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Domestic versus Foreign Banking Institutions. An Analysis from CAMELS Model

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ABSTRACT

The purpose of this project (from now on, the "**Project**") is to analyze a sample of banking institutions of the Spanish banking sector between the years 2013 and 2017 through the CAMELS model to determine whether domestic or foreign banks have more probability to go bankrupt. To do this, firstly we analyze the main bankruptcy predictive models to outline the advantages of the CAMELS model. Then, we review the implementation of the CAMELS model in several empirical articles. In detail, we go through the comparative studies of domestic and foreign bank's probability to go bankrupt to propose our hypothesis. Finally, using a fifty-three banking institutions' sample, we test our hypothesis through several statistical methodologies, being the regression analysis the most relevant one. The results show that foreign banking institutions have less probability to go bankrupt than domestic banking institutions.

*El objetivo de este proyecto (de ahora en adelante, el "**Proyecto**") es analizar una muestra de instituciones bancarias del sistema bancario español entre los años 2013 y 2017 mediante el modelo CAMELS para determinar qué bancos, nacionales o extranjeros, tienen más probabilidades de quiebra. Para hacer esto, primeramente analizamos los principales modelos de predicción de quiebra para destacar las ventajas del modelo CAMELS. Después, revisamos la implementación del modelo CAMELS en diversos artículos empíricos. Específicamente, consideramos los estudios comparativos sobre la probabilidad de quiebra de bancos nacionales y extranjeros para proponer nuestra hipótesis. Finalmente, usando una muestra de cincuenta y tres instituciones bancarias, contrastamos nuestra hipótesis usando diferentes métodos estadísticos, siendo el análisis de regresión el más relevante. Los resultados obtenidos muestran que las instituciones bancarias extranjeras tienen menos probabilidad de quiebra que las instituciones bancarias nacionales.*

KEYWORDS

CAMELS - Bankruptcy - Banking Sector - Domestic Banks - Foreign Banks

CAMELS - Bancarrota - Sector Bancario - Bancos Nacionales - Bancos Extranjeros

I. INTRODUCTION

The banking sector is a vital factor of every country's economy, including the Spanish economy, because it enables the investment of capital acting as an intermediary to all industries, ranging from agriculture, construction, textile, and manufacturing. The bankruptcy of the banking sector can create a ripple effect leading to the mistrust in the financial system, the investments' slump, the markets' fell, the appreciation of the currencies, and even a worldwide financial crisis like the one that battered the world just a few years ago. Therefore, the search for the perfect bankruptcy predictive model has been the object of study by many authors in the course of history. The purpose of this project (from now on, the "Project") is to analyze a sample of banking institutions of the Spanish banking sector between the years 2013 and 2017 through the CAMELS model to determine whether domestic or foreign banking institutions have more probability to go bankrupt.

Firstly, we examine the banking sector bankruptcy effects and we analyze the main bankruptcy predictive models since the 1960s to nowadays including the initial Altman's Z-Score model, the recent Artificial Neuronal Networks model and the CAMELS model. The CAMELS model is a recognized bankruptcy predictive model that American bank supervisory authorities use to rate banking institutions according to six parameters represented by its acronym: Capital Adequacy, Assets Quality, Management Quality, Earnings and Profitability, and Sensitivity to Market Risk. Banks are given an average score by assigning each parameter a rate from one to five, being a rating of one the best and a rating of five the worst. We choose as a guide to perform our empirical analysis the CAMELS model because it can be implemented exclusively with the accounting data published by banking institutions and because it enables us to compare different banking institutions overcoming the limitations of the other studied bankruptcy predictive models.

Afterwards, we review the implementation of the CAMELS model in several empirical articles. In detail we go through the comparative studies of domestic and foreign bank's probability to go bankrupt to propose the hypothesis that Spanish domestic banking institutions are less likely to go bankrupt than foreign banking institutions. Then, we select sample of fifty-three banking institutions, we explain the model, variables and methodology chosen, and we test our hypothesis through several statistical methodologies, being the regression analysis the most relevant one. To conclude, we determine if the CAMELS model is a significant system to predict banking institutions' bankruptcy, and whether domestic or foreign banking institutions have more probability to go bankrupt in the Spanish industry after the worldwide financial crisis period.

II. BANKRUPTCY PREDICTIVE MODELS IN THE BANKING INDUSTRY

In this section, we introduce the banking sector bankruptcy effects in order to understand why this industry has been the object of study by many authors in the course of history. Afterwards, we explain the main bankruptcy predictive models since the 1960s to nowadays including the initial Altman's Z-Score model, the recent Artificial Neuronal Networks model, and the CAMELS model to argue the reasons why we choose this last methodology to guide the implementation of our empirical analysis.

2.1. BANKRUPTCY EFFECTS

The banking sector is the set of institutions (banking institutions), resources (financial assets), and markets that allow the exchange of money. The banking sector works channeling funds from those who are net savers (i.e., who spend less than their income) to those who are net spenders (i.e., who spend more than their income). In order to achieve this objective, the banking sector uses two main ways. On the one hand, direct or market-based finance via financial markets. On the other hand, indirect or bank-based finance via financial intermediaries (European Central Bank, 2019). Thus, the banking sector is a vital factor of every country's economy, including the Spanish economy, because it enables the investment of capital acting as an intermediary to all industries, ranging from agriculture, construction, textile, and manufacturing.

As a crucial factor of every country's economy, the banking sector is highly regulated. The main pieces of financial legislation were adopted in the United States when the Congress passed the Banking Acts of 1933 and 1935, which created the Federal Deposit Insurance Corporation (from now on, FDIC)[1], and also the structure of the Federal Reserve System (from now on, FED)[2]. The American Banking Acts of 1933 and 1935 were precedent-setting, and other countries started creating other pieces of legislation leading to the creation of the Basel Committee on Banking Supervision (from now on, BCBS), which created much of the normative, requirements and standards for banking institutions that persist at present (López del Rio, 2015).

