,093
	PT	16	3	7	3	0,579	0,828	0,707	1	1	1	0,287	0,385	0,287
	ES	42	3	12	3	0,467	0,752	0,632	1	1	1	0,049	0,197	0,093
	PT*	42	5	9	5	0,783	0,884	0,855	1	1	1	0,347	0,534	0,347
	ES*	58	3	14	3	0,472	0,772	0,614	1	1	1	0,049	0,235	0,093

*First-stage DEA analysis based on the isolated region sample

Table 15 presents some descriptive statistics for the estimates obtained through the DEA estimator (EMS) applying both CRS and VRS models. The average efficiency scores appear to be higher 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. Moreover, this discrepancy between CRS and VRS models seems to be perpetuated when analysing each region individually. Nonetheless, both models present an increase on average efficiency scores over the studied time period, with the scores of 0.402, 0.654, and 0.61 (i.e. TE, PTE, and SE) in 2013, comparing to the scores of 0.498, 0.773, and 0.653, in 2016, considering all sampled Iberian banks, although the same tendency can be noticed for PT and ES regions, individually.

The number of efficient Iberian banks considering technical and scale efficiency (i.e. TE and SE) seems to be constant over the analysed period, with five efficient banks in the first two years, and four and six in 2015 and 2016, respectively. On the other hand, the number of efficient Iberian banks considering pure technical efficiency (i.e. PTE) appears to be increasing over time, i.e. 13, 16, 16, and 19, for 2013, 2014, 2015, and 2016, respectively.

The average PTE is higher than the average SE for each of the 4-year period, considering Iberian banks in general and both Portuguese and Spanish banks specifically (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. Moreover, only 3 out of 58 sampled Iberian banks have achieved average SE scores of 1 (i.e. optimal scale efficiency) during the 4-year period (Table 14), namely Banco Cooperativo Espanol (ES), BNP Paribas España SA (ES), and Finantipar SA (PT).

When analysing each individual region (i.e. PT and ES) within the full Iberian sample, findings suggest that Portuguese banks have constantly better average TE, PTE, and SE scores throughout the studied period, in comparison to Spanish banks. This means that, on average, Portuguese banks are more efficiently managed and operate closer to the optimal scale efficiency than their Spanish counterparts.

4.2 Banks´ IC analysis

This sub-chapter starts with the presentation of the IC measures obtained through the application of the VAIC™ method explained in the previous chapter (see also appendix 6), during the period from 2013 to 2016. Annual and mean values for each variable, i.e. VAIC™, HCE, SCE, and CEE, can be seen in Table 16.

Table 16 *– Annual and average IC measures of Iberian banks during the period from 2013 to 2016*

Country	DMU	Bank	VAIC					HCE					SCE					CEE				
			2013	2014	2015	2016	Mean	2013	2014	2015	2016	Mean	2013	2014	2015	2016	Mean	2013	2014	2015	2016	Mean
PT	1	Banco L. J. Carregosa, S.A.	5,192	1,884	1,981	1,946	2,751	4,079	1,435	1,464	1,453	2,108	0,755	0,303	0,317	0,312	0,422	0,357	0,146	0,200	0,182	0,221
ES	2	Caixabank, S.A.	1,884	2,656	2,363	2,658	2,391	1,401	1,965	1,731	1,946	1,760	0,286	0,491	0,422	0,486	0,421	0,197	0,200	0,211	0,227	0,209
ES	3	BFA Tenedora de Acciones SAU	4,331	4,492	4,837	2,931	4,148	3,329	3,527	3,839	2,232	3,232	0,700	0,716	0,739	0,552	0,677	0,303	0,249	0,259	0,147	0,239
ES	4	Liberbank SA	3,505	3,664	2,424	3,238	3,207	2,481	2,754	1,802	2,417	2,363	0,597	0,637	0,445	0,586	0,566	0,427	0,273	0,177	0,235	0,278
ES	5	Renta 4 Banco, S.A.	2,708	2,944	2,928	2,499	2,770	1,782	1,902	1,897	1,630	1,803	0,439	0,474	0,473	0,387	0,443	0,487	0,568	0,558	0,482	0,524
ES	6	Ibercaja Banco SA	2,760	3,178	2,598	2,704	2,810	1,980	2,227	1,866	1,961	2,008	0,495	0,551	0,464	0,490	0,500	0,284	0,400	0,269	0,253	0,302
ES	7	Abanca Corporacion Bancaria SA	3,160	4,209	4,081	1,934	3,346	2,299	3,271	3,162	1,497	2,557	0,565	0,694	0,684	0,332	0,569	0,296	0,244	0,235	0,105	0,220
ES	8	Kutxabank SA	2,190	2,713	2,376	2,481	2,440	1,629	2,016	1,778	1,862	1,821	0,386	0,504	0,437	0,463	0,448	0,175	0,193	0,161	0,156	0,171
ES	9	Banco Caminos SA	4,417	3,892	3,139	3,089	3,634	3,453	3,027	2,371	2,331	2,795	0,710	0,670	0,578	0,571	0,632	0,253	0,196	0,190	0,187	0,207
ES	10	Banco Inversis SA	1,131	2,612	2,235	1,882	1,965	0,942	1,635	1,428	1,376	1,345	-0,061	0,389	0,300	0,273	0,225	0,250	0,588	0,507	0,233	0,395
ES	11	CIMD Group	2,597	2,703	2,356	2,202	2,465	1,373	1,368	1,284	1,225	1,312	0,271	0,269	0,221	0,184	0,236	0,953	1,066	0,851	0,793	0,916
PT	12	Santander Totta SGPS	3,244	3,272	4,985	4,062	3,891	2,429	2,469	3,949	3,137	2,996	0,588	0,595	0,747	0,681	0,653	0,227	0,209	0,289	0,244	0,242
PT	13	Caixa Economica Montepio Geral	1,443	4,342	2,034	2,095	2,479	1,164	3,212	1,483	1,559	1,855	0,141	0,689	0,326	0,359	0,378	0,139	0,441	0,225	0,177	0,246
PT	14	Caixa Geral de Depositos	1,838	2,099	2,406	1,398	1,935	1,394	1,563	1,747	1,103	1,452	0,282	0,360	0,428	0,094	0,291	0,162	0,176	0,232	0,201	0,192
PT	15	Banco Comercial Português, SA-Millennium bcp	1,991	3,463	4,280	5,287	3,755	1,387	2,535	3,238	4,236	2,849	0,279	0,605	0,691	0,764	0,585	0,325	0,323	0,351	0,287	0,322
PT	16	Banco Bilbao Vizcaya Argentaria (Portugal) SA	0,136	0,349	1,428	1,656	0,892	0,627	0,678	1,106	1,302	0,928	-0,594	-0,474	0,096	0,232	-0,185	0,103	0,144	0,226	0,122	0,149
PT	17	Caixa - Banco de Investimento SA	4,900	4,873	3,679	5,360	4,703	3,962	3,959	2,894	4,396	3,803	0,748	0,747	0,654	0,773	0,730	0,190	0,167	0,131	0,191	0,169
ES	18	Banco Bilbao Vizcaya Argentaria SA-BBVA	3,496	3,483	3,553	3,511	3,511	2,585	2,605	2,650	2,584	2,606	0,613	0,616	0,623	0,613	0,616	0,298	0,262	0,281	0,313	0,289
ES	19	Bankia, SA	3,161	3,965	3,924	3,443	3,623	2,357	3,052	3,024	2,636	2,767	0,576	0,672	0,669	0,621	0,635	0,227	0,240	0,231	0,186	0,221
ES	20	Bankinter SA	3,817	3,751	3,907	3,547	3,756	2,866	2,820	2,942	2,631	2,815	0,651	0,645	0,660	0,620	0,644	0,300	0,285	0,305	0,297	0,297
ES	21	Banco Popular Espanol SA	3,835	4,046	3,643	1,907	3,357	2,936	3,131	2,792	1,440	2,575	0,659	0,681	0,642	0,306	0,572	0,239	0,234	0,209	0,161	0,211
ES	22	Colonya, Caixa d'Estalvis de Pollensa	2,790	2,809	3,520	0,780	2,475	1,996	2,011	2,550	0,844	1,850	0,499	0,503	0,608	-0,185	0,356	0,295	0,295	0,362	0,121	0,268
ES	23	Caja de Ahorros y Monte de Piedad de Ontinyent	2,847	4,411	3,105	2,709	3,268	2,005	3,326	2,288	1,998	2,404	0,501	0,699	0,563	0,499	0,566	0,340	0,385	0,254	0,212	0,298
ES	24	Confederación Española de Cajas de Ahorros - CECA	3,954	2,497	2,942	2,996	3,097	3,053	1,910	2,261	2,311	2,384	0,672	0,476	0,558	0,567	0,568	0,229	0,111	0,123	0,118	0,145
ES	25	Banco Mediolanum SA	4,347	3,421	2,699	3,533	3,500	3,443	2,608	2,046	2,708	2,701	0,710	0,617	0,511	0,631	0,617	0,194	0,197	0,142	0,194	0,182
ES	26	Banca March SA	2,494	3,711	2,539	2,444	2,797	1,943	2,953	1,977	1,905	2,195	0,485	0,661	0,494	0,475	0,529	0,066	0,096	0,067	0,063	0,073
ES	27	Fundacion Bancaria Caixa Estalvis Pensions De Barcelona	1,643	2,475	2,204	2,138	2,115	1,268	1,843	1,636	1,612	1,590	0,211	0,457	0,389	0,379	0,359	0,164	0,175	0,180	0,147	0,166
ES	28	Banco de Sabadell SA	3,649	4,500	3,941	3,298	3,847	2,722	3,427	2,945	2,407	2,875	0,633	0,708	0,660	0,585	0,646	0,294	0,365	0,336	0,306	0,325
ES	29	Caja Rural de Almendralejo Sociedad Cooperativa d C.	4,328	3,580	3,690	2,767	3,591	3,338	2,710	2,779	2,069	2,724	0,700	0,631	0,640	0,517	0,622	0,289	0,240	0,270	0,181	0,245
PT	30	Haitong Bank SA	2,129	2,565	1,667	-1,211	1,287	1,526	1,751	1,241	0,373	1,222	0,345	0,429	0,194	-1,682	-0,179	0,258	0,385	0,233	0,099	0,244
PT	31	Banco Finantia SA	7,899	9,368	7,699	6,948	7,979	6,834	8,257	6,624	5,948	6,916	0,854	0,879	0,849	0,832	0,853	0,211	0,232	0,226	0,169	0,209
PT	32	Banco Santander Totta SA	3,079	3,063	5,024	4,073	3,809	2,289	2,283	3,957	3,121	2,913	0,563	0,562	0,747	0,680	0,638	0,226	0,217	0,320	0,272	0,259
ES	33	Deutsche Bank SAE	2,297	2,448	2,603	1,539	2,222	1,590	1,663	1,806	1,167	1,556	0,371	0,399	0,446	0,143	0,340	0,336	0,386	0,350	0,229	0,325
PT	34	Caixa Central de Credito Agricola Mutuo - CCCAM	2,343	1,731	2,543	2,418	2,259	1,665	1,296	1,806	1,721	1,622	0,399	0,229	0,446	0,419	0,373	0,278	0,206	0,290	0,278	0,263
ES	35	Bankoa SA	1,974	1,977	2,587	2,013	2,138	1,479	1,485	1,897	1,504	1,591	0,324	0,327	0,473	0,335	0,365	0,172	0,165	0,217	0,174	0,182
ES	36	Santander Consumer Finance	4,901	4,194	4,923	4,575	4,648	3,883	3,277	3,913	3,610	3,671	0,742	0,695	0,744	0,723	0,726	0,276	0,223	0,266	0,242	0,252
ES	37	Caja de Crédito de Los Ingenieros	3,044	2,867	2,474	1,536	2,480	2,203	2,088	1,787	1,198	1,819	0,546	0,521	0,440	0,165	0,418	0,295	0,258	0,247	0,173	0,243
ES	38	Caja Rural de Jaen, Barcelona y Madrid	2,809	2,992	2,702	2,278	2,695	2,083	2,240	2,018	1,704	2,011	0,520	0,554	0,505	0,413	0,498	0,206	0,198	0,179	0,162	0,186
ES	39	Caja Rural de Navarra Sociedad Cooperativa de Crédito	3,490	4,123	3,700	1,998	3,328	2,678	3,220	2,860	1,545	2,576	0,627	0,689	0,650	0,353	0,580	0,185	0,214	0,190	0,100	0,172
ES	40	Caja Rural de Soria Sociedad Cooperativa de Crédito	2,659	2,743	2,934	2,966	2,825	1,981	2,051	2,198	2,225	2,114	0,495	0,512	0,545	0,550	0,526	0,183	0,179	0,191	0,190	0,186
ES	41	Caja Rural de Zamora	4,975	4,969	4,357	3,683	4,496	3,950	3,943	3,412	2,852	3,540	0,747	0,746	0,707	0,649	0,712	0,278	0,279	0,238	0,181	0,244
ES	42	Banco Cooperativo Espanol	7,861	7,389	6,218	5,754	6,806	6,742	6,326	5,237	4,809	5,779	0,852	0,842	0,809	0,792	0,824	0,267	0,221	0,172	0,153	0,203
ES	43	Banco Alcala	1,318	1,472	1,228	0,985	1,250	1,091	1,148	1,008	0,901	1,037	0,083	0,129	0,007	-0,110	0,028	0,144	0,194	0,213	0,193	0,186
ES	44	Banco Caixa Geral SA	-1,798	2,550	3,324	2,886	1,740	0,315	1,905	2,537	2,180	1,734	-2,179	0,475	0,606	0,541	-0,139	0,066	0,169	0,181	0,165	0,145
ES	45	BNP Paribas España SA	1,398	1,446	1,525	1,208	1,394	1,080	1,103	1,136	0,987	1,076	0,074	0,093	0,120	-0,013	0,068	0,244	0,250	0,269	0,234	0,249
ES	46	EBN Banco de Negocios SA-EBN Banco	7,840	5,518	3,234	2,396	4,747	6,533	4,424	2,485	1,772	3,804	0,847	0,774	0,598	0,436	0,664	0,460	0,320	0,152	0,187	0,280
PT	47	Banco BPI SA	2,788	2,028	3,204	2,284	2,576	1,966	1,473	2,320	1,695	1,864	0,491	0,321	0,569	0,410	0,448	0,330	0,233	0,315	0,179	0,264
ES	48	Allfunds Bank SA	5,065	5,789	6,765	5,823	5,860	3,938	4,369	5,237	4,332	4,469	0,746	0,771	0,809	0,769	0,774	0,381	0,649	0,719	0,722	0,618
ES	49	Banco Santander SA	3,669	3,767	3,758	3,778	3,743	2,699	2,804	2,800	2,828	2,783	0,630	0,643	0,643	0,646	0,641	0,340	0,320	0,315	0,303	0,320
PT	50	Banco de Investimento Global SA - BIG	6,470	7,576	6,969	4,547	6,391	5,114	6,169	5,667	3,577	5,131	0,804	0,838	0,824	0,720	0,797	0,552	0,569	0,479	0,250	0,463
PT	51	Banco Invest SA	10,829	4,395	3,205	2,691	5,280	9,438	3,510	2,475	2,046	4,367	0,894	0,715	0,596	0,511	0,679	0,497	0,170	0,133	0,133	0,233
ES	52	Cajamar Caja Rural, S.C.C.	3,130	3,633	2,549	1,795	2,776	2,284	2,675	1,852	1,365	2,044	0,562	0,626	0,460	0,268	0,479	0,284	0,331	0,236	0,162	0,253
ES	53	Criteria CaixaHolding SA	1,895	2,476	2,259	2,370	2,250	-0,646	1,852	1,679	1,777	1,165	2,547	0,460	0,404	0,437	0,962	-0,005	0,164	0,176	0,157	0,123
ES	54	Caja Laboral Popular Coop de credito	2,981	2,807	2,929	2,487	2,801	2,217	2,092	2,194	1,866	2,092	0,549	0,522	0,544	0,464	0,520	0,215	0,193	0,191	0,157	0,189
ES	55	Unicaja Banco SA	4,255	3,217	3,605	2,324	3,350	3,161	2,347	2,627	1,689	2,456	0,684	0,574	0,619	0,408	0,571	0,410	0,296	0,359	0,226	0,323
ES	56	Banco De Credito Social Cooperativo Sa	2,975	3,633	2,102	1,677	2,597	2,162	2,675	1,550	1,295	1,921	0,538	0,626	0,355	0,228	0,437	0,275	0,331	0,198	0,154	0,239
PT	57	Atlântico Europa, Sgps, S.A	2,412	2,725	3,392	2,999	2,882	1,751	1,998	2,490	2,172	2,102	0,429	0,499	0,598	0,540	0,517	0,233	0,228	0,304	0,288	0,263
PT	58	Finantipar - S.G.P.S., S.A.	8,848	9,657	7,659	6,966	8,282	7,733	8,536	6,589	5,969	7,207	0,871	0,883	0,848	0,832	0,859	0,244	0,239	0,222	0,165	0,217
		Mean	3,471	3,605	3,395	2,867	**3,335**	2,689	2,774	2,592	2,225	**2,570**	0,508	0,550	0,538	0,425	**0,505**	0,274	0,281	0,266	0,218	**0,260**

The top 5 Iberian banks with the highest VAIC™ are Finantipar SA (PT), Banco Finantia SA (PT), Banco Cooperativo Espanol (ES), Banco BIG (PT), and Alfunds Bank SA (ES) with averages for the studied period of 8.28, 7.98, 6.81, 6.39, and 5.86, respectively. These banks are also the top 5 performers considering the HCE variable, in the same order, with scores of 7.21, 6.92, 5.78, 5.13, and 4.47, respectively.