Along with the massive amount of regulation, recent trends show that the banking industry has become

[1] The Federal Deposit Insurance Corporation (from now on, FDIC) is a government corporation that operates as an independent agency guarantying the safety of its member banking institutions.

[2] The Federal Reserve System (the FED) is the central bank of the United States. It was created in December 1913 by the Congress to provide the nation with a safer, more flexible, and more stable financial system (Board of Governors of the Federal Reserve System, 2019).

genuinely globalized. The globalization implies both a harmonization of rules and a reduction of barriers that allow the free flow of capital and permits all firms to compete in all markets. The banking institutions' globalization is being driven by advances in data processing and telecommunications, liberalization of restrictions on cross border capital flows, deregulation of domestic capital markets, and greater competition among these markets for a share of the world's trading volume. Trends in other industries and lessons from interstate banking in the United States suggest that as banking globalization progresses, financial services will become more integrated, more competitive, and more concentrated (McElravey, 1990).

As we previously mentioned, the banking sector is a vital factor of every country's economy because it enables the investment of capital acting as an intermediary to all industries. Thus, one of the most critical matters of study in the field in the course of history was, and still is, the financial soundness of banking institutions. A banking crush can create a ripple effect that can impact worldwide, for example, in 2008 the bankruptcy of Lehman Brothers played a significant role in the emergence of the worldwide financial crisis. The fall of Lehman Brothers had a negative impact on their employees, who lost a large portion of their fortunes as the firm's stock fallen and who ended up unemployed. However, for the rest of the financial world, the consequences of Lehman Brothers' bankruptcy were also tremendous when world markets fell as investors sold assets across the board and sought refuge in the safest securities they could find: government bonds (Landom, 2008).

Furthermore, trust in the stability of the financial system took a significant hit when the American government did a 180-degree turn and refused to bail out Lehman Brothers. The mistrust in the banking system, where banking institutions were unwilling to lend money to each other for fear of not getting paid back, caused a dramatic shift that froze credit markets. The worldwide financial crisis changed the mindset of the banking sector and led many experts to conclude that the global economy will likely grow at a slower pace than it has in the past. Sapping growth will be the combination of tighter credit and the need for consumers to save more money each month to offset the significant losses they suffered from plunging real estate values and lost jobs (Shell, 2009).

The banking sector bankruptcy effects have led to a massive amount of empirical studies analyzing the probability of a banking institution's failure. Much of these articles follow bankruptcy predictive models to try to advance the future performance of banking institutions. In the next section, we explain the main bankruptcy predictive models since the 1960s to nowadays including the initial Altman's Z-Score model, the recent Artificial Neuronal Networks model, and the CAMELS model and we argue the reasons why we choose this last methodology to guide the implementation of our empirical analysis.

2.2. BANKRUPTCY PREDICTIVE MODELS

The question about which factors lead to the bankruptcy of enterprises and, specifically, which factors lead to the bankruptcy of banking institutions has been tried to be answered by many authors over the years. Some financial experts have blamed multiple variables such as inadequate management, short profitability, liquidity problems or changes in the market. In the same way, the perfect bankruptcy predictive model has been searched by many authors over the years. There is a vast number of bankruptcy predictive models in the literature and in the following section, we explain the main ones since the 1960s to nowadays including the initial Altman's Z-Score model, the recent Artificial Neuronal Networks model, and the CAMELS model.

It is worth mentioning that even though some of the models that we explain in this section did not appear in the first place explicitly applied to banking institutions, we include them in the Project because they were used by various authors in their studies to analyze the performance of banks. For example, the Altman's Z-Score appeared explicitly applied to manufacturing companies but it was used in 2016 by Maria Anagnostopoulos and Ioannis Kokkoris in their article *"Altman Z-Score Bankruptcy Analysis in the Greek Banking Sector"*, or in 2017 by Muam Mar Khaddafi in the study *"Analysis Z-score to Predict Bankruptcy in Banks Listed in Indonesia Stock Exchange"*. In the same way, the Artificial Neuronal Network model was used in 1991 by Tam K. Y in the publication "*Neural Network Models and the Prediction of Bank Bankruptcy*", or in 2007 by Tam Kar Yan and Melody Kiang in the study *"Bank Failures: A Neural Network Approach".*

Also, even though the first operational bankruptcy predictive models were developed during the 1960s, it is worth mentioning the studies developed in the 1930s by Smith and Winakor that found that the number of total assets was a good variable to predict the bankruptcy of an enterprise (Smith & Winakor, 1935). However, the studies up to the 1960s were considered rather informal and it was not until that decade that started the use of mathematical and statistical tools with the objective of predicting the probability to go bankrupt. During the 1960s, one of the most well-known bankruptcy predictive models was developed using the discriminant analysis technique: the Altman's Z-Score model (Altman, 1968).

2.2.1. ALTMAN'S Z-SCORE MODEL

The discriminant analysis is a set of mathematical and statistical tools used to interpret the data given by observing various variables study altogether. The discriminant analysis assumes that we already know to which group belongs each observed data (for example, bankrupt or operative) and finds the linear combination that better differentiates the data from each group. Once the discriminate function is found, it can be used to classify new study cases. Among the more valuable studies using this technique to analyze the financial soundness of enterprises we find Beaver (1966) and Altman (1968), whose Z-Score model become highly widespread.

Altman was an assistant professor of Finance at New York University's Stern School of Business who published in 1968 the Altman' Z-Score model for predicting the probability to go bankrupt of manufacturing companies. Altman used the discriminant analysis to combine the data of sixty-six manufacturing companies, half of them had been declared in bankruptcy in the two previous years and the other half of them were operative. In order to obtain the discriminate function, Altman calculated different coefficients and various financial ratios classified in five standard categories: liquidity, profitability, leverage, solvency, and activity. After numerous tries, Altman created the discriminate function with the coefficients and the five variables that together gave better results when predicting bankruptcy (Altman, 1968). The original Z-score formula was as follows:

2.1. Original Altman's Z-Score Formula

$$\mathrm{Z} = 0{,}12 * \mathrm{X1} + 0{,}14 * \mathrm{X2} + 0{,}33 * \mathrm{X3} + 0{,}006 * \mathrm{X4} + 0{,}999 * \mathrm{X5}$$

X_1 is the Working Capital dived by the Total Assets

X_2 is the Retained Earnings divided by the Total Assets

X_3 is the EBIT divided by the Total Assets

X_4 is the Market Value Equity divided by the Total Assets

X_5 is the Total Sales divided by the Total Assets

Even though the Altman's Z-Score was originally applied to a sample of manufacturer companies, later it has been applied to other type of enterprises where we can include banking institutions. Therefore, the original Z-Score formula has been re-estimated based on other datasets. Returning to the original Altman's Z-Score formula, the probability to go bankrupt of a company depends on the result of the Z-score. A score greater than 2.99 means that the company is safe from going bankrupt, that is, the company is in the safe zone. A score between 2.99 and 1.81 means that the company has some problems that may lead to the probability of bankruptcy, that is, the company is in the grey zone. A score fewer than 1.81 means that the company is at considerable risk of going bankrupt, that is, the company is in the distress zone (Altman, 1968):

2.2. Table of Original Altman's Z-Score Zones of Discrimination

The result of Z-Score Formula	Zones of Discrimination
> 2.99	Safe Zone
2.99 < X < 1.81	Grey Zone
< 1.81	Distress Zone

Source: Compiled by author using Altman (1968)

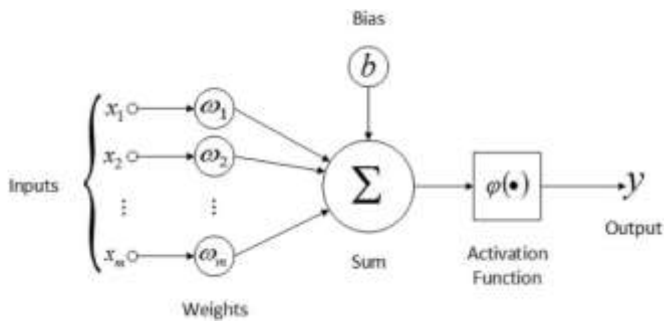
Nevertheless, the Altman's Z-Score has some limitations. When developing the discriminate function, it is necessary to observe a clear discrimination between the observed groups (for example, bankrupt and operative) since the discriminant analysis assumes that we already know to which groups belong each observed data, which is not always the case. For this reason, during the creation of the discriminate function it is common to evaluate the accuracy of the model calculating type I and type II errors. In our example, type I error measures the percentage of companies with financial problems classified as operative companies and type II error measures the percentage of operative companies classified as companies with financial problems.

2.2.2. Artificial Neuronal Network Model

More recently, the advances in computer techniques during the 1990s developed the subject of the artificial intelligence. In this filed, various tool appeared, such as the Expert System or the Artificial Neuronal Network model that can be used to predict bankruptcy. In this subsection, we explain the Artificial Neuronal Network model and its effectiveness. Even though this model is relatively new, the first studies using the Artificial Neural Network model to predict bankruptcy were performed at the turn of the century by W.S. McCulloch and W.H. Pitts (1943), and the first empirical studies were developed by H. White (1988), followed by A. Varfis and C. Vrsion (1990), Soumitra Dutta and Shasi Shekhar (1988) and F.S Wong, P. Z. Wang, T. H. Goh and B.K. Quek (1992) (Cinca & Martín, 1993).

The basis of the Artificial Neuronal Network model is that it can emulate the structure of the biologic neuronal network of living beings and thus, it can solve problems with incomplete or no linear information overcoming the limitations of the discriminant analysis. An artificial neuronal network is formed by a set of individual elements called artificial neurons that can interact between them thanks to the synapse. One neuron is a very merely processor: the information entries from the dendrites to the soma where it is processed and send to other neurons. The intensity of the interrelation between two neurons depends on the synaptic weight that interrelates them, if it is positive, the first neuron will arouse the second neuron, and if it is negative, the first neuron will inhibit the second neuron.

2.3. Graphic of Artificial Neuron



Source: Adapted from Haykin (1994)

2.4. Artificial Neuron Formula

$$y = \sum * \mathrm{Wn} * \mathrm{Xn}$$

n is the neuron

X_n are the input channels

W_n is the synaptic weights

∑ is the sum of the synapsis weights

Φ(.) is the activation function

y is the output

The neuronal network actuates in two different modes: learning or recall. Initially, the neuronal network is aleatory interconnected and has no knowledge stored. In order to allow the neuronal network to relate information, it has to be trained using various examples. If the convenient neuronal network has been chosen for the specific problem and the learning examples have been correctly selected, the neuronal network will be able to generalize from those examples using the recall ability. The calculation that a neuron does operate in recall model is the following[3]: The neuron (n), weights each entry of data that comes from the input channels (X_n) based on the synaptic weight that has associated (W_n), the result goes from the sum (∑) to the activation function, generally a no linear function (Φ(.)), and finally, the neuron gives an output (y) (Guarnieri et al., 2006). That final output of one neuron leads to the rest of the neurons

[3] See 2.3. Graphic of Artificial Neuron

forming the architecture of the network.

The main advantage of this model is that the information that can be input has no restrictions, differing from the statistical methodologies we analyzed in the subsection one. The Neuronal Network model also has a tremendous adaptative capacity to changes in the examples that they analyze because the most recent data adjust the model each time. Nevertheless, some authors have outlined the limits of this predictive technique saying that creating the model is a time-consuming process and that the sample of enterprises that are useful to train the model is determining for the effectiveness of the model, and thus, the selection of a wrong sample to train the model can lead to its failure. Other limitations include that this model lacks a theoretical foundation and that the results are sometimes difficult to interpret. For all of that, even though artificial intelligence seems to be the future of bankruptcy predictive models, we choose not to select this methodology to perform to empirical analysis.