Moreover, 4 of the abovementioned banks are also amongst the top five performers considering SCE, namely Criteria Caixa Holding SA (ES), Finantipar SA (PT), Banco Finantia SA (PT), Banco Cooperativo Espanol (ES), and Banco BIG (PT), with averages of 0.962, 0.859, 0.853, 0.824, and 0.797, respectively. On the other hand, when considering CEE top five performers only 2 out of the 5 VAIC™ top 5 performers remain for this category, namely Alfunds Bank SA and Banco BIG, in 2nd (0.618) and 4th (0.463) positions, respectively.

These findings suggest the HCE component is the major contributor for the main aggregate VAIC™ result, followed by the SCE component, and that CEE is the component with the lowest impact on the overall VAIC™ measure (Table 16). Moreover, Iberian banks´ VAIC™, HCE, SCE, and CEE, averages are of 3.35, 2.57 (i.e. 77% of VAIC), 0.505 (i.e. 15,1% of VAIC), and 0.26 (i.e. 7.9% of VAIC), respectively, which corroborates the abovementioned statement. Thus, this study infers that Iberian sampled banks were generally more effective at creating VA from their IC (i.e. mainly HC, and also SC).

4.3 IC and performance nexus analysis

This sub-chapter starts with a summary of the applied variables statistics applied in the second-stage analysis (i.e. econometric analysis), some of them, already mentioned on the previous sub-chapters, as can be seen in Table 17. Subsequently, the results obtained from the application of the regression models explained in sub-chapter 3.4 are presented.

Table 17 *- Summarised statistics of Iberian banks: Portuguese and Spanish differentiation*

Variables	Mean			Median			Maximum			Minimum			Standard deviation		
	PT	Iberian	ES	PT	Iberian	ES	PT	Iberian	ES	PT	Iberian	ES	PT	Iberian	ES
VAIC	3,822	3,335	3,149	3,141	2,978	2,943	10,829	10,829	7,861	-1,211	-1,798	-1,798	2,472	1,711	1,273
HCE	3,083	2,570	2,374	2,305	2,221	2,2	9,438	9,438	6,742	0,373	-0,646	-0,646	2,142	1,468	1,054
SCE	0,491	0,505	0,51	0,566	0,551	0,547	0,894	2,547	2,547	-1,682	-2,179	-2,179	0,403	0,347	0,325
CEE	0,247	0,260	0,264	0,227	0,231	0,234	0,569	1,066	1,066	0,099	-0,005	-0,005	0,100	0,140	0,152
Lev1	0,889	0,901	0,906	0,919	0,923	0,923	0,960	0,985	0,985	0,768	0,290	0,290	0,056	0,070	0,075
Lev2	0,111	0,099	0,094	0,081	0,077	0,076	0,232	0,710	0,710	0,038	0,015	0,015	0,056	0,070	0,075
Lev3	11,66	12,947	13,44	11,64	12,375	12,44	32,641	67,389	67,389	3,432	0,426	0,426	6,364	7,048	7,250
Size	9,791	10,015	10,1	9,678	10,097	10,19	11,053	12,127	12,127	8,299	8,043	8,043	0,816	0,977	1,021
TE	0,478	0,441	0,427	0,394	0,384	0,383	1	1	1	0,118	0,011	0,011	0,249	0,249	0,249
PTE	0,731	0,707	0,698	0,72	0,702	0,692	1	1	1	0,225	0,031	0,031	0,237	0,257	0,264
SE	0,668	0,630	0,616	0,675	0,624	0,576	1	1	1	0,13	0,082	0,082	0,237	0,244	0,246
Super Ef. (CRS)	1,053	2,466	3,227	1,015	1,175	1,942	1,151	9,830	9,830	1,004	1,004	1,067	0,057	2,621	3,014
Super Ef. (VRS)*	1,252	1,958	2,237	1,113	1,217	1,248	2,181	9,899	9,899	1,006	1,006	1,008	0,293	1,969	2,265

*some banks present "big" values for the Super Efficiency Score on VRS, thus not considered in the above statistics

CRS and VRS super efficiency statistics based on efficient banks only

Table 17 presents some descriptive statistical overview of the obtained variables for the application of the second-stage analysis, considering Iberian banks in general, and also both Portuguese and Spanish banks specifically. By interpreting the obtained results displayed on Table 17, one may infer that Portuguese banks (within the full Iberian sample) present, on average, higher VAIC™ (due to higher HCE), while also presenting better efficiency scores (i.e. higher TE, PTE, and SE) than their Spanish counterparts. On the other hand, Spanish Banks present, on average, higher SCE and CEE measures than Portuguese banks, which means that ES banks are, on average, more efficient at generating value added through SC and CEE, while PT banks are, on average, better at using their HC for creating value.

Moreover, the ES region presents higher average and maximum score values for super efficiency, using both CRS and VRS models, than the PT region, which indicates that top performing Spanish banks have, on average, higher efficiency scores than top performing Portuguese banks, thus setting the "best practices" standard for all the Iberian region.

Furthermore, control variables such as Size and Leverage (i.e. Lev1, Lev2, and Lev3), seem to indicate that Spanish banks are, on average, bigger and, proportionately, more dependent on third party capital than Portuguese banks.

Table 18 *- 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	

*VRS and CRS based on Super efficiency scores

The correlation matrix (Table 18), retrieved from Stata 14, for all the selected variables for the second-stage analysis (Iberian sample), show Lev3 and HCE, to be the variables with 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 (Table 17 and 18) for the application of the regression models presented in chapter 3 (i.e. quantile and fractional), using Stata 14.

Table 19 *- Selected results of the OLS and quantile regressions applying both CRS and VRS super efficiency models*

Independent variables	OLS regression		Quantile Regression											
			Q (0.10)		Q (0.25)		Q (0.50)		Q (0.75)		Q (0.90)		Q (0.95)	
	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
HCE	.2278 (.00)***	.18 (.001)***	.86 (.00)***	.11 (.00)***	.11 (.00)***	.11 (.00)***	.117 (.00)***	.12 (.00)***	.139 (0.054)*	.12 (.192)	.38 (.083)*	.538 (.451)	.532 (.194)	1.1 (.193)
SCE	-.2475 (.121)	-.353 (.148)	-.036 (.6)	-.087 (.369)	-.067 (.55)	-.014 (.918)	-.0612 (.598)	-.12 (.457)	-.171 (.638)	-.438 (.429)	-1.413 (.229)	- 2.78 (.556)	-2.634 (.321)	-6.2 (.233)
CEE	-1.104 (.001)***	-.991 (.044)**	-.45 (.009)***	-.234 (.226)	-.612 (.00)***	-.453 (.015)**	-.634 (.013)	-.478 (.125)	-.495 (.065)*	-.498 (.184)	-.672 (.163)	-1.28 (.143)	-2.136 (.067)*	-3.3 (.007)***
SIZE	-.3424 (.00)***	-.362 (.00)***	-.042 (.164)	.0414 (.536)	-.06 (.009)***	.0215 (.719)	-.085 (.00)***	-.06 (.55)	-.107 (.056)*	-.168 (.046)**	-.21 (.079)*	-.075 (.601)	-.371 (.088)*	-.113 (.419)
Lev1	-16.984 (.769)	-79.19 (.370)	-14.1 (.202)	-67 (.002)***	-16.34 (.385)	-55.3 (.011)**	-10.52 (.54)	-56.4 (.030)**	-10.24 (.804)	-75 (.075)*	-4.127 (.925)	8.8 (.894)	-3.13 (.959)	25 (.675)
Lev2	-13.365 (.817)	-75.63 (.392)	-14.3 (.199)	-68 (.002)***	-16.49 (.379)	-55.4 (.013)**	-10.29 (.554)	-55.5 (.033)**	-9.477 (.822)	-73.22 (.072)*	3.65 (.934)	20.6 (.766)	7.88 (.898)	49.5 (.418)
Lev3	.11569 (.00)***	.11 (.00)***	.00554 (.275)	.0067 (.441)	.0081 (.190)	.011 (.372)	.0152 (.070)*	.036 (.112)	.0278 (.625)	.058 (.35)	.153 (.004)***	.146 (.023)**	.146 (.003)***	.18 (.012)**
Constant	18.941 (.744)	81.95 .355	14.59 (.190)	67.2 (.003)***	17.03 (.368)	55.28 (.013)**	11.45 (.505)	57.05 (.033)**	11.305 (.786)	76.6 (.069)*	4.52 (.920)	-9 (.894)	6.05 (.923)	-24.8 (.684)
Observations	228	228	228	228	228	228	228	228	228	228	228	228	228	228
R^2 / Pseudo R^2	0.5765	0.3257	0.1580	0.1132	0.1466	0.0839	0.1325	0.0781	0.1557	0.0557	0.2992	0.1967	0.4423	0.3514
Dependent variable: Efficiency based on both CRS and VRS models; p-values in parenthesis; *, **, *** means significant at 10%, 5%, and 1%, respectively;														
DMU 49 was removed due to "big" value in VRS model;														

In table 19, selected quantile regression estimates (with OLS comparison) are shown considering both CRS and VRS super efficiency scores as dependent variables. Results of the quantile regression indicate a positive and significative influence of HCE over efficiency scores (both CRS and VRS models) for the quantiles of 10%, 25%, and 50%, which means that lower efficiencies (i.e. 10% and 25%) to median (i.e. 50%) are positively and significantly related to HCE (i.e. VAIC™ major component, as seen in sub-chapter 4.2). Considering only the CRS model, results show also a positive, but less significant influence of HCE over higher performers pertaining to the 75% and 90% quantiles.

Moreover, results indicate a negative but not significant effect of SCE on the efficiency scores, which means that HCE is the only IC related VAIC™ component with a significant effect on banks´ performance. The other non-IC related VAIC™ component, i.e. CEE, appears to have a negative and significant effect on Iberian banks´ efficiency, in the 10%, 25%, 75%, and 95% quantiles, considering the CRS model, and in the 25% and 95% quantiles, considering the VRS model. In essence, results show that CEE has a negative and significant impact on bottom (i.e. low performers) and top quantiles (i.e. high performers), especially considering the CRS model.

Furthermore, results indicate that SIZE (i.e. logarithm of a bank´s total assets) has a negative and significant effect on the overall Iberian banks´ efficiency (i.e. all quantiles except for the bottom 10%), considering a CRS model. On the other hand, while considering a VRS model, estimates only show a negative and significant impact of the SIZE variable on Iberian banks´ efficiency scores for the upper 75% and 90% quantiles.

Additionally, results show similar high coefficients (i.e. strong impact) for the Lev1 (i.e. total debt to total assets) and Lev2 (i.e. Equity to total assets) control variables, which appear to have a negative and significant effect on the 10%, 25%, 50% and 75% quantiles (only on the VRS model), thus excluding the extreme top performing Iberian banks. This means that banks´ efficiency on the aforesaid quantiles (VRS model only) are negatively and significantly impacted by financial leverage increases, either from debt (i.e. Lev1) or equity (i.e. Lev2).

Conversely, the other applied financial risk variable, Lev3 (i.e. total liabilities to shareholder´s equity), appears to have a positive and significant effect on top performing Iberian banks (i.e. 90% and 95% quantiles), considering both CRS and VRS models. Results also indicate a less significant and positive relationship between Lev3 and median performers (i.e. 50% quantile), but only for the CRS model. A possible explanation for this is that Iberian banks´ efficiency scores, on the aforementioned quantiles, are positively and significantly impacted by a possible increase in use of third party capital (i.e. liabilities) instead of banks´ own capital (i.e. shareholder´s equity).

Moreover, results indicate higher coefficients of determination (i.e. Pseudo R^2) for the top extreme quantiles, i.e. for the 90% and 95% quantiles, considering both CRS and VRS models. The CRS model presents the higher determination coefficient for the 95% quantile with a r-squared of 0.4423, which means that 44.23% of the dependent variable variance can be explained by that selection of independent variables, considering that specific model and quantile. On the other hand, considering the VRS model, the highest obtained determination coefficient is also for the 95% quantile, but with a r-squared result of 0.3514, which means that 35.14% of dependent variable variance can be explained by the selected independent variables.

Considering the Portuguese and Spanish isolated samples, for the quantile regression (see appendix 14) results indicate that Spanish isolated sample presents more similar results to the Iberian sample, than the Portuguese isolated one, which means that the Portuguese isolated sample as a low impact within the results of Iberian sample. Results indicate a positive and significant effect of HCE on banks' efficiency (CRS only), in the 25%, 50% and 75% quantiles for the PT isolated sample, and in the 25% and 50% quantiles for the ES isolated sample.

Also, SCE appears to have a positive and significative effect on banks´ efficiency (VRS only) in the 25% and 75% quantiles for the PT isolated sample. Conversely, results show a negative a significative impact of SCE on banks´ efficiency (CRS only), in the 10% and 25% quantiles for the ES isolated sample.

Moreover, results do not show any significant effect of CEE on banks´ efficiency for the PT isolated sample, while for the ES isolated sample, results indicate a negative and significant effect of CEE on banks´ efficiency in the 10% and 25% quantile (considering CRS), and in the 75% quantile (considering VRS).

Furthermore, for the PT isolated sample, the SIZE control variable appears to have negative and significant effect on banks´ efficiency throughout all quantiles, considering VRS, and in the 25% and 50% quantiles, considering CRS. On the other hand, for the ES isolated sample, results show only a negative and significant impact of SIZE on the banks´ efficiency in the 75% quantile, considering CRS.

The financial risk control variables, Lev1 and Lev2, do not show any significant impact on banks´ efficiency, for the PT isolated sample. On the other hand, these variables appear to have a negative and significant effect on banks´ efficiency, in the 10% and 25% quantiles (VRS only), for the ES isolated sample. Moreover, the control variable, Lev3, seems to have a positive and significant impact on banks' efficiency, in the 10%, 25%, 50% (both CRS and VRS), and 75% (CRS only), for the PT isolated sample. On the other hand, for the ES isolated sample, results show a positive and significant impact of Lev3 on banks' efficiency, in the 75% quantile (VRS only), and in the 90% quantile (for both CRS and VRS).

Finally, R-squared results seem to be more consistent (less variance) throughout all quantiles, for the PT isolated sample, but still, with highest r-squared results of 0.3702 (CRS) and 0.3758 (VRS) in the bottom 10% quantile. Conversely, as previously mentioned, results obtained for the ES isolated sample are more similar to the full Iberian sample, with r-squared results being much higher in the top quantile (90%), i.e. 0.4248 (CRS) and 0.3666 (VRS).

Table 20 *– Estimation results for the fractional regression models (Iberian sample)*

	One-part models				Two-part models											
					1st part				2nd part							
	Logit		Cloglog		Logit		Cloglog		Logit		Probit		Loglog		Cloglog	
	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
HCE	.54653 (.00)***	.3964 (.00)***	.36 (.00)***	.2371 (.00)***	.688 (.00)***	.449 (.001)***	.625 (.00)***	.3601 (.00)***	.442 (.00)***	.3216 (.00)***	.261 (.00)***	.2006 (.000)***	.265 (.000)***	.236 (.00)***	.31 (.00)***	.2264 (.00)***
SCE	-.64 (.021)**	-.5856 (.166)	-.34 (.041)**	-.2867 (.080)*	-.799 (.266)	-.34 (.560)	-.659 (.314)	-.23613 (.628)	-.405 (.107)	-.4436 (.078)*	-.237 (.137)	-.2791 (.062)*	-.24 (.142)	-.331 (.079)*	-.251 (.215)	-.3 (.043)**
CEE	-2.64 (.00)***	-1.01 (.059)*	-2.23 (.00)***	-.7058 (.035)**	-7.21 (.036)**	-2.414 (.094)*	-7.31 (.019)**	-2.037 (.095)*	-2.012 (.00)***	-.132 (.776)	-1.175 (.00)***	-.0853 (.762)	-1.06 (.000)***	-.0319 (.918)	-1.69 (.00)***	-.20673 (.559)
SIZE	-.2864 (.00)***	.048 (.645)	-.22 (.00)***	.0505 (.489)	-1.28 (.008)***	-.16023 (.420)	-1.18 (.010)***	-.1545 (.363)	-.14341 (.037)**	.20535 (.070)*	-.086 (.042)**	.1319 (.061)*	-.0865 (.034)**	.1376 (.099)*	-.11 (.073)*	.1635 (.039)**
Lev1	-14.35 (.697)	-358.5 (.001)***	-4.434 (.892)	-155.4 (.00)***	482.8 (.835)	-48.74 (.814)	470 (.829)	-44.19 (.807)	-3.42 (.913)	-336.41 (.001)***	-.5204 (.978)	-187.13 (.00)***	.965 (.959)	-304.014 (.001)***	.54 (.984)	-152.5 (.00)***
Lev2	-18.5 (.616)	-359.17 (.001)***	-7.3 (.823)	-156.07 (.00)***	486.3 (.833)	-49.09 (.813)	473.5 (.827)	-444.281 (.806)	-8.63 (.782)	-336.92 (.001)***	-3.43 (.857)	-187.43 (.00)***	-1.4 (.941)	-304.1 (.001)***	-3.643 (.892)	-153 (.00)***
Lev3	.00589 (.627)	.013 (.447)	.0081 (.284)	.0075 (.401)	.119 (.068)*	.0133 (.663)	.11 (.048)**	.0181 (.388)	-.0146 (.366)	.024 (.329)	-.0082 (.399)	.0145 (.316)	-.0063 (.485)	.02103 (.269)	-.01216 (.385)	.0142 (.324)
Constant	16.9 (.649)	358.32 (.001)***	6.03 (.854)	154.8 (.00)***	-474.62 (.837)	48.82 (.814)	-462.62 (.831)	44.038 (.808)	4.73 (.881)	333.95 (.001)***	1.27 (.948)	185.56 (.00)***	.025 (.999)	302.63 (.001)***	.177 (.995)	150.3 (.001)***
Observations	232	232	232	232	232	232	232	232	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	0.296	0.22583	0.294	0.2269	0.286	0.2212	0.2955	0.2337

Dependent variable: Efficiency scores based on both CRS and VRS models; z-values in parenthesis; *, **, *** means significant at 10%, 5%, and 1%, respectively;

In table 20, selected fractional regression estimates are shown considering both CRS and VRS efficiency scores (i.e. TE and PTE) as dependent variables. 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 (CRS only), and in one-part cloglog and all second-part of the two-part models (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.