2.2.3. CAMELS MODEL

The United States became an industrial and financial power in the later part of the nineteenth century after the World War I. The country's situation led in an unprecedented increase in the number of banking institutions which reached 30,000 branches by 1920. However, failures during the Great Depression in the 1930s were responsible for the disappearance of about 15,000 branches and created a general distrust in the banking system. Against this background, the United States Congress passed the Banking Acts of 1933 and 1935 that created the structure of the FED and the FDIC. The FDIC operated as an independent agency guarantying the safety of accounts at member banking institutions by providing insurances up to $250,000 per deposit in each insured bank.

As effects of the depression, the banking industry began to undergo structural changes due to a wave of bank mergers which led to a decrease in the number of institutions and the consolidation of some banks exacerbating the disparities between financial institutions (Roussakis, 2014). The idea of a uniform insurance per deposit seemed outdated because that way low-risk banking institutions had to subsidize high-risk banking institutions. Thus, to rate the financial soundness of individual banks the FDCI started making use of many tools. In 1978, the FED and the FDCI popularize the CAMEL model (without the letter S of acronym).

The CAMEL model, like it was known at the begging, gave an economic and financial methodology to evaluate five critical variables of the quality of banking institutions giving each bank an average score by assigning each variable a rate from one to five, being a rating of one the best and a rating of five the worst.

The variables analyzed were: Capital Adequacy, Assets Quality, Management Quality, Earnings and Profitability, and Liquidity. In 1996, trying to develop a method that could include the financial risk was added the last letter to the acronym, Sensitivity to the Market Risk, leading to the appearance of the CAMELS model (Federal Reserve Bank of San Francisco, 1999). Each of those variables can be defined as:

- **Capital Adequacy:** The capital of an organization is its wealth measured in the form of money. Capital is taken as a sign of financial strength of banking institutions because it measures their capability to confront external problems and unexpected losses. Even more, after the BCBS established minimum standards for every banking institution exists a minimum capital requirement (Business Dictionary, 2019).
- **Assets Quality:** The assets of an organization are the things that it has acquired or purchased and that have a money value, either their cost, book value, market value or residual value. The assets of banking institutions enable them to achieve their objective of channeling funds from those who are net savers to those who are net spenders.
- **Management Quality:** The permanency of banking institutions in the sector depends on the way these are operated. Even though managers are not involved in the day to day operations, they should provide a clear guide of politics, methods and appropriate practices to the level of risk of those operations.
- **Earnings and Profitability:** The earnings and profits of an organization are the surplus remaining after the total cost is deducted from total revenue, and the basis on which tax is computed and the dividend is paid. Earnings and profits give banking institutions economic resources to operate and continue growing (Business Dictionary, 2019).
- **Liquidity:** The liquidity of an organization is the ability of its current assets to meet its current liabilities. To maintain financial soundness banking institutions should take in consideration the liquidity levels and compare those with the necessities of capital considering the institution's size, complicity and the risk in which is involved (Business Dictionary, 2019).
- **Sensitivity to Market Risk:** The sensitivity to market risk reflects the degree to which changes in interest rates, foreign exchange rates, commodity prices or equity prices can adversely affect an organist's earnings or capital. Banking institutions that ignore these risks are more likely to go bankrupt (FDCI, 2019).

In order to describe each of the variables explained above, the CAMELS model uses financial ratios. It is crucial to notice that even though the CAMELS model tries harmonizing the variables that cause bankruptcy of banking institutions, the scope of financial ratios that describe each of the variables differ from countries and supervisory institutions. That is the reason why we are going to summarize the main used financial ratios in the following table. As it will be explained in Chapter III, we use as a guide to select the financial ratios that describe each of the CAMELS variables the Gikas & Hyz article (2015) because we found that this writing summarizes the opinion of the majority of the literature and explains the financial ratios in deep detail. Those financial ratios are:

2.5. Table of Financial Ratios

Capital Adequacy	Capital Adequacy Ratio (CAR)
Assets Quality	Net Non-Performing Assets (NPA)
Management Quality	Expenses to Revenues (ER)
Earnings and Profitability	Return of Assets (ROA) Return of Equity (ROE)
Liquidity	Current Assets to Total Assets (CATA) Loans to Deposits (LTD)
Sensitivity to Market Risk	Volatile Liabilities to Total Assets (VL)

Source: Source: Compiled by author using Gikas & Hyz (2015)

It is worth emphasizing that after the emergence of the CAMELS model, many consulting agencies started developing this methodology leading to the creation of new bankruptcy predictive models. Buniack and Co., a consulting firm created by Leonard Buniack, Luis Enrique Piña, Cristian Pared and Marco Antonio López and specialized in the development of management practices and professional services for banking institutions in Latin America, created an innovative bankruptcy predictive model, the CAMELS-B-COM. This model appeared as an extension of the studied CAMELS model (Buniack and Co., 2019).

The CAMELS-B-COM takes in consideration, in addition to the financial data of banking institutions, the qualitative data of banks. If the original CAMELS model includes the following variables represented by its acronym: Capital Adequacy, Asset Quality, Management Quality, Earnings and Profitability, Liquidity, and Sensitivity to Market Risk, the CAMELS-B-COM adds to the analysis: Business, Compliance, Operational Risk and Risk-Adjusted Performance Management. Those variables can be explained as:

- **Business**: The business variable analyses the business unit management. This variable evaluates the market depth, the competitive position, the growth strategies, and the business model of banking institutions. The sounder banking institutions will follow strategies that consider the necessities of the customers and the risk associated with each segment of the financial market.

- **Compliance**: This variable measures the grade of adequacy and disposition of the banking institution to comply with the financial normative, standards and requirements. Also, this variable evaluates the management board and all the other organisms that define the corporate government considering aspects such as the extent in which these banking institutions follow legislation, the effectiveness in meeting the standards and the level of knowledge of the management organisms of the regulatory issues.
- **Operational Risk**: The operational risk is the prospect of loss resulting from inadequate or failed procedures, systems or policies applied to the day to day activities. Operational risk includes employee errors, systems failures, and fraud or other criminal activities. Human capital policies, tight selection processes, strict controls, and different strategies, reduce operational risk (Investopedia, 2019).
- **Risk-Adjusted Performance Management**: This variable measures the management efforts in avoiding risk in general taking into consideration the organizational culture, the strategic plan, and the underlying risk plan. We can distinguish between risk-acceptant banking institutions, those who invest in more uncertain assets, more risk operations or that are more exposed to the market, and risk-averse banking institutions which are more likely to avoid risk in general.

The CAMELS-B-COM model is a more complete bankruptcy predictive model than the CAMELS model. However, many problems arise when we try to quantify the B-COM variables, so we find the CAMELS model a more accuracy bankruptcy predictive model. Thus, we decide to select the CAMELS model to guide the implementation of our empirical analysis because it overcomes the limitations of the Altman's Z-Score's discriminate function but without entering in the complexities of developing the Neuronal Artificial Network model or the CAMELS-B-COM model. In addition, since the first appearance of the CAMELS model in 1978, this bankruptcy predictive model has been consistently used by the literature to compare the probability to go bankrupt of domestic and foreign banking institutions, which is the main purpose of the Project.

2.3. THE CAMELS MODEL: DOMESTIC VERSUS FOREIGN BANKING INSTITUTIONS

This subsection has two purposes. Firstly, we briefly analyze the most recent empirical articles that implement the CAMELS model. We group these articles in two different categories. On the one hand, the articles that perform financial analyses of specific banks or banking industries through the CAMELS model. On the other hand, the articles that perform comparative analyses between two groups of banking institutions through the CAMELS model. Secondly, we examine in greater detail the most influent comparative studies that contrast the probability to go bankrupt of domestic and foreign banks paying particular attention to the methodologies and results obtained to propose the hypothesis that will be contrasted in our empirical analysis.

There is a large amount of recent literature concerning the CAMELS model. One group of articles perform financial analyses of specific banks or banking industries through the CAMELS model. Some articles analyze individual banking institutions to stress the advantages and disadvantages of banking institutions' merges and acquisitions, such as Walker (2018), leading to the conclusion that the CAMELS model allows to outline the differences in the situation of banking institutions before and after merges and acquisitions. Other articles examine banking industries in general within a given period of time, such as Gupta (2014) in the Indian industry between 2009 and 2013; Hashim (2015) in the Malaysian industry between 2008 and 2011; Gikas & Hyz (2015) in the Greek industry between 2008 and 2013; Rahman & Islam (2017) in the Bangladeshi industry between 2009 and 2013; or AbRahim et al. (2018) in the ASEAN[4] countries between 1997 and 2011, all leading to the conclusion that the CAMELS model is a useful tool that allows categorizing banking institutions depending on their financial performance and helps evaluate the overall situation of a banking industry.

Another group of articles perform comparative analyses between two categories of banking institutions through the CAMELS model. Some studies compare conventional banking institutions and Islamic banking institutions, such as Rafiq (2016), who conclude that conventional banks perform better at the liquidity ratio and Islamic banks perform better at the capital and management ratios. Some other articles compare public sector and private sector banking institutions, such as Srinivasan & Saminathan (2016) or Bothra (2018) in India, leading to the conclusion that public banking institutions are less likely to go bankrupt. One last category of articles, the category of examination in the following paragraphs, compare the probability to go bankrupt of domestic and foreign banking institutions (Kosmidou, 2004; Berger, 2005; Lensink & Naaborg, 2007; Sturm & Williams, 2008; Sheng-Hung & Chien-Chang, 2010; Ping, 2013; Dash & Das, 2015; Chen et al., 2017; and Pelletier, 2018).

From this group of articles that compare the probability to go bankrupt of domestic and foreign banking institutions, some articles focus on the impact that foreign ownership has on <u>M</u>anagement Quality (Berger, 2005 and Sturm & Williams, 2008). These articles led to the conclusion that management in foreign

[4] The Association of Southeast Asian Nations (ASEAN) is formed by ten members: Brunei Darussalam, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Vietnam.

banking institutions is poorer than in domestic banking institutions because of the difficulties that cross-border management itself implies, like the lack of communication between the headquarters and the branches. The inadequate management performance in foreign banking institutions negatively impacts the other CAMELS variables increasing the bankruptcy's probability of these institutions.

Some other articles study the effect of banking institutions' foreign ownership on Earnings and Profitability (Kosmidou, 2004; Lensink & Naaborg, 2007; and Sheng-Hung & Chien-Chang, 2010). These articles show that earnings and profitability in domestic banking institutions are, in general, better than in foreign banking institutions and that this low profits and net margins negatively impact the overall financial situation of these foreign banking institutions placing them at worst position than the domestic banking institutions. One last group of articles focus on all the CAMELS parameters to evaluate the probability to go bankrupt of domestic and foreign banking institutions, one good example is the article from Dash & Das (2015). This article evaluates all the CAMELS parameters of a sample of Indian banking institutions between 2003 and 2008 to compare the probability to go bankrupt of domestic and foreign banks. The authors conclude that, even though there is a trend of improvement in all the CAMELS parameters for both categories of banking institutions, the domestic banking institutions are less likely to go bankrupt than the foreign banking institutions.

While it is true that some literature supports the hypothesis that foreign banking institutions are less likely to go bankrupt than domestic banking institutions [for example, Chen et al. (2017) or Pelletier (2018)], these articles seem to be less than the articles that support the hypothesis that domestic banking institutions are less likely to go bankrupt than foreign banking institutions. Moreover, these empirical articles seem to be performed only in emerging economies such as the Sub-Saharan economy (Pelletier, 2018) or emerging countries in general (Chen et al., 2017). Our purpose is to compare the probability of bankruptcy of the domestic banking institutions versus foreign banking institutions in the Spanish industry between 2013 and 2017. Therefore, the literature found is more coherent with the hypothesis that domestic banking institutions are less likely to go bankrupt than foreign banking institutions.