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 20). 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. R^2).

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).

In essence, as can be seen in table 20, conducting a two-part fractional regression presents the advantage of analysing, first, why some banks are on the efficiency frontier while others are not (i.e. first-part models), and, second, the distance of inefficient banks to the frontier (i.e. second-part models), which appears to be a better way of displaying the real impact of each covariate on banks´ efficiency (i.e. DEA scores).

As e.g., results for the two-part model (Table 20), indicate consistent 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 obtained results for this regression, HCE is positively and significantly related to, first, DEA scores of efficient banks (i.e. firs-part), and second, DEA scores of inefficient banks (i.e. second-part). On the other hand, e.g., 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 positive and significant impact on inefficient Iberian banks´ PTE.

Also, e.g., r-squared results seem to be higher, considering VRS, in the second-part models, which means that obtained results 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.

Additionally, an effort was made to conduct the same fractional regression models presented above, using both isolated PT and ES samples (as was the case for the quantile regression). However, Stata 14 software could not run the previously applied fractional model commands for the isolated samples (possibly due to smaller ES and PT sample sizes).

4.4 Discussion

As previously mentioned, this study applies a two-stage analysis as 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 regression models (i.e. quantile and fractional) in order to infer about the effect of IC efficiency (using VAIC™ components) on performance (as measured by banks´ efficiency scores).

Results obtained in the first-stage analysis (see sub-chapter 4.1) show that the averages of Iberian banks´ TE and PTE, during the period from 2013 to 2016, are of 44.1% and 70.7%, respectively. Also, when analysing each individual region (i.e. PT and ES) within the full Iberian sample, findings suggest that Portuguese banks have constantly better average TE, PTE, and SE scores throughout the studied period, in comparison to Spanish banks. This may be an indication that Portuguese banks are, on average, being more efficiently managed and operating closer to the optimal scale efficiency than their Spanish counterparts. Nevertheless, results indicate higher standard deviations for the Spanish banks´ efficiency scores, which reflects on Iberians´ top and bottom five ranks, predominantly occupied by Spanish banks (see 4.1)

In essence, findings from the first-stage analysis 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.

Nonetheless, findings also show an increase on average efficiency scores (for both CRS and VRS) over the studied time period, with the scores of 0.402, 0.654, and 0.61 (i.e. TE, PTE, and SE) in 2013, comparing to the scores of 0.498, 0.773, and 0.653, in 2016, considering all sampled Iberian banks, although the same tendency can be noticed for PT and ES regions, individually. Thus, findings suggest a continuous improvement of efficiency scores for the studied samples (i.e. Iberian, PT, and ES), over the four-year period.

Furthermore, IC analysis (see 4.2) shows that the average VAIC™, during the period from 2013 to 2016, is of 3.335, 3.822, and 3.149 for Iberian, Portuguese, and Spanish banks, respectively. Portuguese banks (within the full Iberian sample) present, on average, higher VAIC™ (due to higher HCE), while also presenting better efficiency scores (i.e. higher TE, PTE, and SE) than their Spanish counterparts. On the other hand, Spanish Banks present, on average, higher SCE and CEE measures than Portuguese banks, which means that ES banks are, on average, more efficient at generating value added through SC and CE, while PT banks are, on average, better at using their HC for creating value.

Additionally, results show HCE to be the VAIC™ component with the highest value, considering the Iberian region in general, and each country individually, which corroborates the results obtained by Al-Musali & Ismail (2014), Chen Goh (2005), Gigante & Previati (2011), and Ousama & Fatima (2015).

Results obtained in the second-stage analysis (see sub-chapter 4.3), 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 Al-Musali & Ismail (2014), Aziz & Hashim (2017), Irawanto et al. (2017), Meles et al., (2016), Nawaz (2017), Nawaz & Haniffa (2016), Ousama & Fatima (2015), Ozkan et al. (2017), Thakur, (2017), and Tiwari & Vidyarthi (2018).

Moreover, 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 significant in all the applied regression and models – see Table 19 and 20). These findings are in line with the results obtained by Aziz & Hashim (2017), Iqbal & Zaib (2017), Nawaz (2017), and Ozkan et al. (2017).

Furthermore, results show CEE (i.e. non-IC related VAIC™ component) to have a negative and significant relationship between banks´ performance (i.e. TE and PTE), in both quantile and fractional regressions (although, not significant for all quantile and fractional models – see Table 19 and 20). These findings contradict all the revised literature that related CEE and banks´ performance (see appendix 2), such as Al-Musali & Ismail (2014), Alhassan & Asare (2016), Iqbal & Zaib (2017), Jafarnezhad & Tabari (2016), and Nawaz & Haniffa (2016), which found a positive and significant relationship between those variables.

Also, findings suggest inconclusive results for the SIZE variable, showing a negative and significant effect of that variable on banks´ efficiency, in some of the quantiles and fractional models (see Table 19 and 20), 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 (see Table 20). Other authors have found inconclusive results when trying to infer about a possible relationship between a SIZE variable (i.e. representative of a bank´s size, normally related to the total assets variable), and banks´ performance, such as Iqbal & Zaib (2017) and Kehelwalatenna & Premaratne (2014). Martins (2018), on the other hand, found that the Size variable had a major positive influence on Portuguese banks´ overall efficiency.

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 indicate a negative effect of Lev1 and Lev2 on less efficient (considering quantile regression) or inefficient (considering fractional regression second-part of the two-part models) Iberian banks´ PTE, which is line with results obtained by Ozkan et al. (2017) and Vidyarthi (2018). Also, Basílio, Pires, & Reis (2016), found contradictory results when inferring about the effect of a Lev2-like (capitalisation) variable on PT and ES banks´ overall efficiency (TE). These later authors found the Lev2-like variable to have a positive and significant effect on PT banks´ overall efficiency, and also, a negative and significant impact on ES banks´ overall efficiency.

Conversely, while seeing significant effects only, results show Lev3 to have a positive and significant impact on more efficient (considering quantile regression) or efficient (considering fractional regression first-part of the two-part models) on Iberian banks´ PTE, and only on more efficient (considering quantile regression) Iberian banks´ TE, which contradicts the negative impact of a Lev3-like variable on bank´s performance found by Iqbal & Zaib (2017), and the inconclusive results, using the same leverage variable, found by Ousama & Fatima (2015).

Nonetheless, a caveat should be made, as one should keep in mind, that the majority of the authors cited above, used more traditional financial indicators (e.g. ROA, ROE, ATO, Tobin´s q, and EPS) for assessing banks´ performance (see appendix 2), instead of the DEA, which was selected for this study.

Chapter 5 Conclusion

In this study, a two-stage analysis was conducted in order to address several proposed research questions (see chapter 1) related to Iberian (Portuguese and Spanish) banks in general, and each country, individually, during the period from 2013 to 2016.

Therefore, the main purpose of this dissertation´s 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, VRS, and Super efficiency 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 both quantile and fractional (one part and two-part models) regressions.

First-stage analysis findings (see sub-chapter 4.1) show that the averages of Iberian banks´ TE and PTE, during the period from 2013 to 2016, are of 44.1% and 70.7%, respectively. Also, when analysing each individual region (i.e. PT and ES) within the full Iberian sample, findings suggest that Portuguese banks have constantly better average TE, PTE, and SE scores throughout the studied period, in comparison to Spanish banks. This may be an indication that Portuguese banks are, on average, being more efficiently managed and operating closer to the optimal scale efficiency than their Spanish counterparts. Also, findings show an increase on average efficiency scores (for both CRS and VRS), over the studied four-year period, for all sampled Iberian banks, although the same tendency can be noticed for PT and ES regions, individually.

Furthermore, findings from the conducted IC analysis show that the average VAIC™, during four-year period, was of 3.335, 3.822, and 3.149 for Iberian, Portuguese, and Spanish banks, respectively. Thus, Portuguese banks (within the full Iberian sample) present, on average, higher VAIC™ (due to higher HCE), while also presenting better efficiency scores (i.e. higher TE, PTE, and SE) than their Spanish counterparts.

On the other hand, Spanish Banks present, on average, higher SCE and CEE measures than Portuguese banks, which means that ES banks are, on average, more efficient at generating value added through SC and CE than PT banks, while PT banks are, on average, better at using their HC for creating value than ES banks. Also, findings suggest HCE to be the VAIC™ component with the highest value, therefore being a preponderant source of IC efficiency.

Finally, second-stage analysis findings suggest a positive and significant relationship between HCE and sampled banks´ performance. Conversely, results suggest a negative and significant impact of both SCE and CEE on sampled banks´ performance. Thus, at the IC-related sub-component level, only HCE has a positive and significant impact on the efficiency scores of the selected banks (i.e. TE and PTE), which may be an indication of 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, and also on Portuguese and Spanish banks´ performance, specifically.

This study´s main limitations are inherent to the adoption of the VAIC™ method (see Table 4 for this method´s advantages and limitations), and to the constrains imposed by the availability of the data. Also, despite using some IC components (i.e. representing some of the most important IC dimensions mentioned in the literature review), which are encompassed in the VAIC™ method, as independent variables, in a way of inferring about their impact on banks´ performance, these dimensions do not represent IC as whole, and thus, are not representative of the overall effect of IC on performance.

Therefore, future research can include a modified variant of VAIC™ (see appendix 5), 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. Further efforts should be made to better comprehend exactly how and why each individual IC component may have an impact on banks´ efficiency, thus allowing for the optimisation of IC management and for a more efficient application of intangible resources. Additionally, the chosen methodology for this study can be replicated in other countries or regions, by using primary and/or secondary data.

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Appendices

Appendix 1 – Prior studies relating VAIC™ to performance

Authors	Sample	Methodology	Findings/ Significant Relationships
(Firer & Williams, 2003)	75 publicly traded firms from South Africa from business sectors heavily reliant on intellectual capital; 2001 (1 year)	VAIC & Financial KPIs (correlation and linear multiple regression analysis.)	HCE – between ATO, MB SCE + between ROA CEE + between MB
(Mavridis, 2004)	141 Japanese banks between 2000 and 2001 Performance = (VAIC – SCE) and VA	Financial Data only; Applies VAIC method (regression models)	+ relationship between VA, and Physical Capital and HC Banks with highest performance have high usage of HC and less usage of Physical Capital;
(M. Chen et al., 2005)	Taiwan Stock Exchange 1992 – 2002 (11 Years) Tests 3-year lag	VAIC & Financial KPIs (regression models)	VAIC + between ROA, ROE, MB, GR, EP HCE + between ROA, ROE, MB, GR, EP SCE + between ROA, MB CEE + between ROA, ROE, MB, GR, EP
(Shiu, 2006)	80 Taiwanese Listed Technological Companies 2003 (1 year); Also tests 1-year lag	VAIC & Financial KPIs (Multiple linear regression)	VAIC + between ROA, MB HCE – between ATO, MB CEE + between ROA, ROE, MB, GR, EP
(Appuhami, 2007)	33 Thailand banks; 2005 (1 Year); Annual reports + share market trading information	VAIC & Financial KPIs (Multiple linear regression)	VAIC + between MR CEE – between MR
(Kujansivu & Lönnqvist, 2007)	Approximately 20.000 Finnish companies per year (11 industry sectors); 2001-2003 (3 years)	VAIC & CIV models (Correlation analysis	Unclear relationship between the value and efficiency of IC; Calculating IC value by dividing the value of a company´s IC by the value of its tangible assets was found to be illustrative in comparting different industries;
(Kamath, 2008)	Top 25 firms in the drug and pharmaceutical industry in India; 1996-2006 (10 years)	VAIC & Financial KPIs (Linear multiple regression)	The major contribution to VAIC is HCE rather than CEE or SCE; SCE – between ATO and ROA, but + between MB; HCE + between ATO, ROA, but – between MB; VAIC – between MB (Firms with high ICE are significantly undervalued in the market);
(Makki, Lodhi, & Rahman, 2008)	LSE-25 listed companies (Lahore stock exchange); 2002-2007 (6 years); cross-sectional;	VAIC measurement, evaluation and ranking;	Best performing companies are those with good results in using HC;
(Chan, 2009a)	33 constituent companies of Hang Seng Index, Hong Kong Stock Exchange. 2001 – 2005 (5 Years)	VAIC & Financial KPIs (Multiple linear regression	VAIC + between ROA, ROE HCE – between ATO, MB SCE + between ROA, ROE CEE + between ROA, ATO, MB, ROE

Where: MB = Market to Book Ratio, MV = Market Value, BV = Book value, ROA = Return on Assets, ROE = Return on Equity, GR = Revenue Growth, EP = Employee Productivity, ATO = Asset Turnover, MR = Capital Gain on Shares; KS = knowledge Sharing, RDE = Innovation Capital Efficiency; ASR = Annual Stock Returns

Authors	Sample	Methodology	Findings/ Significant Relationships
(Ghosh & Mondal, 2009)	80 Indian companies from software and pharmaceutical sectors; 2002-2006 (5 years)	VAIC & Financial KPIs (Multiple linear regression)	IC is the positive predictor of profitability; Investors are not influenced by IC performance of the selected companies;
(Ting & Lean, 2009)	20 Financial institutions in Malaysia 1999-2007 (9 years)	VAIC & Financial KPIs (Multiple linear regression)	VAIC + between ROA HCE + between ROA CEE + between ROA
(Ahangar, 2011)	1 famous Iranian business company; 1980-2009 (30 years)	VAIC & Financial KPIs (Linear multiple regression)	HCE + between ROA; ATO + between ROA; ATO, HCE + between Growth in Sales; CEE – between Growth in Sales; HCE + between Employee Productivity; CEE - between Employee Productivity;
(Chang & Hsieh, 2011)	367 Taiwanese semiconductor organizations; 2000-2008 (8 years)	Modified VAIC (adds RDE) & Indicators (Pearson correlation & Multiple linear regression)	CEE + between OP; Besides RDE, IC components have a negative association with FP & Stock Market Performance; RDE + between OP, FP & Stock Performance (SP); Intellectual Property Rights + between OP & SP;
(Maditinos et al., 2011)	96 Greek companies listed in Athens Stock Exchange from 4 sectors; 2006-2008 (3 years)	VAIC & Financial KPIs (Multiple linear regression)	Failed to support most of hypothesis that related IC with performance and as a strategic asset; Only found: HCE + between ROE; Greek companies seem to place more faith and value in Physical Capital than in IC;
(Rehman et al., 2011)	12 Modaraba companies	VAIC & Financial KPIs (Multiple linear regression)	HCE; SCE, CEE + between FP; HCE, SCE, CEE + between ROE; HCE, SCE, CEE + between EPS; CEE + between ROI;
(Veltri & Silvestri, 2011)	All firms listed on the Italian Stock belonging to the financial sector Exchange; 2006-2008 (3 years)	VAIC & Ohlson model (modified) - POLS	+ relationship between accounting values and MV on the one hand, and IC components (VAIC) and MV on the other; Investors attach more relevance to HCE than to SCE; HCE plays an indirect role in the relation between IC and MV;
(M. Wang, 2011)	Taiwanese companies; 2001-2008 (8 years)	VAIC & Financial KPIs	VAIC + between ROA, Market Capitalisation; VAIC – between Operating Cash flows;
(Alipour, 2012)	39 Iranian insurance companies; 2005-2007 (3 years)	VAIC & Financial KPIs (PLS; Multiple linear regression)	VAIC + between ROA; HCE + between ROA; SCE + between ROA; CEE + between ROA;
(Javornik et al., 2012)	12.000 Slovenian companies; 1995-2008 (14 years)	VAIC & Financial KPIs (OLS and Panel regression)	Tests on VAIC are inconclusive; Although most of the hypothesis had been confirmed, the results are of limited use; High degree of correspondence between the rank of IC investment efficiency and the improvement in the financial performance rank;