At the sight of the reviewed literature, we have defined our hypothesis. We have found a vast number of articles developed in different countries and years that support that domestic banking institutions are less likely to go bankrupt than foreign banking institutions, while just a few articles developed in emerging economies support that foreign banking institutions are less likely to go bankrupt than domestic banking institutions. Therefore, we propose the following hypothesis for our empirical study:

Hypothesis: Domestic banking institutions are less likely to go bankrupt than foreign banking institutions

III. EMPIRICAL STUDY

After all the theoretical research developed in the previous chapters, in Chapter IV we design the framework for our empirical analysis. To entirely design this framework, in the first section of this chapter we select the sample and explain the model, the variables, and the methodology that guides our empirical analysis. In the second section, we interpret the descriptive and explanatory results obtained in the implementation of our empirical analysis.

3.1. SAMPLE, MODEL, VARIABLES, AND METHODOLOGY

As we previously mentioned, in this section we select the sample from the banking institutions gathered under the Spanish Banking Association (Asociación Española de Banca), we choose the variables of our model, and we elect the methodology that guides our empirical analysis. The objective of this section is to set a framework to develop in the second section our empirical analysis to contrast the proposed hypothesis that domestic banking institutions are less likely to go bankrupt than foreign banking institutions.

3.1.1. SAMPLE

In order to contrast our hypothesis that domestic banking institutions are less likely to go bankrupt than foreign banking institutions, makes good sense to select a sample formed by all the banking institutions operative in the Spanish industry between 2013 and 2017. For the selection of the banking institutions of the sample, we base ourselves in the databases of the Spanish Banking Association (from now on, AEB).

Under the AEB database, are gathered all the banking institutions with a banking card[5] operative in the Spanish banking sector. Therefore, under the AEB database two categories of banking institutions are grouped. On the one hand, domestic banking institutions with their headquarters in Spain that have a banking card in the Spanish industry. On the other hand, foreign banking institutions with their

[5] The banking card is document issued by the Bank of Spain to all the operative banking institutions of the industry disregard of the country they are headquartered. Having a banking card requires to fill some minimum standards like assessing to the Risk Information Center (from the Spanish, CIR), all the loans, credits, guarantees, and risks in general the banking institution has with their clients. However, having a banking card gives absolute rights to the banking institution to operate in Spain.

headquarters in other countries, both Europeans and non-Europeans, that have a baking card in the Spanish industry (Asociación Española de Banca, 2019). In the first place, we considered to include in the sample all the banking institutions under the AEB. Nonetheless, not all these banking institutions have published accounting information between 2013 and 2017 and we filtered some of them. Thus, the final sample consists of a total of fifty-three banking institutions with available information for the period considered. Out of the whole of fifty-three banking institutions: twenty-nine are domestic banking institutions because they are headquartered in Spain, and twenty-four are foreign banking institutions because they are headquartered in other countries, both Europeans and non-Europeans. The table listing all the banking institutions under the AEB, differentiating between the two categories of banking institutions used in the Project, domestic and foreign, is shown in Annex I[6].

It is interesting to note that it exists another banking association in Spain, the Confederation of Spanish Saving Banks (Confederación Española de Cajas de Ahorro). Under the Confederation of Spanish Saving Banks (hereinafter, CECA) were gather all the saving banks operative in the Spanish industry. However, if we take a brief look to the history of the Spanish banking industry since the XX century to nowadays it can be appreciated that after the 2008 financial crisis, many Spanish financial institutions went bankrupt, and the government was forced to perform a restructuration of these financial institutions merging the majority of the saving banks into one final former banking institution[7]. Nowadays, from all the saving banks gathered under the CECA only two of them did not become former banking institutions, *Caixa Ontinyent* y *Colonya* and *Caixa Pollença* and therefore, those institutions are the only two firms under the CECA not considered former banking institutions (Confederación Española de Cajas de Ahorro, 2019). Nevertheless, we exclude all of the banking institutions under the CECA from the sample because its past as saving banks makes them different from former banking institutions in its strategy and structure. Thus, we can sum up that the final sample consists of a total of fifty-three banking institutions, twenty-nine are domestic banking institutions because they are headquartered in Spain and twenty-four are foreign banking institutions because they are headquartered in other countries, European and non-European.

3.1.2. MODEL AND VARIABLES

The model and the variables to contrast the hypothesis that domestic banking institutions are less likely

[6] Annex I depicts the banks under the AEB at December 2013. Nevertheless, as with the banking institutions under the CECA, some banking institutions under the AEB disappeared between the year 2013 and 2017. The banking institutions that changed for that period are not included in Annex I.

[7] For example, the Galician saving banks, *Caixa Galicia* and *Caixa Nova*, merged into NCG Bank (nowadays known as ABANCA S.A.) or the Catalan saving bank, *Caja de Ahorros* and *Pensiones de Barcelona*, led to Caixa Bank, S.A.

to go bankrupt than foreign banking institutions are:

3.1. Model's Formula

$$\mathrm{CAMELS}_{\mathrm{it}} = \alpha + \beta 1(\mathrm{FOREIGN})_{\mathrm{it}} + \text{Year variables}_{\mathrm{it}} + \mu_{\mathrm{it}}$$

FOREIGN is a dummy variable that represents the type of ownership of the observed banking institution and it is the independent variable. FOREIGN can only take values of either 0, when the banking institution is domestic, that is, when the banking institution is headquartered in Spain, or 1, when the banking institution is foreign, that is, the banking institution is headquartered in other countries, European or non-European. As a reminder, the table listing the banking institutions of the sample, differentiating between the two types of banking institutions' ownership used in the Project, domestic and foreign, is shown in Annex I.

Year variables are dummy variables to control by years the sample and μ represents the error term.

CAMELS represents the banking institutions' probability to go bankrupt and it is the dependent variable. CAMELS can take values ranging from 1 to 5. The higher the CAMELS score (the closer the CAMELS score to 5) the higher the probability of a banking institution to go bankrupt and the lower the CAMELS score (the closer the CAMELS score to 1) the lower the probability of a banking institution to go bankrupt.

CAMELS is composed by six parameters represented by its acronym: <u>C</u>apital Adequacy, <u>A</u>sset Quality, <u>M</u>anagement Quality, <u>E</u>arnings and Profitability, <u>L</u>iquidity, and <u>S</u>ensitivity to Market Risk. Financial ratios describe each of these parameters yet, as previously mentioned in Chapter II, the scope of financial ratios that develop each of these parameters differ from countries, supervisory authorities and rating institutions. For this reason, we believe necessary to rely on the literature to select the ratios that will describe the CAMELS variable's parameters. Even though there is a huge amount of studies, one study is especially relevant to us because of the amount of detail depicted in the selection of its financial ratios: the Gikas & Hyz (2015) study. In the following paragraphs, we briefly explain the financial ratios pulled from the named article.

To describe **<u>C</u>apital Adequacy**, we select the Capital Adequacy ratio (from now on, CAR), because this ratio is included in Gikas & Hyz (2015), but mainly because is a requirement of the BCBS to use this ratio to measure the capital adequacy of banking institutions. The CAR ratio is expressed as the result of dividing Tier I and Tier II by the risk-weighted assets of a banking institution. Tier I and Tier II ratios represent a broader view of the book value of the total equity of a banking institution[8]. The risk-weighted assets express the assets of a banking institution depending on their risk. Risk-weighted assets are calculated by grouping all the assets of a banking institution depending on their risk and pondering each group by a percentage given by the BCBS in the tables gathered in Basile III[9]. Nevertheless, the only information we have access to are the reports published by the AEB for the banking institutions under its control and these reports only include accounting information such as balance sheets and income statements. Neither Tier I, Tier II or the risk-weighted assets can be calculated with the given accounting information. Thus, we decide to assume that the CAR ratio is express by the total equity (replacing Tier I and Tier II ratios) divided by the total assets (replacing risk-weighted assets)[10]. In such a way, the CAR ratio measures the amount of risky assets that can be absorbed by the shareholder's equity. Thus, the higher the value of the CAR ratio, the better the capital adequacy of the banking institution because it means more capability to absorb risky assets.

3.2. Capital Adequacy Ratio (CAR) Formulas

$$\mathrm{CAR} = \frac{\mathrm{Tier\ I} + \mathrm{Tier\ II}}{\mathrm{Risk\ Weighted\ Assets}} \qquad \mathrm{CAR1} = \frac{\mathrm{Total\ Equity}}{\mathrm{Total\ Assets}}$$

To describe **A̲ssets Quality**, following Gikas & Hyz (2015), we chose the Net Non-Performing Assets ratio (from now on, NPA). The NPA ratio is expressed as the result of dividing the net non-performing assets by the total loans of a banking institution. The net non-performing assets are the defaulting assets that a banking institution should have collected at least ninety days ago. These assets are usually depicted in the shareholders and investors' information but not in the accounting information. Therefore, we decide to assume that the net non-performing assets are those represented by the *Losses due to Impairment of Financial Assets* income statement's account, since it is the only accounting information that measures the losses due to default. The total loans represent one of the main activities of a banking institution, to give credit to clients, and are specifically shown in the *Total Loans* balance sheet's account. In such a

[8] Tier I ratio is the called the core capital, it consists of a necessary capital represented by ordinary shares and retained earnings. Tier II is greater than Tier I, in addition to the Tier I, it includes the preferred shares with a fixed maturity and long-term debt with a minimum maturity of more than five years. It also includes accounting items that make capital even laxer: it includes additional capital incorporating items such as undisclosed reserves, revaluation reserves, general reserves for credit losses, hybrid instruments (debt/equity capital), equity instruments and subordinated debt.

[9] The BCBS in Basile III differentiates between various groups of assets depending on their risk, for example, AAA+ assets, AAA assets or AA assets, and gives each group a different ponderation, for example, 4% to the AAA+ assets, 5% to the AAA assets, or 6% to the AA assets.

[10] The simplifications and assumptions are applied to all the select sample, so they do not change the final results or conclusions obtained.

way, the NPA ratio measures the amount of non-payed loans out of the total loans given to clients. Therefore, when is negative, the lower the value of the NPA ratio, the better the quality of the assets of a banking institution because it means a lower amount of defaulted given loans.

3.3. Net Non-Performing Assets (NPA) Formulas

$$\mathrm{NPA} = \frac{\text{Net Non} - \text{Performing Assets}}{\text{Total Loans}} \qquad \mathrm{NPA1} = \frac{\text{Losses due to Impairment of Financial Assets}}{\text{Total Loans}}$$

To describe **<u>M</u>anagement Quality**, basing ourselves in Gikas & Hyz (2015), we chose the Expenses to Revenues ratio (hereon, ER). The ER ratio is expressed as the result of dividing the overhead expenses by the net operating revenues. The overhead expenses and the net operating revenues represent respectively the revenues and the expenses obtained by a banking institution in the development of its core activity, in lending money to clients. Thus, we decide to select certain accounts in the incomes statements to calculate each concept because as it should be remembered, the only data given to us by the AEB are the balance sheets and the income statements of the banking institutions. On the one hand, under the overhead expenses, we assume that are gather the *Other Operating Expenses*, *Administration Expenses* and *Depreciations* income statement's accounts. On the other hand, the net operating revenues are represented by the *Gross Margin* income statement's account. Consequently, the ER ratio measures the expenses made in proportion with the income gained by a banking institution and so, the lower the value of the ER ratio the better the management quality because the senior management have the ability to make more profits incurring in less expenses.