Where: MB = Market to Book Ratio, MV = Market Value, BV = Book value, ROA = Return on Assets, ROE = Return on Equity, ICE = Intellectual Capital Efficiency; ROI = Return on Investment; ROS = Return on Sales; ATO = Asset Turnover; OP = Operational Performance; FP = Financial Performance; RDE = Innovation Capital Efficiency

Authors	Sample	Methodology	Findings/ Significant Relationships
(Pal & Soriya, 2012)	105 pharmaceuticals, and 102 textile companies in India; 2000-2010 (10 years)	VAIC & Financial KPIs (Correlations and OLS used on panel data)	Higher difference between MV and BV in the pharmaceutical industry than on the textile one; ROE is higher on pharmaceutical industry; IC + between (not significant) MB, ROA and ROE on both sectors; IC – between ATO; ICE + between (not significant) MV in pharmaceutical industry;
(Joshi et al., 2013)	Top 40 financial sector companies listed in the ASX (Australian Securities Exchange); 2006-2008 (3 years)	VAIC & Financial KPIs (Multiple linear regression)	Higher HCE results in higher VAIC; CEE + between ROA; HCE + between CEE, SCE; No evidence of VAIC impacting performance;
(Celenza & Rossi, 2014)	23 Italian listed companies; 2003-2008 (6 years)	VAIC & Financial KPIs (Multiple linear regression); Two phases	First phase: no statistically significant relationship between MB, ROI, ROE and VAIC found; Second Phase: Significant relationship found between VAIC and MV, ROE, ROS, ROI;
(Goswami & Maji, 2016)	100 listed Indian firms from engineering and steel sectors; 1999-2012 (14 years)	VAIC & Financial KPIs (Panel data regression model)	VAIC + between ROA; ICE and CEE + between ROA; HCE + between ROA; Impact of IC efficiency on ROA is greater in knowledge-based sector than in traditional sector;

Where: MB = Market to Book Ratio, MV = Market Value, BV = Book value, ROA = Return on Assets, ROE = Return on Equity, ICE = Intellectual Capital Efficiency; ROI = Return on Investment; ROS = Return on Sales; ATO = Asset Turnover; EPS = Earnings Per Share; ASR = Annual Stock Returns; GR = Growth rate;

Appendix 2 – Prior studies relating VAIC™ to performance in the banking sector

Authors	Sample	Methodology & Variables	Findings/ Significant Relationships
(Chen Goh, 2005)	8 Kuwaiti Banks; 1997-2006 (10 year-period)	VAIC (Ranking according to VAIC and comparison with traditional ranking) VAIC ranking: HCE, SCE, CEE; Traditional ranking: Asset, Net Profit, Shareholder Equity;	All banks have relatively higher HCE than SCE and CEE; There were significant differences between rankings of bank according to efficiency and traditional accounting measures;
(El-Bannany, 2008)	Major British Banks Group (MBBG); 1999-2005 (7 years)	VAIC (Multiple regression analysis) Dependent: VAIC; Independent: LOGITIN, HASS; FASS; SERV, ROE, ITAGASS; Control: n/a	Mean IC performance (VAIC) – 10.8; The regression model is significant and explains 85 % of the relationship between IC performance and the independent variables; LOGITIN, FASS, SERV – between VAIC; HASS, ROE, ITAGASS + between VAIC;
(Abdulsalam, Al-Qaheri, & Al-Khayyat, 2011)	Major British Banks Group (MBBG); 1999-2005 (7 years)	VAIC (Ranking according to VAIC & Multiple regression analysis) Dependent: Value Added Independent: CE, HC Control: NonComm	Similar results when using either the VAIC ranking or the HCE component ranking; Different results for the ranking based on CEE compared to VAIC or HCE; CE, HC + between VA;
(Gigante & Previati, 2011)	22 Italian banks; 2003-2007 (5 years)	VAIC + KPI (Multiple regression analysis) Dependent: MR Independent: VAIC, HCE, SCE, CEE Control: n/a	Banks with the most financial success using tradition methods of analysis, had actually performed poorly according to the VAIC analysis (the poor performance 2 years later confirmed the VAIC previous results); Italian Banks have higher value of HCE than SCE and CEE; At least one independent variable (HCE, SCE, CEE) has + correlation with MR; IC has + impact on capital gain shares;
(Al-Musali & Ismail, 2014)	11 commercial banks listed in Saudi Stock Exchange (Tadawel); 2008-2010 (3 years)	VAIC + KPIs (Multiple regression analysis) Dependent: ROE, ROA; Independent: VAIC, HCE, SCE, CEE; Control: Bank size (SIZE), global financial crisis (CRIS)	Saudi banks present lower IC performance compared to their counterparts in developed and emerging economies (Benchmark); Results suggest that the capability of examined banks to create value is mainly dependent on HCE; VAIC, HCE + between ROA, ROE; CEE + between ROE;

Where: LOGITINit = "Investment in IT systems" = Natural logarithm of total cost of hardware and software of computing systems for bank i in year t; HASSit = "Bank's relative efficiency" = The ratio of bank i assets divided by total banking market assets in year t; FASSit = "Barriers to entry" = The ratio of fixed assets to total assets for bank i in year t; SERVit = "Efficiency of investment in IC" = The ratio of labour costs to total revenue for bank i in year t; ITAGASSit = The ratio of intangible assets to total assets for bank i in year t; CE = Capital Employed; MRit = "Investors' capital gain on shares of firm 'i' during the 't' period" = (Pt1-Pt0/Pt0)*100; where: Pt1= Market Price per share of firm i at the end of the period t; Pt0 = Market Price per share of firm i at the beginning of period t; CRIS = "global financial crisis" = value is 1 for the years of 2008 and 2009, and zero otherwise, SIZE = Total Assets;

Authors	Sample	Methodology & Variables	Findings/ Significant Relationships
(Kehelwalatenna & Premaratne, 2014)	191 banking firms listed on the New York Stock Exchange; 2000-2011 (12 years/ 46 quarters)	VAIC (Dynamic panel regressions - Generalized Method of Moments) Dependent: ATO, ROE2, RG, MBh Independent: ICE (IC) Control: Size, Lev, PC, Risk	Results suggest that IC + impacts the performance and value creation of banking firms. Nevertheless, Physical assets contribute substantially more to value-creating process; ICE + between ATO, ROE2, RG; Size – between ATO, RG, MB; Size + between ROE2; Lev + between ATO, ROE2; Lev – between RG, MB PC + between ATO, ROE2, RG; Risk + between ATO, ROE2, RG; Risk – between MB
(Ousama & Fatima, 2015)	16 Islamic banks in Malaysia; 2008-2010 (3 years)	VAIC + KPIs (Regression analysis – OLS, Pearson) Dependent: ROA, ROE Independent: VAIC & Components Control: SIZE, LEVERAGE	VAIC + between ROE, ROA, SIZE; CEE + between ROA, ROE, SIZE; SCE + between ROE, SIZE; HCE + between ROE, SIZE; SIZE + between ROA, ROE; LEVERAGE – inconclusive results The study found that HCE was higher than SCE and CEE; However, CEE seemed to contribute more to profitability;
(Alhassan & Asare, 2016)	18 banks in Ghana; 2003-2011 (9 years)	VAIC & MPI (Panel-corrected standard errors technique) Dependent: MPI Independent: VAIC & Components Control: CRL5, SIZE;	VAIC, SIZE + between MPI; CRL5 – between MPI; HCE, CEE + between MPI; SCE – no significant impact; Productivity growth seems to be largely driven by efficiency changes rather than technological changes;
(Kehelwalatenna, 2016)	191 banking firms listed on the New York Stock Exchange; 2000-2011 (12 years; four sub-samples (pre- and post-crisis)	VAIC & Financial KPIs (Structural stability tests & dynamic regression models for panel data) Dependent: ATO, ROA1, ROE2, RG Independent: ICE (IC) Control: Size2, Size3, Lev1, Lev4, PC1, PC3, Risk2	Contrary to theoretical expectations, the impact of IC on performance is inconsistent during financial crisis; Incapability of HC (applies to PC as well) to create value during crisis for sampled firms; There seems to be a deterioration of the reputation of IC as a strategic asset in the emergence of financial turbulence in the economy;
(Jafarnezhad & Tabari, 2016)	11 banks listed in the Tehran Stock Exchange; 2009-2013 (5 years)	VAIC & Financial KPIs (Panel data – correlation coefficient & regression analysis) Dependent: EPS, ROA, ROE; Independent: HCE, SCE, CEE; Control: n/a	HCE – between ROE, EPS; SCE + between ROE, EPS; CEE + between ROA; A main part of assets is financing from attracted deposits (debt) & capital is small part of the bank´s capital structure; HC is one of the most impacting components affecting on banks performance;
(Kaupelytė & Kairytė, 2016)	118 (52 small & 66 large) European listed banks; 2005-2014 (10 years); pre-, during, and post financial crisis;	VAIC & Financial KPIs (Multiple regression analysis) Dependent: VAIC, NIM, ROA, ROE, DP, GE, LIQ, SOL, TIER1 Independent: HCE, SCE, CEE Control: Total assets, Leverage 1 & 2;	Authors conclude that intellectual capital had negative impact on large banks financial performance after the financial crisis and negative impact on small banks financial performance before the financial crisis;

Where: RG = "Revenue growth" = [(current year's revenue/last year's revenue) – 1] * 100%; MB = "Market valuation" = Market-to-book value ratio ([number of shares outstanding * average stock price of an ordinary share]/average equity of shareholders); Lev = Leverage; PC = Physical Capital; PC&variants & Size&variants & Leverage&variants & ROA & variants & ROE & variants = See Table in Appendix 4; MPI = Malmquist Productivity Index; CRL5 = 5 bank loan concentration ratio; NIM & DP & GE & LIQ & SOL & TIER1 & EPS & Total assets = See Table in Appendix 4

Authors	Sample	Methodology & Variables	Findings/ Significant Relationships
(Meles et al., 2016)	5.749 US commercial banks; 2005-2012 (8 years)	VAIC & Financial KPIs (2 linear models; Pooled OLS for panel data) Dependent: ROAA, ROAE Independent: VAIC, HCE, SCE; Control: LLP/L, LOANS/TA, SIZE, GDP, STATE;	VAIC, HCE + between ROAA, ROAE; HCE has the highest impact on performance; STATE dummies have no particular impact on profitability;
(Nawaz & Haniffa, 2016)	64 Islamic financial institutions operating in 18 countries; 2007-2011 (5 years);	VAIC & ROA (Pearson´s correlation + regression models) Dependent: ROA Independent: VAIC & Components Control: InFSize, Risk, Sub, Listing;	Mean IC performance (VAIC) – 3.93; Correlation results: HCE was the main value driver; VAIC, HCE, CEE + between ROA; Regression results: VAIC, HCE, CEE + between ROA; Risk – between ROA;
(Singh, 2016)	Top 20 Indian banks (10 private & 10 public); 2007 – 2011 (5 years);	VAIC & ROA - benchmarking (coefficient of variation, exponential growth rates, trend analysis, Yule´s coefficient, the coefficient of correlation, F- & T-Tests;) Dependent: ROA Independent: VAIC & Components Control: n/a	Private sectors have performed better regarding the creation of IC; Sampled banks ROA was still below the international benchmark of > 1%; The major cause for lower IC and the reduced ROA is disproportionate to the increase CE & escalating non-performing assets in the Indian banking sector; ROA is intimately & highly associated with IC (Yule´s coeff.);
(Aziz & Hashim, 2017)	16 Islamic banks in Malaysia; 2009-2016 (8 years)	VAIC & KPIs (panel-corrected standard errors estimation technique – panel regression model) Dependent: VAIC, ATO Independent: HCE, SCE, CEE, RCE Control: SIZE, RISK, LEV;	VAIC – between ATO (moderate, r = -0,299); CEE+ between ATO (Strong); SCE – between ATO (moderate); HCE + between ATO (Weak); SIZE (moderate), RISK (High) + between VAIC; SCE + between VAIC (strong); CEE – between VAIC (moderate); SCE & CEE made-up VAIC Value
(Iqbal & Zaib, 2017)	27 banks (19 commercial & 8 Microfinance and investment) listed in the Pakistanis Stock Exchange; 2008-2015 (8 years)	VAIC & KPIs (Generalised Least Squared model - GLS) Dependent: ROA, ROE, Tobin´s q; Independent: HCE, SCE, CEE, VAIC (IC variables) + CG* variables; Control: Size, Lv;	IC had stronger relations with Financial Performance (FP) than CG; Commercial banks: HCE – between ROA, Tobin´s q; HCE – (insignificant) between ROE; SCE + between ROA, ROE; SCE – between Tobin´s q; CEE + between ROA, ROE, Tobin´s q; CEE is the most effective component of IC contributing to FP; Size + between ROA, ROE; Leverage – between ROA, ROE; Microfinance and investment banks: HCE, CEE + between ROA, ROE, Tobin´s q; Size + between ROE; Size – between Tobin´s q; Leverage – between ROA, ROE, Tobin´s q;

Where: ROA & variants & ROE & variants & LLP/L & LOANS/TA & GDP & Size&variants & Risk&variants & Tobins´q&variants & Leverage&variants & Sub = See Table in Appendix 4; STATE = set of dummy variables each equal to 1 if the bank's headquarter is located in the corresponding State and zero otherwise; Listing = Listing status, yes or no; CG* = Corporate Governance variables (see Iqbal, 2017, p.187);

Authors	Sample	Methodology & Variables	Findings/ Significant Relationships
(Irawanto et al., 2017)	33 banking companies listed on the Indonesian Stock Exchange; 2013-2014 (2 years)	VAIC & ROA (ANOVA regression model, T-testing, R-square model) Dependent: ROA; Independent: HCE, SCE, CEE, VAIC + CG variables; Control: GCG, ITS;	Correlational analysis: HCE, SCE, GCG + between ROA; GCG + between HCE, SCE; ITS + between CEE; Findings: HCE has a positive effect on financial performance;
(Nawaz, 2017)	47 Islamic banks operating in the Gulf Cooperation Council region; Pre- & Post-financial crisis; 2006-2007 & 2009-2010 (2 years);	VAIC & KPIs (Correlation analysis, panel regression – multivariate analysis, Cross-sectional OLS regression) Dependent: ROA; Tobin´s q; Independent: HCE, SCE, CEE, VAIC; Control: LnSSB, LnBSize, Lev;	VAIC, HCE, CEE + between ROA (pre- & pro-crisis); SCE + between ROA (pre-crisis); SCE – between ROA (post-crisis); VAIC, HCE, CEE, SCE + between Tobin´s q (pre-crisis); LnBSize + between Tobin´s q (pre- & post-crisis); Lev + between ROA (post-crisis); Finding suggest that IC generally improves profitability and market valuation;
(Ozkan et al., 2017)	44 Turkish banks; 2005-2014 (10 years)	VAIC & ROA (regression models – Pearson correlation analysis) Dependent: ROA; Independent: VAIC, HCE, SCE, CEE; Control: LNTA, LEV, DEPOSIT, PARTICIPATION;	Mean IC performance (VAIC) – 3.89; Correlation results: VAIC, HCE, CEE + between ROA; HCE is the variable with the highest correlation with ROA; SCE – (but insignificant) between ROA; Regression results: Components of VAIC are better at explaining profitability than VAIC alone; VAIC + (insignificant) between ROA CEE, HCE + between ROA; CEE has higher impact on ROA; LEV – between ROA;
(Thakur, 2017)	40 listed private & public banks in India; 2013-2015 (3 years)	VAIC & Financial KPIs (panel regression method) Dependent: ROA, ROE; Independent: VAIC, HCE, SCE, SCE; Control: SIZE	Mean IC performance (VAIC) – 5.438; VAIC, CEE, HCE + between ROA, ROE; SIZE – between ROE; CEE, HCE + between ROA; CEE has stronger impact on ROA, ROE, rather than HCE and SCE;
(Tiwari & Vidyarthi, 2018)	39 public & private banks listed in Bombay/Mumbai Stock Exchange; 1999-2015 (17 years)	VAIC + Modified VAIC & Financial KPIs (Panel fixed effects technique) Dependent: ROA, ROE; Independent: HCE, SCE, CEE, RCE, VAIC, MVAIC; SCE*RCE, HCE*RCE, CEE*RCE, CEE*HCE; Control: Size, Leverage;	Mean VAIC & MVAIC – 3.45 & 3.49; Indian banking industry has no evidence of impact of sub-prime crisis on their VAIC & MVAIC; HC & SC have significant positive association with banks profitability; Results suggest that IC efficiency of private sector banks is better than public sector banks in India;

Where: GCG = Variable used for the measurement of Corporate Governance (DK); ITS = Categorical variable that shows CEO's support for the policies created for the company´s technology; LnSSB = log of total number of Shariah advisors; LnBSize = log of total assets; LNTA = Bank size (Natural Log of total assets); DEPOSIT/PARTICIPATION = Dummy variables take value 1 for deposit or participation banks, or 0 otherwise; ROA & variants & ROE & variants & Size&variants & Risk&variants & Tobins´q&variants & Leverage&variants = See Table in Appendix 4

Authors	Sample	Methodology & Variables	Findings/ Significant Relationships
Applying both VAIC & DEA in the banking sector			
(Yalama & Coskun, 2007)	All the banks listed on Istanbul Stock Exchange (ISE) for the period 1995-2004 (Except year 2001; 9 years)	VAIC + DEA (CCR-model) input-oriented; 3 different portfolios compared Inputs: Portfolio1 (VAIC); Portfolio2 (CEE); Portfolio3 (MV/BV per share) Outputs: ROA, ROE, LDR	Efficiency values are not stable annually and different efficiency level ranking among the banks are observed for every year; The average efficiency values are calculated: 0.706, 0.560, 0.666, 0.646, 0.590, 0.783, 0.483, 0.581 and 0.585 for year 1995, 1996, 1997, 1998, 1999, 2000, 2002, 2003 and 2004 respectively; Based on these values the ratio of transforming IC into profitability is calculated as 61.3 percent in the banking sector; Portfolio 1 (based on IC) seems to have the highest return annually; Thus, it is assumed that IC seems to be a more important factor than physical capital for banks.
(Vidyarthi, 2018)	38 listed Indian banks; 2005-2016 (12 years)	VAIC + Modified VAIC & DEA + Tobit regression; Input-and-Output selection based on intermediation approach; Inputs: Total non-&interest expenses; Outputs: Deposits, Loans&Advances, investments; Dependent: TE, PTE, SE; Independent: VAIC, MVAIC, CEE, HCE, SCE, RCE; a Control: Size, Leverage;	Mean VAIC&MVAIC – 3.19 & 3.2; Mean HCE&SCE – 2.38 & 0.452; Mean CEE& RCE – 0.356 & 0.017; Mean TE & PTE & SE – 0.895 & 0.93 & 0.964; VAIC (+), MVAIC (+), Size (+), Lev (-) between TE, PTE, SE; IC has low (+) impact on efficiency

Where: LDR = loans/deposit ratio; PTE = Pure Technical Efficiency; TE = Technical Efficiency; SE = Scale Efficiency; ROA & variants & ROE & variants & Size&variants & Risk&variants & Tobins´q&variants & Leverage&variants = See Table in Appendix 4

Appendix 3 – Prior studies using DEA for measuring firms' performance

Authors	Sample	Methodology & Variables	Findings/ Significant Relationships
Applying IC related variables			
(C.-H. Tsai et al., 2017)	Top 21 listed and over-the-counter (OTC) Twainese corporations of the semiconductor industry from Market Observation Post System (MOPS 2009)	DEA – BCC & CCR models – multi-input-multi-output model Outputs: Y1; Y2; Y3 Inputs[1]: IC & CG (e.g. H5 + H6 + I2 + M2) Control: n/a DMU: "Corporations" analysed	Taiwanese semiconductor industry is advised to increase operation performance through improving CRS and VRS efficiencies; Study confirms inefficient issues regarding resource allocation of semiconductor corporations;
Applying VAIC			
(Long Kweh et al., 2013)	25 Malaysian public-listed software companies; 2010 (1 year)	DEA – BCC & CCR – Input oriented model Outputs: Tobin´s Q; ROE Inputs: HCE; SCE; CEE Control: n/a DMU: "Companies" from Main-market and Ace-market	Eduspec Holdings Berhad is the most efficient company with the highest frequency of reference; IC plays an important role in value creation; Sampled companies invest most of their resources in HCE as compared to SCE and CEE; Main-market companies have greater HCE and CEE, but lower SCE than ACE-market companies; Main-market companies are less efficient than the ACE-market companies;
(Kalantar, 2014)	15 automotive industry and component manufacturers (Tehran Stock Exchange); 2006 – 2010 (5 years);	VAIC + Malmquist + DEA (CCR – Output oriented approach) Outputs: ROA; ROE; RI Inputs: VAIC™ Control: n/a DMU: "Years" of study	The brake pad company had the best performance among selected companies, due to maximum performance of its IC; Companies should invest more in IC to improve their efficiency/performance; HC is considered as a strategic and a key factor for improving efficiency; Most companies in automotive industry and component manufacturers do not operate at optimal scale;
(Venugopal et al., 2018)	Titan company Limited (India); 1997 - 2016 (20 years)	VAIC & DEA - CCR – Output model (IC indices as input; and FP measures as outputs); Outputs: ROA; ROE; EPS; MCAP; Inputs: VAIC™; HCE; SCE; CEE Control: n/a	Only 6 best performing years out of the 20 studied by the efficiency analysis;(2007; 2011 to 2013; 2015 to 2016); Some years were close to perfect efficiency (1), but the others showed very poor utilisation of IC to impact performance;

Where: DMU = Decision Making Units; RI = Stock Return; FP = Financial Performance; Tobin´s Q = MV/BV of total assets; EPS = Earnings Per share (Income available to equity shareholders/average outstanding shares); MCAP = Market Capitalisation (Average outstanding shares * current market price); CG = Corporate Governance; H5 = Operating profit of each person; H6 = Additional value of employee; I2 = Productivity of R&D; M2 = Ownership share held by second-largest shareholder; Y1 = Operating income; Y2 = ROA; Y3 = Tobin´s Q ((Net income+ interest * (1- ratio))/Averaged total assets * 100); Inputs[1] =too many discriminated variables to fit in, see (Tsai, 2017, p. 200)

Authors	Sample	Methodology & Variables	Findings/ Significant Relationships
Applying DEA in the banking sector (no IC relation)			
(Ghaeli, 2017)	26 US banks; Fiscal year of 2016;	DEA – CCR model Outputs: Net Revenue Inputs: Total assets + Number of employees Control: n/a DMU: "Banks"	Santander Bank is the most efficient bank operating in the United States followed by SunTrust Bank and HSBC; Other banks preserve lower efficiency compared with these three banks;
(H.-H. Liu, 2018)	29 foreign commercial banks in Taiwan; 2011-2014 (4 years);	3-stage DEA model (distinguishing environmental effects and statistical noise from pure performance evaluation); emphasizes intermediation approach; Outputs: Interest Revenue* + Non-interest revenue* Inputs: Operating resources* Control: n/a DMU: "Banks"	Operational efficiency values after being adjusted for external environmental factors and statistical noise tend to be higher than the non-adjusted values; Most of the foreign banks need to reduce more of their inputs in the third stage than in the first stage to achieve relative efficiency; Using a three-stage DEA approach, efficiency scores can function as a more specific and precise set of criteria for true managerial efficiency;
(Novickytė & Droždz, 2018)	6 commercial banks in Lithuania; 2012-2016 (5 years); Data source: Bank of Lithuania + Association of Lithuanian Banks	DEA (CRS & VRS) – 5 alternative models with different input-output combinations; Based on production, profitability, and intermediation approaches; Outputs: Operating Profit + Loans + Profit before tax + Net interest income Inputs: Deposits + Labour expenses + Debts to banks and other financial institutions Control: n/a DMU: "Banks"	The Lithuanian bank's efficiency analysis based on the VRS assumption shows that better results are demonstrated by the local banks; The technical efficiency analysis based on the CRS assumption shows other results: the banks owned by the Nordic parent group and the branches have higher pure efficiency than local banks and have success at working at the right scale; larger Lithuanian banks (subsidiaries) applied a more appropriate business model than smaller (local) banks;
(Ouenniche & Carrales, 2018)	109 UK commercial banks (1987-2015 - 29 years); Data from Bankscope;	DEA with a regression-based feedback mechanism + DEA models without explicit inputs (WEI) or outputs (WEO); Used Intermediation approach Outputs: Ability to provide: financial services* + generate revenue* Inputs: Resources* + Costs* Control: Size[1] + Market Share[1]+ Gross profitability[1] + Operational expenses[1] +Origin[1] DMU: "Years" of study	Empirical results suggest that, on average, the commercial banks operating in the UK—whether domestic or foreign—are yet to achieve acceptable levels of overall TE, PTE, and SE; In general, a linear regression-based feedback mechanism proves effective at improving discrimination in DEA unless the initial choice of inputs and outputs is well informed;

Where: PTE = Pure Technical Efficiency; TE = Technical Efficiency; SE = Scale Efficiency; Resources* = Labour as measured by Personnel Expenses + Capital as measured by Fixed Assets/Physical Capital or Equity/Financial Capital; Costs* = Total Interest Expense + Total Expenses not including Personnel Expense; Financial services* = Gross Loans, Total Customer Deposits; Generate Revenue* = Total Income, Gross Interest and Dividend Income; Size[1] = total income; Market Share[1] = total customer deposits, gross loans; Gross profitability[1] = total income; Operational expenses[1] = personnel expenses; Origin[1] = Domestic or foreign; Interest Revenue* = mainly the revenues from business and personal loans and other portfolio investment; Non-interest revenue* = mainly the revenues from transaction fees, on securities investment and other business revenues; Operating resources* = Personnel expenses, Operating expenses (not including personnel expenses and network expenses), Commercial bank's fixed assets, Total deposits, Network expenses (inputs for providing online banking services) and Bank diversification (means that a bank can extend its product line from the original deposit and loan activities to bonds/securities investments, trusting and assurance, and other novel financial commodities);

Authors	Sample	Methodology & Variables	Findings/ Significant Relationships
(Basílio et al., 2016)	10 Portuguese and 14 Spanish banks; 2008-2013 (6 years)	Two-stage analysis: DEA (input orientation: CRS and VRS) in the first-stage (Intermediation approach) + Generalised Linear model (GLM) applying a fractional response model in the second-stage; Outputs: Loans Inputs: Personnel expenses + Deposits Dependent: DEA scores Independent: Bank-specific variables* + Country-specific and institutional variables* DMU: "Banks"	Spanish banks are, on average, slightly more efficient than Portuguese institutions, with an Overall Technical Efficiency (OTE) average of 81.5 % against 78.3 %; The results obtained revealed that Pure Technical Efficiency (PTE) is higher than the global efficiency score, which is a sign of scale inefficiencies in several banks; Chow test indicates that no statistically significant differences exist, and the determinants of efficiency are similar across countries; Positive and significant effect of Liquidity on overall efficiency; Negative and significant effect of capitalisation on Spanish banks´ efficiency; Positive and significant effect of capitalisation on Portuguese banks´ efficiency;
(Martins, 2018)	26 Portuguese banks; 2005-2010 (6 years)	Two-stage DEA (BCC model); Fractional regression; Involving both Production and Intermediation efficiency; Outputs: (Production: Deposits); (Intermediation: Loans + Gross Value Added + Shareholder Value Creation) Inputs: (Production: Equity + Nº employees + Nº branches); (Intermediation: Deposits) Dependent: DEA scores Independent: (Competition + Human Resources + Dynamics + Finance + Characteristics) * DMU: "Banks"	The global two-stage model, which involves both production and intermediation efficiency, shows an average efficiency level of 69,7% and a standard deviation of 0,143; Fractional regression models show evidence of better specification relative to the linear model; The fractional regression models demonstrate evidence of improved specification comparing to traditional regression models; The variables that appear to have a major positive influence on overall efficiency are internationalization and size;

Where: Bank-specific variables = liquidity (total loans to total deposits ratio) + capitalisation (equity to total assets) + size (log total assets) + risk of insolvency + State owned (dummy) + Spanish (dummy) + not foreign (dummy); Country-specific and institutional variables = GDP_pc growth (gross domestic product per capita growth) + control of corruption + financial development; *(Competition = Market share on loans + market share on deposits + internationalisation + ownership of capital; Human resources = age + antiquity + Level of qualifications; Dynamics = asset growth rate + banking product growth rate + empowerment; Finance = ROA + ROE + risk + solvability + cost of income; Characteristics = dimension + geographical concentration + Nº of employees by branches);

Appendix 4 – Some of the applied variables in the reviewed banking sector related studies

Variables	Type	Author(s)	Description
Return on Assets (ROA)			
ROA*it*	Dependent	Al-Musali, 2014;	Individual bank *i* annual net profit before taxation divided by average total assets in year *t*
ROA	Dependent	Ousama, 2015;	Operating Income/Total assets
ROA1	Dependent	Kehelwalatenna, 2016	Preference dividends adjusted net income/BV of total assets
ROA	Dependent	Kaupelyté, 2016	(Net profit / Total assets) * 100
ROAA	Dependent	Meles, 2016	"Return on Average Assets" = Net income/ Average Total assets
ROA	Dependent	Nawaz, 2016, 2017	Net income available to stockholders/total assets
ROA	Dependent	Iqbal, 2017	(Net income less term preferred dividend + dep) / BV of Total assets
ROA	Dependent	Ozkan, 2017	Net profit / Total assets
ROA	Dependent	Thakur, 2017	Net profit before tax/ Average Total assets
ROA	Dependent	Tiwari, 2018	EBITDA / Total assets
Return on Equity (ROE)			
ROE*it*	Dependent/ Independent	El-bannany, 2008; Al-Musali, 2014;	Individual bank *i* annual net profit before taxation divided by average shareholders' equity in year *t*
ROE2;	Dependent	Kehelwalatenna, 2014, 2016	(Net income/Total Equity); Authors found ROE2 to be the most appropriate proxy measure for profitability amongst other ROA and ROE variants
ROE	Dependent	Ousama, 2015;	(Net income/Shareholders´ Equity)
ROE	Dependent	Kaupelyté, 2016	(Net profit / Total Equity) * 100
ROAE	Dependent	Meles, 2016	"Return on Average Equity" = Net income / ([Total equity beginning of the year + Total equity end of the year] / 2)
ROE	Dependent	Iqbal, 2017	Net income less term preferred dividend / Total common equity
ROE	Dependent	Thakur, 2017	Net profit before tax/ Average shareholder´s equity
ROE	Dependent	Tiwari, 2018	Net income / shareholders' equity
Tobin´s Q			
Tobin´s q	Dependent	Iqbal, 2017	(MV of equity + long term debt) / Total assets
Tobin´s q	Dependent	Nawaz, 2017	(Market capitalization + total liabilities) / total assets
Revenue Growth			
RG	Dependent	Kehelwalatenna, 2014, 2016	"Revenue growth" = [(current year's revenue/last year's revenue) – 1] * 100%.
GDP	Control	Meles, 2016	GDP growth rate between two consecutive years
Assets Turn Over (ATO)			
ATO	Dependent	Al-Musali, 2014;	"Assets turn-over ratio" = (Total revenue/BV of total assets)
ATO	Dependent	Kehelwalatenna, 2014, 2016	"Assets turn-over ratio" = (Total turnover/total assets)
ATO	Dependent	Aziz, 2017	"Assets turn-over ratio" = (Total Revenue/Total assets)
Risk			
ITAGASS*it*	Independent/ Control	El-bannany, 2008; Kehelwalatenna, 2014	"Bank risk" = The ratio of intangible assets to total assets for bank *i* in year *t*
Risk2	Control	Kehelwalatenna, 2016	Credit/Deposit ratio
LLP/L	Control	Meles, 2016	Loan loss provisions/Total loans
Risk	Control	Nawaz, 2016	"Using leverage as proxy" = Total debt/Total assets
RISK	Control	Aziz, 2017	Credit/Deposit ratio
Leverage			
Lev1	Control	Kehelwalatenna, 2014, 2016	(Total debt/total assets)
Lev2	Control	Kehelwalatenna, 2014	(BV of total assets/BV of common equity)
Lev3	Control	Kehelwalatenna, 2014	(Total debt/total equity)
Lev4	Control	Kehelwalatenna, 2014, 2016	(Total liabilities/book value of total assets)
LEVERAGE	Control	Ousama, 2015	(Total liabilities/Shareholders' equity)
Leverage 1	Control	Kaupelyté, 2016	Debt / Equity
Leverage 2	Control	Kaupelyté, 2016	Equity / Total assets
LEV	Control	Aziz, 2017	(Total debt/total assets)

Lv	Control	Iqbal, 2017	Total debts/book value of equity
Lev	Control	Nawaz, 2017	Total debt / total assets
LEV	Control	Ozkan, 2017	Long- Term Debt / Total Assets
LEV	Control	Tiwari, 2018	Total borrowings / total assets
Leverage	Control	Vidyarthi, 2018	Total borrowings / total assets
Size			
SIZE;	Control	Al-Musali, 2014;	Total Assets
Size1	Control	Kehelwalatenna, 2014	Total Assets
Size2	Control	Kehelwalatenna, 2014, 2016	Natural logarithm of market capitalization
Size3	Control	Kehelwalatenna, 2014, 2016	Natural logarithm of the book value of total assets
SIZE	Control	Ousama, 2015;	Total Revenue
SIZE	Control	Alhassan, 2016	Natural logarithm of total assets
Total assets	Control	Kaupelyté, 2016	Log (Total assets)
SIZE	Control	Meles, 2016	Natural logarithm of the book value of total assets
FSize	Control	Nawaz, 2016, 2017	Log of total assets
SIZE	Control	Aziz, 2017	Log of total assets
Size	Control	Iqbal, 2017	Ln (total assets)
LnSSB	Control	Nawaz, 2017	"Size of Shariah supervisory board (SSB)" = Log of total number of Shariah advisors
LNTA	Control	Ozkan, 2017	Natural log of Total Assets
Size	Control	Thakur, 2017	Total Assets
Size	Control	Tiwari, 2018	Natural log of Total Assets
Size	Control	Vidyarthi, 2018	Natural log of Total Assets
Size	Control	Ouenniche, 2018	Total Income
Physical Capital (PC)			
PC1	Control	Kehelwalatenna, 2014, 2016	(Fixed assets/total assets)
PC2	Control	Kehelwalatenna, 2014	(Value addition/book value of the net assets)
PC3	Control	Kehelwalatenna, 2016	Physical Capital Efficiency of the VAIC™ method
Liquidity			
LIQ	Dependent	Kaupelyté, 2016	"Liquidity" = Loans / Deposits
LOANS/TA	Control	Meles, 2016	Total loans/total assets
Others			
LOGITIN*it*	Independent	El-bannany, 2008	"Investment in IT systems" = Natural log of total cost of hardware and software of computing systems for bank *i*, year *t*
HASS*it*	Independent	El-bannany, 2008	"Bank's relative efficiency" = The ratio of bank *i* assets divided by total banking market assets in year *t*
FASS*it*	Independent	El-bannany, 2008	"Barriers to entry" = The ratio of fixed assets to total assets for bank *i* in year *t*
SERVit	Independent	El-bannany, 2008	"Efficiency of investment in IC" = The ratio of labour costs to total revenue for bank *i* in year *t*
MR*it*	Dependent	Gigante, 2011	"Investors' capital gain on shares of firm 'i' during the 't' period" = (Pt1-Pt0/Pt0) *100; where : Pt1= Market Price per share of firm *i* at the end of the period *t*; Pt0 = Market Price per share of firm *i* at the beginning of period *t*
CRIS	Control	Al-Musali, 2014;	"global financial crisis" = value is 1 for the years of 2008 and 2009, and zero otherwise
MB	Dependent	Kehelwalatenna, 2014;	"Market valuation" = Market-to-book value ratio ([number of shares outstanding * average stock price of an ordinary share]/average equity of shareholders)
NIM	Dependent	Kaupelyté, 2016	"Net interest margin" = (Net interest earnings/Total assets) *100
DP	Dependent	Kaupelyté, 2016	Productivity of employees = Net interest/Number of employees
GE	Dependent	Kaupelyté, 2016	"General Efficiency" = Net interest/ Operational expenses
SOL	Dependent	Kaupelyté, 2016	"Solvency" = (Net profit + Depreciation)/Total liabilities
TIER 1 ratio	Dependent	Kaupelyté, 2016	Tier 1 capital/Risk weighted capital
Sub	Control	Nawaz, 2016	"Firm complexity" = Total number of subsidiaries
Marketshare	Control	Ouenniche, 2018	Total customer deposits

Appendix 5 – Original VAIC™ and variants specifics

<table>
<tr><th colspan="6">Original VAIC™ and variants: necessary variables for calculating each dimension</th></tr>
<tr><th>Author</th><th>Proposed Method</th><th>HCE</th><th>SCE</th><th>CEE</th><th>RCE</th></tr>
<tr><th colspan="6">Original VAIC™</th></tr>
<tr><td>(Pulic, 1998, 2004)</td><td>VAIC™</td><td>$\frac{VA}{HC}$</td><td>$\frac{SC}{VA}$</td><td>$\frac{VA}{CE}$</td><td>n/a</td></tr>
<tr><td colspan="6">Where: VA = overall income (outputs) – all costs except labour (inputs) = Operating Profit (OP) + Employee Costs (EC) + Depreciation (D) + Amortisation (A); HC = overall labour expenditures; SC = VA – HC; CE = all necessary financial funds = BV of the net assets of a firm or Total assets – Intangible assets at end of period; Other authors using original VAIC™ method: (El-bannany, 2008); (Abdulsalam, 2011); (Gigante, 2011); (Al-Musali, 2014); (Kehelwalatenna, 2014); (Ousama, 2015); (Jafarnezhad, 2016); (Kaupelyté, 2016); (Meles, 2016); (Nawaz, 2016); (Singh, 2016); (Iqbal, 2017); (Nawaz, 2017); (Ozkan, 2017); (Thakur, 2017)</td></tr>
<tr><th colspan="6">VAIC™ variants</th></tr>
<tr><td>(Nazari, 2007)</td><td>Extended VAIC</td><td>Same as original</td><td>$\frac{(CC + InC + PC)}{VA}$</td><td>Same as original</td><td>n/a</td></tr>
<tr><td colspan="6">Where: VA = same; HC = same; SC = VA – HC = CC + Organisational Capital (OC) = CC + InC (Innovation Capital) + Process Capital (PC); CC = Marketing costs; InC = R&D expenditure; PC = SC – InC – CC;</td></tr>
<tr><td>(Kehelalatenna, 2016)</td><td>VAIC™ variant</td><td>Same as original</td><td>$\left[\frac{(VA - HC)}{VA}\right] - RCE$</td><td>Same as original</td><td>$\frac{RC}{VA}$</td></tr>
<tr><td colspan="6">Where: VA = OP + EC + D + A HC = same; CE = same; RC = Sales, marketing and advertising expenses; Other authors using this same variant: (Azis, 2017)</td></tr>
<tr><td>(Nadeem, 2017)</td><td>Adjusted VAIC</td><td>Same as original</td><td>$\frac{VA}{INVC}$</td><td>Same as original</td><td>n/a</td></tr>
<tr><td colspan="6">Where: VA = OP + EC + D + A + R&D; INVC = SC= Innovation Capital = R&D (includes copyrights); CE = same; Data Source: Bloomberg (Only able to obtain R&D data for Developed and emerging economies)</td></tr>
<tr><td>(Tiwari, 2018)</td><td>MVAIC</td><td>Same as original</td><td>Same as original</td><td>Same as original</td><td>$\frac{RC}{VA}$</td></tr>
<tr><td colspan="6">Where: VA = Same; HC = same; SC = same; CE = Total assets - current assets; RC = Sum of Advertisement, marketing, selling and distribution costs Data Source: Centre for Monitoring Indian Economy;</td></tr>
<tr><td>(Vidyarthi, 2018)</td><td>MVAIC™</td><td>Same as original</td><td>Same as original</td><td>Same as original</td><td>$\frac{RC}{VA}$</td></tr>
<tr><td colspan="6">Where: VA = Same = Outputs (total bank revenue made up of interest and non-interest income including fees and commissions) – Inputs (bank´s operational cost consisting of interest, administration and other expenses - personnel; HC = same; SC = same; CE = same; RC = advertising expenditure and other expenditure related to maintaining relationship between customers, suppliers, shareholders and the government;</td></tr>
</table>

Appendix 6 – Selection and calculation of variables

Variables	Author(s)	Calculation
DEA variables		
Outputs	Ouenniche; Vidyarthi, 2018;	Total net loans and advances (customers + banks); Total Deposits (customers + banks); Net Interest Income
Inputs	Ouenniche; Vidyarthi, 2018;	Total operating expenses; Number of employees; Fixed assets;
VAIC™ variables		
Value Added (VA)	Adapted from Alhassan, 2016; and Vidyarthi, 2018;	Bank´s operating revenues – Bank´s overall expenses (administrative + operating – labour, expenses)
Capital Employed (CE)	Pulic, 1998, 2004; Vidyarthi, 2018	Bank´s net assets = Total assets – Total Liabilities
Human Capital (HC)	Pulic, 1998, 2004;	Labour expenses
Structural Capital (SC)	Pulic, 1998, 2004;	VA-HC
Capital Employed Efficiency (CEE)	Pulic, 1998, 2004;	VA/CE
Human Capital Efficiency (HCE)	Pulic, 1998, 2004;	VA/HC
Structural Capital Efficiency (SCE)	Pulic, 1998, 2004;	SC/VA
Value Added Intellectual Coefficient (VAIC)	Pulic, 1998, 2004;	CEE + HCE + SCE
Other regression variables		
Leverage (Lev1)	Kehelwalatenna, 2014, 2016; Nawaz, 2017;	Total debt/total assets
Leverage (Lev2)	Kaupelyté, 2016	Equity / Total assets
Leverage (Lev3)	Ousama, 2015	Total liabilities/Shareholders' equity
Size	Alhassan, 2016; Kaupelyté, 2016; Nawaz, 2016, 2017; Aziz, 2017; Iqbal, 2017; Ozkan, 2017; Tiwari, 2018; Vidyarthi, 2018;	Natural log of Total Assets

Appendix 7 – Super Efficiency amongst Spanish (isolated sample), Portuguese (isolated sample), and Iberian banks (full sample), respectively, from 2013 to 2016

DMU No.	Bank	Super Efficiency (CRS)					Super Efficiency (VRS)				
		2013	2014	2015	2016	Mean	2013	2014	2015	2016	Mean
2	Caixabank, S.A.						1,216	1,140			1,178
11	CIMD Group			1,107		1,107		1,036	1,066	1,107	1,070
21	Banco Popular Espanol SA			1,008		1,008			1,182	1,008	1,095
23	Caja de Ahorros y Monte de Piedad de Ontinyer	1,067		1,316		1,192	1,077	1,142	1,119	1,316	1,163
25	Banco Mediolanum SA	1,043		2,821		1,932	1,664	1,642	2,248	2,821	2,094
33	Deutsche Bank SAE		1,212	1,995	1,985	1,731		1,281	1,552	1,995	1,609
35	Bankoa SA	1,138		1,450		1,294	1,633	1,632	1,898	1,450	1,653
37	Caja de Crédito de Los Ingenieros SCC			big*		big*	big*	big*	big*	big*	big*

*The value "big" appears when the score is excessively high for the EMS software to measure

DMU No.	Bank	Super Efficiency (CRS)					Super Efficiency (VRS)				
		2013	2014	2015	2016	Mean	2013	2014	2015	2016	Mean
1	Banco L. J. Carregosa, S.A.						1,768	1,676	1,643	1,860	1,737
12	Santander Totta SGPS	1,013				1,013	1,044	1,044	1,103		1,064
13	Caixa Economica Montepio Geral							1,244			1,244
14	Caixa Geral de Depositos						big*	big*	big*	big*	big*
15	Banco Comercial Português, SA-Millennium bcp						big*	big*	big*	big*	big*
16	Banco Bilbao Vizcaya Argentaria (Portugal) SA	1,095	1,471	1,742	1,682	1,497	1,127	1,519	1,760	1,867	1,568
17	Caixa - Banco de Investimento SA						1,125	1,036			1,080
31	Banco Finantia SA	1,014	1,190		1,108	1,104	1,018	1,194		1,134	1,115
32	Banco Santander Totta SA	1,019				1,019	1,050				1,050
47	Banco BPI SA	1,109			1,471	1,290	1,214	1,132	1,258	2,434	1,509
50	Banco de Investimento Global SA - BIG							1,052			1,052
51	Banco Invest SA	1,449	1,565	1,341		1,452	1,572	1,962	1,530	2,470	1,883
57	Atlântico Europa, Sgps, S.A			1,182	1,494	1,338		1,209	1,346	1,818	1,457
58	Finantipar - S.G.P.S., S.A.	1,012	1,013	1,542	1,005	1,143	1,047	1,044	1,549	1,009	1,162

*The value "big" appears when the score is excessively high for the EMS software to measure

DMU No.	Bank	Super Efficiency (CRS)					Super Efficiency (VRS)				
		2013	2014	2015	2016	Mean	2013	2014	2015	2016	Mean
1	Banco L. J. Carregosa, S.A.						1,464	1,417	1,451	1,295	1,407
2	Caixabank, S.A.									1,069	1,069
3	BFA Tenedora de Acciones SAU						1,216	1,140			1,178
16	Banco Bilbao Vizcaya Argentaria (Portugal) SA				1,015	1,015				1,061	1,061
18	Banco Bilbao Vizcaya Argentaria SA-BBVA							1,036	1,066	1,107	1,070
19	Bankia, SA								1,066	1,170	1,118
21	Banco Popular Espanol SA						1,013	1,081	1,218		1,104
22	Colonya, Caixa d'Estalvis de Pollensa						1,091	1,129	1,181		1,133
28	Banco de Sabadell SA								1,182	1,008	1,095
31	Banco Finantia SA		1,101		1,071	1,086		1,113		1,073	1,093
33	Deutsche Bank SAE	1,067				1,067	1,067	1,142	1,119	1,030	1,090
36	Santander Consumer Finance						1,664	1,642	2,248	2,763	2,079
42	Banco Cooperativo Espanol	9,830	9,274	4,851	1,942	6,474	9,899	9,325	4,854	1,971	6,512
43	Banco Alcala						1,440	1,279	1,248	1,497	1,366
44	Banco Caixa Geral SA		1,199	1,509	1,851	1,520		1,211	1,552	1,881	1,548
45	BNP Paribas España SA	1,974	2,660	3,563	1,117	2,329	3,703	7,416	8,208	3,691	5,755
46	EBN Banco de Negocios SA-EBN Banco	1,120				1,120	1,633	1,632	1,889	1,422	1,644
47	Banco BPI SA									2,181	2,181
49	Banco Santander SA						big*	big*	big*	big*	big*
51	Banco Invest SA						1,090	1,461	1,113	1,302	1,242
57	Atlântico Europa, Sgps, S.A									1,068	1,068
58	Finantipar - S.G.P.S., S.A.	1,012	1,013	1,151	1,004	1,045	1,022	1,014	1,152	1,006	1,048

*The value "big" appears when the score is excessively high for the EMS software to measure

Appendix 8 – Rankings of Iberian banks according to the first-stage DEA from 2013 to 2016

Country	DMU	Bank	2013		2014		2015		2016		Overall	
			CRS*	VRS*	CRS*	VRS*	CRS*	VRS*	CRS*	VRS*	CRS*	VRS*
PT	**1**	Banco L. J. Carregosa, S.A.	21	6	41	7	34	7	51	10	38	6
ES	**2**	Caixabank, S.A.	44	21	36	17	40	19	37	14	41	20
ES	**3**	BFA Tenedora de Acciones SAU	22	8	14	11	26	21	32	27	23	17
ES	**4**	Liberbank SA	51	43	46	48	47	46	43	40	46	43
ES	**5**	Renta 4 Banco, S.A.	57	57	58	58	57	57	57	57	58	57
ES	**6**	Ibercaja Banco SA	47	36	45	43	55	52	40	42	51	46
ES	**7**	Abanca Corporacion Bancaria SA	48	46	44	44	53	38	35	39	45	41
ES	**8**	Kutxabank SA	55	41	54	36	49	37	31	38	48	37
ES	**9**	Banco Caminos SA	24	39	34	51	18	44	16	41	25	44
ES	**10**	Banco Inversis SA	11	24	11	24	33	29	44	28	19	25
ES	**11**	CIMD Group	46	31	57	47	58	51	58	48	57	45
PT	**12**	Santander Totta SGPS	29	25	29	29	32	24	17	31	30	26
PT	**13**	Caixa Economica Montepio Geral	38	52	17	34	38	36	42	49	37	47
PT	**14**	Caixa Geral de Depositos	56	16	56	22	50	22	29	20	52	21
PT	**15**	Banco Comercial Português, SA-Millennium bcp	50	29	35	28	27	31	21	22	35	27
PT	**16**	Banco Bilbao Vizcaya Argentaria (Portugal) SA	49	55	28	53	20	45	5	16	12	40
PT	**17**	Caixa - Banco de Investimento SA	17	34	16	31	13	26	26	33	14	32
ES	**18**	Banco Bilbao Vizcaya Argentaria SA-BBVA	23	17	24	15	23	15	30	12	27	18
ES	**19**	Bankia, SA	26	15	18	18	15	16	15	11	20	16
ES	**20**	Bankinter SA	35	18	30	23	22	23	19	25	29	23
ES	**21**	Banco Popular Espanol SA	13	13	15	14	14	9	34	23	16	13
ES	**22**	Colonya, Caixa d'Estalvis de Pollensa	20	9	20	12	9	11	24	24	13	11
ES	**23**	Caja de Ahorros y Monte de Piedad de Ontinyent	18	35	10	19	11	27	22	37	11	28
ES	**24**	Confederación Española de Cajas de Ahorros - CECA	27	48	37	56	51	56	38	52	40	55
ES	**25**	Banco Mediolanum SA	12	27	13	27	28	33	39	36	18	33
ES	**26**	Banca March SA	53	54	51	54	52	55	52	56	54	56
ES	**27**	Fundacion Bancaria Caixa Estalvis Pensions De Barcelona	52	22	43	21	42	20	45	29	43	22
ES	**28**	Banco de Sabadell SA	41	20	33	25	21	10	27	18	34	19
ES	**29**	Caja Rural de Almendralejo Sociedad Cooperativa d C.	10	23	12	32	12	32	12	35	10	31
PT	**30**	Haitong Bank SA	16	44	25	52	44	54	47	55	36	53
PT	**31**	Banco Finantia SA	6	14	4	13	6	17	4	13	5	15
PT	**32**	Banco Santander Totta SA	32	26	32	33	35	30	23	32	33	29
ES	**33**	Deutsche Bank SAE	4	11	6	10	8	13	9	17	6	10
PT	**34**	Caixa Central de Credito Agricola Mutuo - CCCAM	43	51	53	55	39	53	48	53	44	54
ES	**35**	Bankoa SA	37	47	39	50	24	40	10	26	24	38
ES	**36**	Santander Consumer Finance	7	4	7	4	7	4	7	3	7	4
ES	**37**	Caja de Crédito de Los Ingenieros	36	53	23	46	30	50	25	47	32	52
ES	**38**	Caja Rural de Jaen, Barcelona y Madrid	25	49	22	49	16	42	20	46	21	49
ES	**39**	Caja Rural de Navarra Sociedad Cooperativa de Crédito	54	56	55	57	54	58	55	58	56	58
ES	**40**	Caja Rural de Soria Sociedad Cooperativa de Crédito	30	45	31	39	25	34	11	30	22	34
ES	**41**	Caja Rural de Zamora	15	37	19	38	17	39	14	34	15	35
ES	**42**	Banco Cooperativo Espanol	1	2	1	2	1	3	1	5	1	2
ES	**43**	Banco Alcala	39	7	52	8	56	8	53	7	55	7
ES	**44**	Banco Caixa Geral SA	8	19	3	9	3	6	2	6	3	8
ES	**45**	BNP Paribas España SA	2	3	2	3	2	2	3	2	2	3
ES	**46**	EBN Banco de Negocios SA-EBN Banco	3	5	9	5	5	5	54	8	8	5
PT	**47**	Banco BPI SA	31	30	27	26	29	25	8	4	17	12
ES	**48**	Allfunds Bank SA	28	32	40	37	45	49	56	54	50	42
ES	**49**	Banco Santander SA	19	1	26	1	19	1	28	1	26	1
PT	**50**	Banco de Investimento Global SA - BIG	14	33	21	35	36	41	33	45	28	36
PT	**51**	Banco Invest SA	9	10	8	6	10	14	18	9	9	9
ES	**52**	Cajamar Caja Rural, S.C.C.	42	40	48	40	43	43	49	50	47	48
ES	**53**	Criteria CaixaHolding SA	58	58	42	20	41	18	41	21	53	30
ES	**54**	Caja Laboral Popular Coop de credito	40	50	38	45	37	47	36	43	39	50
ES	**55**	Unicaja Banco SA	34	38	50	41	48	35	46	44	42	39
ES	**56**	Banco De Credito Social Cooperativo Sa	45	42	49	42	46	48	50	51	49	51
PT	**57**	Atlântico Europa, Sgps, S.A	33	28	47	30	31	28	13	15	31	24
PT	**58**	Finantipar - S.G.P.S., S.A.	5	12	5	16	4	12	6	19	4	14

*based on Super Efficiency Scores

Appendix 9 – First-stage DEA scores of Iberian banks (assuming super efficiency)

Country	DMU	Bank	2013		2014		2015		2016		Overall	
			CRS*	VRS*	CRS*	VRS*	CRS*	VRS*	CRS*	VRS*	CRS*	VRS*
PT	1	Banco L. J. Carregosa, S.A.	0,423	1,464	0,253	1,417	0,372	1,451	0,287	1,295	0,334	1,407
ES	2	Caixabank, S.A.	0,231	0,779	0,274	0,945	0,307	0,971	0,398	1,069	0,303	0,941
ES	3	BFA Tenedora de Acciones SAU	0,387	1,216	0,500	1,140	0,437	0,881	0,437	0,883	0,440	1,030
ES	4	Liberbank SA	0,209	0,473	0,227	0,434	0,259	0,483	0,360	0,641	0,264	0,508
ES	5	Renta 4 Banco, S.A.	0,055	0,208	0,046	0,214	0,053	0,211	0,124	0,246	0,069	0,220
ES	6	Ibercaja Banco SA	0,219	0,540	0,228	0,482	0,171	0,359	0,381	0,615	0,250	0,499
ES	7	Abanca Corporacion Bancaria SA	0,213	0,436	0,235	0,468	0,190	0,551	0,424	0,644	0,265	0,525
ES	8	Kutxabank SA	0,176	0,496	0,176	0,548	0,234	0,558	0,447	0,650	0,258	0,563
ES	9	Banco Caminos SA	0,384	0,512	0,311	0,402	0,477	0,502	0,549	0,615	0,430	0,508
ES	10	Banco Inversis SA	0,575	0,728	0,572	0,797	0,385	0,744	0,354	0,880	0,471	0,787
ES	11	CIMD Group	0,219	0,637	0,052	0,441	0,033	0,404	0,049	0,521	0,088	0,501
PT	12	Santander Totta SGPS	0,338	0,711	0,341	0,671	0,387	0,808	0,547	0,818	0,403	0,752
PT	13	Caixa Economica Montepio Geral	0,273	0,323	0,460	0,607	0,323	0,568	0,374	0,495	0,357	0,498
PT	14	Caixa Geral de Depositos	0,118	0,912	0,155	0,848	0,212	0,878	0,456	0,995	0,235	0,908
PT	15	Banco Comercial Português, SA-Millennium bcp	0,212	0,660	0,289	0,675	0,436	0,700	0,536	0,960	0,368	0,749
PT	16	Banco Bilbao Vizcaya Argentaria (Portugal) SA	0,212	0,225	0,344	0,354	0,457	0,491	1,015	1,061	0,507	0,533
PT	17	Caixa - Banco de Investimento SA	0,452	0,582	0,471	0,656	0,598	0,763	0,473	0,763	0,498	0,691
ES	18	Banco Bilbao Vizcaya Argentaria SA-BBVA	0,385	0,876	0,378	1,036	0,446	1,066	0,449	1,107	0,414	1,021
ES	19	Bankia, SA	0,357	0,974	0,440	0,944	0,520	1,066	0,560	1,170	0,469	1,038
ES	20	Bankinter SA	0,298	0,813	0,336	0,838	0,450	0,847	0,542	0,931	0,406	0,857
ES	21	Banco Popular Espanol SA	0,482	1,013	0,492	1,081	0,547	1,218	0,424	0,960	0,486	1,068
ES	22	Colonya, Caixa d'Estalvis de Pollensa	0,426	1,091	0,411	1,129	0,674	1,181	0,496	0,945	0,502	1,086
ES	23	Caja de Ahorros y Monte de Piedad de Ontinyent	0,430	0,559	0,666	0,916	0,659	0,759	0,529	0,690	0,571	0,731
ES	24	Confederación Española de Cajas de Ahorros - CECA	0,356	0,412	0,270	0,274	0,212	0,225	0,398	0,456	0,309	0,342
ES	25	Banco Mediolanum SA	0,568	0,694	0,514	0,677	0,434	0,619	0,382	0,697	0,474	0,672
ES	26	Banca March SA	0,194	0,287	0,211	0,343	0,192	0,229	0,235	0,306	0,208	0,291
ES	27	Fundacion Bancaria Caixa Estalvis Pensions De Barcelona	0,203	0,751	0,236	0,866	0,290	0,945	0,347	0,878	0,269	0,860
ES	28	Banco de Sabadell SA	0,246	0,809	0,313	0,790	0,456	1,182	0,466	1,008	0,370	0,947
ES	29	Caja Rural de Almendralejo Sociedad Cooperativa d C.	0,611	0,743	0,527	0,647	0,652	0,684	0,638	0,720	0,607	0,698
PT	30	Haitong Bank SA	0,456	0,458	0,373	0,381	0,283	0,320	0,336	0,385	0,362	0,386
PT	31	Banco Finantia SA	0,992	0,995	1,101	1,113	0,912	0,992	1,071	1,073	1,019	1,043
PT	32	Banco Santander Totta SA	0,331	0,703	0,332	0,643	0,365	0,728	0,500	0,799	0,382	0,718
ES	33	Deutsche Bank SAE	1,067	1,067	0,931	1,142	0,790	1,119	0,776	1,030	0,891	1,090
PT	34	Caixa Central de Credito Agricola Mutuo - CCCAM	0,232	0,340	0,199	0,299	0,313	0,353	0,329	0,446	0,268	0,359
ES	35	Bankoa SA	0,280	0,414	0,264	0,409	0,445	0,523	0,760	0,886	0,437	0,558
ES	36	Santander Consumer Finance	0,828	1,664	0,853	1,642	0,834	2,248	0,931	2,763	0,862	2,079
ES	37	Caja de Crédito de Los Ingenieros	0,286	0,318	0,384	0,447	0,393	0,440	0,490	0,567	0,388	0,443
ES	38	Caja Rural de Jaen, Barcelona y Madrid	0,374	0,409	0,390	0,430	0,508	0,516	0,539	0,576	0,452	0,483
ES	39	Caja Rural de Navarra Sociedad Cooperativa de Crédito	0,178	0,218	0,161	0,221	0,180	0,190	0,168	0,197	0,172	0,206
ES	40	Caja Rural de Soria Sociedad Cooperativa de Crédito	0,335	0,446	0,334	0,503	0,444	0,587	0,653	0,856	0,441	0,598
ES	41	Caja Rural de Zamora	0,467	0,533	0,414	0,522	0,496	0,529	0,601	0,734	0,494	0,580
ES	42	Banco Cooperativo Espanol	9,830	9,899	9,274	9,325	4,851	4,854	1,942	1,971	6,474	6,512
ES	43	Banco Alcala	0,269	1,440	0,200	1,279	0,154	1,248	0,184	1,497	0,202	1,366
ES	44	Banco Caixa Geral SA	0,807	0,810	1,199	1,211	1,509	1,552	1,851	1,881	1,341	1,363
ES	45	BNP Paribas España SA	1,974	3,703	2,660	7,416	3,563	8,208	1,117	3,691	2,329	5,755
ES	46	EBN Banco de Negocios SA-EBN Banco	1,120	1,633	0,791	1,632	0,927	1,889	0,175	1,422	0,753	1,644
PT	47	Banco BPI SA	0,335	0,644	0,344	0,698	0,427	0,804	0,821	2,181	0,482	1,082
ES	48	Allfunds Bank SA	0,355	0,636	0,255	0,537	0,263	0,456	0,144	0,411	0,254	0,510
ES	49	Banco Santander SA	0,428	big	0,359	big	0,457	big	0,456	big	0,425	big
PT	50	Banco de Investimento Global SA - BIG	0,469	0,584	0,395	0,566	0,354	0,519	0,434	0,584	0,413	0,563
PT	51	Banco Invest SA	0,695	1,090	0,809	1,461	0,662	1,113	0,543	1,302	0,677	1,242
ES	52	Cajamar Caja Rural, S.C.C.	0,235	0,510	0,214	0,494	0,287	0,511	0,319	0,468	0,264	0,496
ES	53	Criteria CaixaHolding SA	0,011	0,031	0,241	0,886	0,291	0,978	0,375	0,964	0,229	0,715
ES	54	Caja Laboral Popular Coop de credito	0,257	0,403	0,266	0,463	0,337	0,468	0,409	0,592	0,317	0,481
ES	55	Unicaja Banco SA	0,308	0,528	0,213	0,494	0,249	0,586	0,338	0,587	0,277	0,549
ES	56	Banco De Credito Social Cooperativo Sa	0,227	0,492	0,214	0,494	0,260	0,464	0,316	0,465	0,254	0,479
PT	57	Atlântico Europa, Sgps, S.A	0,321	0,684	0,224	0,660	0,393	0,756	0,626	1,068	0,391	0,792
PT	58	Finantipar - S.G.P.S., S.A.	1,012	1,022	1,013	1,014	1,151	1,152	1,004	1,006	1,045	1,048
		Mean	0,581	0,905	0,589	1,000	0,568	0,973	0,532	0,782	0,568	0,954

*based on Super Efficiency Scores

Appendix 10 – Ranking and first-stage DEA scores of Portuguese banks (isolated sample)

Country	DMU	Bank	2013		2014		2015		2016		Overall	
			CRS*	VRS*	CRS*	VRS*	CRS*	VRS*	CRS*	VRS*	CRS*	VRS*
PT	1	Banco L. J. Carregosa, S.A.	15	3	15	4	14	4	16	6	15	4
PT	12	Santander Totta SGPS	6	10	8	11	6	9	7	10	7	10
PT	13	Caixa Economica Montepio Geral	10	13	6	6	11	11	14	16	11	13
PT	14	Caixa Geral de Depositos	9	1	12	1	12	1	11	1	13	1
PT	15	Banco Comercial Português, SA-Millennium bcp	12	2	13	2	9	2	8	2	12	2
PT	16	Banco Bilbao Vizcaya Argentaria (Portugal) SA	3	6	2	5	1	3	1	5	1	5
PT	17	Caixa - Banco de Investimento SA	8	7	7	13	10	13	13	13	9	12
PT	30	Haitong Bank SA	14	15	14	15	15	16	12	14	14	15
PT	31	Banco Finantia SA	5	11	3	8	5	10	4	8	5	9
PT	32	Banco Santander Totta SA	4	8	11	14	8	12	9	11	8	11
PT	34	Caixa Central de Credito Agricola Mutuo	16	16	16	16	16	15	15	15	16	16
PT	47	Banco BPI SA	2	5	9	9	7	8	3	4	4	6
PT	50	Banco de Investimento Global SA - BIG	11	14	5	10	13	14	6	12	10	14
PT	51	Banco Invest SA	1	4	1	3	3	6	10	3	2	3
PT	57	Atlântico Europa, Sgps, S.A	13	12	10	7	4	7	2	7	6	7
PT	58	Finantipar - S.G.P.S., S.A.	7	9	4	12	2	5	5	9	3	8

*based on Super Efficiency Scores (estimations conducted using the isolated PT sample)

Country	DMU	Bank	2013		2014		2015		2016		Overall	
			CRS*	VRS*	CRS*	VRS*	CRS*	VRS*	CRS*	VRS*	CRS*	VRS*
PT	1	Banco L. J. Carregosa, S.A.	0,65	1,77	0,43	1,68	0,62	1,64	0,35	1,86	0,51	1,74
PT	12	Santander Totta SGPS	1,01	1,04	0,82	1,04	0,98	1,10	0,83	0,96	0,91	1,04
PT	13	Caixa Economica Montepio Geral	0,95	0,95	0,92	1,24	0,82	0,99	0,53	0,53	0,80	0,93
PT	14	Caixa Geral de Depositos	0,98	big	0,76	big	0,79	big	0,62	big	0,79	big
PT	15	Banco Comercial Português, SA-Millennium bcp	0,75	big	0,71	big	0,89	big	0,82	big	0,79	big
PT	16	Banco Bilbao Vizcaya Argentaria (Portugal) SA	1,09	1,13	1,47	1,52	1,74	1,76	1,68	1,87	1,50	1,57
PT	17	Caixa - Banco de Investimento SA	1,00	1,13	0,92	1,04	0,85	0,90	0,54	0,84	0,83	0,98
PT	30	Haitong Bank SA	0,71	0,71	0,57	0,59	0,54	0,60	0,57	0,59	0,60	0,62
PT	31	Banco Finantia SA	1,01	1,02	1,19	1,19	0,99	0,99	1,11	1,13	1,08	1,09
PT	32	Banco Santander Totta SA	1,02	1,05	0,78	1,00	0,91	0,97	0,76	0,91	0,87	0,98
PT	34	Caixa Central de Credito Agricola Mutuo	0,48	0,66	0,35	0,51	0,51	0,63	0,49	0,56	0,46	0,59
PT	47	Banco BPI SA	1,11	1,21	0,79	1,13	0,95	1,26	1,47	2,43	1,08	1,51
PT	50	Banco de Investimento Global SA - BIG	0,85	0,95	0,97	1,05	0,63	0,64	0,84	0,87	0,82	0,88
PT	51	Banco Invest SA	1,45	1,57	1,57	1,96	1,34	1,53	0,76	2,47	1,28	1,88
PT	57	Atlântico Europa, Sgps, S.A	0,71	0,97	0,79	1,21	1,18	1,35	1,49	1,82	1,04	1,34
PT	58	Finantipar - S.G.P.S., S.A.	1,01	1,05	1,01	1,04	1,54	1,55	1,00	1,01	1,14	1,16

*based on Super Efficiency Scores (estimations conducted using the isolated PT sample)

Appendix 11 – Rankings of Spanish banks (isolated sample) according to the first-stage DEA from 2013 to 2016

Country	DMU	Bank	2013		2014		2015		2016		Overall	
			CRS*	VRS*	CRS*	VRS*	CRS*	VRS*	CRS*	VRS*	CRS*	VRS*
ES	2	Caixabank, S.A.	30	17	24	14	27	15	25	12	26	15
ES	3	BFA Tenedora de Acciones SAU	15	7	10	9	21	18	21	19	17	12
ES	4	Liberbank SA	36	31	33	35	30	34	30	26	32	32
ES	5	Renta 4 Banco, S.A.	41	41	42	42	41	41	41	41	42	41
ES	6	Ibercaja Banco SA	34	25	32	31	39	38	28	29	35	34
ES	7	Abanca Corporacion Bancaria SA	33	34	31	33	37	27	23	30	30	30
ES	8	Kutxabank SA	40	29	39	24	34	25	20	27	34	27
ES	9	Banco Caminos SA	19	27	23	38	15	32	10	28	21	31
ES	10	Banco Inversis SA	10	18	8	13	24	17	31	20	15	16
ES	11	CIMD Group	38	22	41	25	42	35	42	37	41	28
ES	18	Banco Bilbao Vizcaya Argentaria SA-BBVA	13	13	14	12	19	12	19	11	18	13
ES	19	Bankia, SA	17	11	13	15	12	13	11	9	12	11
ES	20	Bankinter SA	23	15	20	19	20	19	14	13	22	17
ES	21	Banco Popular Espanol SA	9	10	9	11	10	9	22	15	10	10
ES	22	Colonya, Caixa d'Estalvis de Pollensa	14	8	16	10	7	8	13	10	9	8
ES	23	Caja de Ahorros y Monte de Piedad de Ontinyent	16	23	7	16	8	20	12	22	8	20
ES	24	Confederación Española de Cajas de Ahorros	20	33	26	40	35	40	26	38	27	39
ES	25	Banco Mediolanum SA	8	14	12	20	22	21	27	25	13	19
ES	26	Banca March SA	37	39	37	39	36	39	36	40	38	40
ES	27	Fundacion Bancaria Caixa D Estalvis	35	20	30	18	28	16	32	21	29	18
ES	28	Banco de Sabadell SA	28	16	21	21	17	10	18	14	24	14
ES	29	Caja Rural de Almendralejo	7	19	11	22	9	22	8	24	7	21
ES	33	Deutsche Bank SAE	4	9	4	8	6	11	5	8	5	9
ES	35	Bankoa SA	27	36	27	37	16	29	6	18	19	26
ES	36	Santander Consumer Finance	5	5	5	5	5	4	4	3	4	5
ES	37	Caja de Crédito de Los Ingenieros	25	37	17	32	23	33	16	34	23	37
ES	38	Caja Rural de Jaen, Barcelona y Madrid	18	35	19	36	11	28	15	32	16	35
ES	39	Caja Rural de Navarra	39	40	40	41	38	42	39	42	40	42
ES	40	Caja Rural de Soria	24	32	22	27	18	23	7	17	20	23
ES	41	Caja Rural de Zamora	12	24	15	26	13	26	9	23	11	24
ES	42	Banco Cooperativo Espanol	1	2	1	2	1	3	1	4	1	2
ES	43	Banco Alcala	29	4	38	4	40	5	38	6	39	4
ES	44	Banco Caixa Geral SA	6	12	3	7	3	7	2	5	3	7
ES	45	BNP Paribas España SA	2	3	2	3	2	2	3	2	2	3
ES	46	EBN Banco de Negocios SA-EBN Banco	3	6	6	6	4	6	37	7	6	6
ES	48	Allfunds Bank SA	22	21	29	23	33	30	40	39	36	25
ES	49	Banco Santander SA	11	1	18	1	14	1	17	1	14	1
ES	52	Cajamar Caja Rural, S.C.C.	31	28	34	28	26	31	34	36	31	33
ES	53	Criteria CaixaHolding SA	42	42	28	17	29	14	29	16	37	22
ES	54	Caja Laboral Popular Coop de credito	26	38	25	34	25	36	24	31	25	38
ES	55	Unicaja Banco SA	21	26	36	29	32	24	33	33	28	29
ES	56	Banco De Credito Social Cooperativo Sa	32	30	35	30	31	37	35	35	33	36

*based on Super Efficiency Scores (estimations conducted using the isolated ES sample)

Appendix 12 – First-stage DEA scores of Spanish banks (isolated sample)

Country	DMU	Bank	2013		2014		2015		2016		Overall	
			CRS*	VRS*	CRS*	VRS*	CRS*	VRS*	CRS*	VRS*	CRS*	VRS*
ES	2	Caixabank, S.A.	0,27	0,78	0,30	0,95	0,31	0,97	0,40	1,07	0,32	0,94
ES	3	BFA Tenedora de Acciones SAU	0,45	1,22	0,54	1,14	0,44	0,88	0,44	0,88	0,47	1,03
ES	4	Liberbank SA	0,23	0,47	0,24	0,43	0,28	0,48	0,36	0,68	0,28	0,52
ES	5	Renta 4 Banco, S.A.	0,06	0,21	0,05	0,21	0,05	0,22	0,12	0,27	0,07	0,23
ES	6	Ibercaja Banco SA	0,25	0,54	0,24	0,48	0,17	0,36	0,38	0,65	0,26	0,51
ES	7	Abanca Corporacion Bancaria SA	0,25	0,44	0,25	0,47	0,20	0,55	0,42	0,64	0,28	0,52
ES	8	Kutxabank SA	0,20	0,50	0,18	0,55	0,25	0,56	0,45	0,68	0,27	0,57
ES	9	Banco Caminos SA	0,39	0,52	0,31	0,40	0,48	0,50	0,58	0,66	0,44	0,52
ES	10	Banco Inversis SA	0,58	0,78	0,57	0,98	0,38	0,91	0,35	0,88	0,47	0,89
ES	11	CIMD Group	0,22	0,66	0,05	0,54	0,03	0,48	0,05	0,52	0,09	0,55
ES	18	Banco Bilbao Vizcaya Argentaria SA-BBVA	0,48	0,88	0,42	1,04	0,45	1,07	0,46	1,11	0,45	1,02
ES	19	Bankia, SA	0,42	0,97	0,48	0,94	0,54	1,07	0,56	1,17	0,50	1,04
ES	20	Bankinter SA	0,34	0,81	0,36	0,84	0,45	0,85	0,54	1,03	0,42	0,88
ES	21	Banco Popular Espanol SA	0,58	1,01	0,54	1,08	0,55	1,22	0,42	0,97	0,52	1,07
ES	22	Colonya, Caixa d'Estalvis de Pollensa	0,46	1,10	0,41	1,13	0,72	1,37	0,54	1,15	0,54	1,19
ES	23	Caja de Ahorros y Monte de Piedad de Ontinyent	0,44	0,57	0,67	0,92	0,71	0,79	0,55	0,78	0,59	0,76
ES	24	Confederación Española de Cajas de Ahorros	0,37	0,44	0,27	0,27	0,21	0,22	0,40	0,51	0,31	0,36
ES	25	Banco Mediolanum SA	0,59	0,87	0,53	0,80	0,43	0,74	0,38	0,70	0,48	0,78
ES	26	Banca March SA	0,22	0,30	0,22	0,35	0,21	0,23	0,23	0,31	0,22	0,30
ES	27	Fundacion Bancaria Caixa D Estalvis	0,24	0,75	0,25	0,87	0,29	0,95	0,35	0,88	0,28	0,86
ES	28	Banco de Sabadell SA	0,28	0,81	0,33	0,79	0,47	1,18	0,47	1,01	0,39	0,95
ES	29	Caja Rural de Almendralejo	0,66	0,77	0,53	0,65	0,70	0,72	0,64	0,75	0,63	0,72
ES	33	Deutsche Bank SAE	1,07	1,08	0,93	1,14	0,79	1,12	0,78	1,32	0,89	1,16
ES	35	Bankoa SA	0,30	0,43	0,26	0,41	0,47	0,53	0,76	0,91	0,45	0,57
ES	36	Santander Consumer Finance	1,04	1,66	0,88	1,64	0,83	2,25	0,93	2,82	0,92	2,09
ES	37	Caja de Crédito de Los Ingenieros	0,34	0,41	0,41	0,48	0,42	0,49	0,49	0,58	0,41	0,49
ES	38	Caja Rural de Jaen, Barcelona y Madrid	0,40	0,43	0,39	0,43	0,55	0,55	0,54	0,59	0,47	0,50
ES	39	Caja Rural de Navarra	0,21	0,23	0,17	0,23	0,18	0,19	0,17	0,24	0,18	0,22
ES	40	Caja Rural de Soria	0,34	0,45	0,33	0,50	0,45	0,59	0,65	0,92	0,45	0,62
ES	41	Caja Rural de Zamora	0,48	0,55	0,41	0,52	0,53	0,55	0,61	0,76	0,51	0,60
ES	42	Banco Cooperativo Espanol	9,83	9,91	9,27	9,43	5,00	5,01	2,17	2,22	6,57	6,64
ES	43	Banco Alcala	0,27	2,49	0,20	2,07	0,15	1,99	0,18	1,95	0,20	2,13
ES	44	Banco Caixa Geral SA	0,82	0,88	1,21	1,28	1,51	1,55	1,98	2,00	1,38	1,43
ES	45	BNP Paribas España SA	1,97	3,70	2,66	8,36	3,56	9,88	1,12	3,69	2,33	6,41
ES	46	EBN Banco de Negocios SA-EBN Banco	1,14	1,63	0,79	1,63	0,94	1,90	0,20	1,45	0,77	1,65
ES	48	Allfunds Bank SA	0,35	0,75	0,25	0,62	0,26	0,52	0,15	0,41	0,25	0,57
ES	49	Banco Santander SA	0,52	big	0,39	big	0,49	big	0,48	big	0,47	big
ES	52	Cajamar Caja Rural, S.C.C.	0,27	0,51	0,22	0,49	0,31	0,51	0,32	0,52	0,28	0,51
ES	53	Criteria CaixaHolding SA	0,01	0,04	0,26	0,89	0,29	0,98	0,37	0,96	0,23	0,72
ES	54	Caja Laboral Popular Coop de credito	0,30	0,40	0,29	0,46	0,37	0,47	0,41	0,62	0,34	0,49
ES	55	Unicaja Banco SA	0,36	0,53	0,22	0,49	0,27	0,59	0,34	0,59	0,30	0,55
ES	56	Banco De Credito Social Cooperativo Sa	0,26	0,49	0,22	0,49	0,28	0,46	0,32	0,53	0,27	0,50

*based on Super Efficiency Scores (estimations conducted using the isolated ES sample)

Appendix 13 – Correlation matrixes of the applied variables in the second-stage DEA (Portuguese and Spanish isolated samples)

	TE	PTE	HCE	SCE	CEE	SIZE	Lev1	Lev2	Lev3
TE	1								
PTE	0.5604*	1							
	0.0000								
HCE	0.2491	-0.0226	1						
	0.0641	0.8687							
SCE	0.1132	0.0655	0.6624*	1					
	0.4060	0.6317	0.0000						
CEE	-0.0637	-0.1788	0.3816*	0.4166*	1				
	0.6408	0.1873	0.0037	0.0014					
SIZE	-0.0248	-0.3743*	-0.2711	-0.1172	0.0147	1			
	0.8563	0.0045	0.0433	0.3897	0.9146				
Lev1	0.0638	-0.1309	-0.6570*	-0.4875*	-0.0311	0.6829*	1		
	0.6402	0.3363	0.0000	0.0001	0.8200	0.0000			
Lev2	-0.0638	0.1310	0.6569*	0.4875*	0.0310	-0.6830*	-1.0000*	1	
	0.6405	0.3359	0.0000	0.0001	0.8208	0.0000	0.0000		
Lev3	0.2319	-0.0160	-0.5552*	-0.4632*	-0.0846	0.6921*	0.9180*	-0.9180*	1
	0.0855	0.9069	0.0000	0.6096	0.0003	0.5353	0.0000	0.0000	

VRS and CRS based on Super efficiency scores (based on isolated PT sample: 56 observations)

	TE	PTE	HCE	SCE	CEE	SIZE	Lev1	Lev2	Lev3
TE	1								
PTE	0.8656*	1							
	0.0000								
HCE	0.4693*	0.2712*	1						
	0.0000	0.0004							
SCE	0.0741	-0.0572	0.4744*	1					
	0.3459	0.4668	0.0000						
CEE	-0.0744	-0.0507	0.1550	0.0187	1				
	0.3436	0.5192	0.0476	0.8126					
SIZE	-0.0243	-0.0887	0.1198	0.1949	-0.3077*	1			
	0.7575	0.2588	0.1265	0.0124	0.0001				
Lev1	0.1681	0.1018	0.2141*	-0.2461*	-0.1547	0.2779*	1		
	0.0314	0.1947	0.0059	0.0015	0.0480	0.0003			
Lev2	-0.1675	-0.1016	-0.2136*	0.2459*	0.1551	-0.2819*	-0.9999*	1	
	0.0320	0.1956	0.0060	0.0015	0.0473	0.0003	0.0000		
Lev3	0.6799*	0.4512*	0.4581*	0.1238	-0.1086	0.3642*	0.5174*	-0.5178*	1
	0.0000	0.0000	0.0000	0.1141	0.1665	0.0000	0.0000	0.0000	

VRS and CRS based on Super efficiency scores (based on isolated ES sample: 164 observations)

Appendix 14 – Selected results of the OLS and quantile regressions applying both CRS and VRS super efficiency models: Portuguese and Spanish isolated samples

Independent variables		OLS regression		Quantile Regression									
				Q (0.10)		Q (0.25)		Q (0.50)		Q (0.75)		Q (0.90)	
		CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
HCE	PT	.1006 (.001)***	-.03 (.448)	.07 (.111)	.0228 (.558)	.146 (.006)***	-.015 (.760)	.11971 (.013)**	.0303 (.595)	.106 (.042)**	-.0033 (.954)	.0585 (.600)	.0132 (.889)
	ES	.3464 (.00)***	.3186 (.010)***	.12923 (.007)***	.1609 (.108)	.1377 (.009)***	.078 (.495)	.1463 (.356)	.1233 (.709)	.36 (.375)	.6 (.379)	.814 (.191)	1.23 (.241)
SCE	PT	.185 (.142)	.4341 (.016)**	.193 (.590)	.16 (.389)	.086 (.830)	.311 (.086)*	.134 (.589)	.295 (.148)	-.067 (.752)	.517 (.031)**	.477 (.131)	.625 (.276)
	ES	-.68 (.002)***	-1.12 (.004)***	-.284 (.035)**	-.3132 (.524)	-.26 (.089)*	-.196 (.692)	-.23 (.749)	-.158 (.915)	-.82 (.670)	-2.9 (.377)	-3.2 (.379)	-6.4 (.332)
CEE	PT	-.951 (.034)**	-.81 (.196)	.117 (.853)	-.2827 (.633)	-.634 (.404)	-.81 (.299)	-.6265 (.517)	-.39125 (.696)	-.446 (.663)	-.69 (.523)	-1.2 (.218)	-1.66 (.320)
	ES	-1.27 (.001)***	-1.342 (.048)**	-.394 (.038)**	-.11736 (.726)	-.57 (.003)***	-.1153 (.800)	-.43 (.187)	.0087 (.989)	-.48 (.244)	-.99 (.067)*	-1.37 (.066)	-1.6 (.208)
SIZE	PT	-.247 (.002)***	-.455 (.00)***	-.105 (.417)	-.467 (.00)***	-.2628 (.056)*	-.461 (.00)***	-.22 (.028)**	-.3561 (.040)**	-.1711 (.245)	-.626 (.001)***	-.48 (.058)	-.5724 (.049)**
	ES	-.3421 (.00)***	-.414 (.001)***	-.0124 (.763)	.01982 (.851)	-.054 (.164)	-.00276 (.976)	-.09 (.025)	-.059 (.584)	-.11 (.011)**	-.084 (.233)	-.16 (.186)	-.044 (.633)
Lev1	PT	1056.25 (.436)	1487.1 (.436)	603.4 (.598)	1534.6 (.342)	17 (.992)	10.06 (.996)	327.6 (.847)	2220.61 (.356)	2067.8 (.470)	1194.83 (.722)	-1109.96 (.815)	-2454.3 (.666)
	ES	-40.66 (.529)	-106.5 (.349)	-5.54 (.791)	-78.71 (.012)**	-11.4 (.632)	-66.6 (.009)***	-35.21 (.320)	-42.52 (.399)	-17.48 (.577)	-32.7 (.537)	-19.6 (.680)	17.72 (.821)
Lev2	PT	1056.01 (.436)	1490.34 (.435)	604.7 (.596)	1537.7 (.341)	15.5 (.992)	12.365 (.996)	327.86 (.847)	2221.18 (.356)	2069.5 (.469)	1190.3 (.723)	-1107.5 (.815)	-2447.9 (.667)
	ES	-35.96 (.578)	-101.33 (.373)	-5.33 (.797)	-78.5 (.012)**	-11.8 (.619)	-65.995 (.010)***	-35.2 (.321)	-41.66 (.410)	-12.8 (.687)	-19.83 (.715)	-4.66 (.919)	43.8 (.585)
Lev3	PT	.067 (.001)***	.084 (.002)***	.061 (.001)***	.0946 (.00)***	.06645 (.002)***	.0814 (.001)***	.07 (.010)*	.06754 (.013)**	.069 (.001)***	.0323 (.433)	.11314 (.101)	.118 (.149)
	ES	.125 (.00)***	.12 (.00)***	.011 (.150)	.018 (.415)	.0101 (.199)	.0191 (.443)	.0184 (.403)	.042 (.239)	.074 (.169)	.134 (.023)**	.14 (.024)**	.139 (.075)*
Constant	PT	-1053.8 (.437)	-1482.7 (.438)	-602.9 (.598)	-1530.7 .343	-14.6 (.993)	-5.73 (.998)	-325.7 (.848)	-2217.01 (.357)	-2066.25 (.470)	-1187.35 (.724)	1114.25 (.814)	2459.4 (.665)
	ES	42.45 (.513)	109.8 (.336)	5.655 (.787)	78.43 (.015)**	12.1 (.614)	66.8 (.011)**	36.2 (.308)	43 (.398)	17.55 (.577)	32.11 (.549)	19.14 (.689)	-18.7 (.809)
Observations	PT	56	56	56	56	56	56	56	56	56	56	56	56
	ES	164	164	164	164	164	164	164	164	164	164	164	164
R^2 / Pseudo R^2	PT	0.4725	0.4002	0.3702	0.3758	0.3579	0.2934	0.3164	0.2464	0.3208	0.3502	0.3335	0.2586
	ES	0.6498	0.3489	0.1473	0.0988	0.1084	0.0538	0.1058	0.0762	0.1570	0.1500	0.4248	0.3666

Dependent variable: Efficiency based on both CRS and VRS models; p-values in parenthesis; *, **, *** means significant at 10%, 5%, and 1%, respectively;
DMU 14, 15 (PT sample), and DMU 49 (ES sample) were removed due to "big" value in VRS model; Q (0.95) removed from command due to PT small sample size
PT and ES regression results based on isolated samples (i.e. 16 banks for PT and 42 banks for ES)