3.4. Expenses to Revenues (ER) Formulas

$$\mathrm{ER} = \frac{\text{Overhead Expenses}}{\text{Net Operating Revenues}} \qquad \mathrm{ER1} = \frac{\text{Other Operating Expenses} + \text{Administration} + \text{Depreciations}}{\text{Gross Margin}}$$

To describe **<u>E</u>arnings and Profitability** the most popular and used financial ratios are the Return on Assets (from now on, ROA) and the Return on Equity (hereon, ROE), also used by Gikas & Hyz (2015). Thus, we decide to select ROA and ROE ratios to illustrate the earnings and profitability. Both ratios can be calculated with the accounting information given by the AEB. The ROA ratio measures the profits made from the total assets of a banking institution, and the ROE ratio measures the profits made from the shareholders' investments of a banking institution. Therefore, it makes good sense to assume that the higher the value for both, ROA and ROE ratios, the better the earnings and the profitability of a banking institution because it means more profits from the owned assets and more profits from the made investment respectively.

3.5. Return on Assets (ROA) and Return on Equity (ROE) Formulas

$$\text{ROA} = \frac{\text{Net Profits}}{\text{Total Assets}} \qquad \text{ROE} = \frac{\text{Net Profits}}{\text{Total Equity}}$$

To describe the **Liquidity,** we select the Current Assets to Total Assets ratio (from now on, CATA) and the Total Loans to Total Customer Deposits ratio (hereon, LTD) because they are the ratios elected in Gikas & Hyz (2015). On the one hand, the CATA ratio is expressed as the result of dividing the current assets by the total assets of a banking institution. The current assets represent the cash and the rest of the assets that are expected to be converted to cash within a year. Nevertheless, banking institutions do not have many current assets in their balance sheets; furthermore, the balance sheets of banking institutions do not even differentiate between current assets and fixed assets. Therefore, we decide to consider as current assets the *Cash and Deposits with Central Banks*, *Negotiation Portfolio* and *Other Financial Assets at Fair Value with Changes in Profits and Losses* balance sheet's accounts. However, total assets are shown explicitly in the balance sheet published by the AEB, so we do not need to make further assumptions to calculate this information. The CATA ratio measures the amount of current assets out of the whole amount of assets of a banking institution and so, the higher the value of the CATA ratio, the better the liquidity of a banking institution.

3.6. Current Assets to Total Assets (CATA) Formulas

$$\text{CATA} = \frac{\text{Current Assets}}{\text{Total Assets}} \qquad \text{CATA1} = \frac{\text{Cash} + \text{Negotiation Portfolio} + \text{Other Financial Assets at Fair Value}}{\text{Total Assets}}$$

On the other hand, the LDT ratio is calculated by dividing the total loans by the total customer deposits of a banking institution. Total loans, we recall from the NPA ratio explanation, are shown explicitly in the *Total Loans* balance sheet's account, yet, we need to make various simplification and assumptions to calculate the total customer deposits. We decide to assume that total customer deposits information is represented by all the liabilities under the name *Deposits* of the accounting information, that is, all deposit in the *Negotiation Portfolio*, *Other Financial Assets at Fair Value with Changes in Profits and Losse*s and the *Financial liabilities at Amortized Cost balance* sheet´s accounts. In such a way, the LDT ratio compares the amount of the total loans given with the amount of the granted loans of a banking institution and so, the higher the LDT ratio, the better the liquidity of a baking institution because it means that it has more conferred money than lent money.

3.7. Loans to Deposits (LTD) Formulas

$$\mathrm{LTD} = \frac{\text{Total Loans}}{\text{Total Customer Deposits}} \qquad \mathrm{LTD1} = \frac{\text{Total Loans}}{\begin{array}{c}\text{Negotiation Portfolio} + \\ \text{Other Financial Assets at Fair Value} + \\ \text{Financial Liabilities at Amortized Cost}\end{array}}$$

To describe **Sensitivity to Market Risk**, basing ourselves in Gikas & Hyz (2015), we chose the Total Volatile Liabilities to Total Assets (from now on, VL). The VL ratio is expressed as the result of dividing the total volatile liabilities by the total assets. The volatility measures how the banking institution's profitability has deviated from its historical average. A high deviation means that the returns of the banking institution have experienced strong variations, while a low deviation indicates that those returns have been much more stable over time (Morningstar, 2019). Thus, the volatile liabilities are those returns of a banking institution that have experienced strong variations over time. The only data given to us by the AEB are the balance sheets and the income statements of its banking institutions and this accounting information does not expressly include the volatile liabilities. Therefore, we assume that the volatile liabilities are all the balance sheet's accounts which returns are not constant over time, that is, *Negotiation Portfolio*, *Other Financial Assets at Fair Value with Changes in Profits and Losses*, *Financial Assets Available for Sale* and *Derivates and Coverages* balance sheet's accounts. The total assets are shown explicitly in the balance sheet published by the AEB, so we do not need to make further assumptions to calculate this information. Consequently, the VL ratio measures the amount of assets susceptible of experiencing changes over time from the whole amount of total assets and so, the lower the value of the VL ratio, the less sensitive to market risk is the banking institution because less volatile assets it has.

3.8. Volatile Liabilities to Total Assets (VL) Formulas

$$\mathrm{VL} = \frac{\text{Total Volatile Liabilities}}{\text{Total Assets}} \qquad \mathrm{VL1} = \frac{\begin{array}{c}\text{Portfolio} + \text{Other Assets at Fair Value} + \\ \text{Assets Available for Sale} + \text{Derivates}\end{array}}{\text{Total Assets}}$$

To calculate the CAMELS variable of each banking institution, following Gikas & Hyz (2015), we compute a CAMELS weighted average according to the Final Rules of Large Bank Pricing with the following standard weights: Capital Adequacy 20%, Asset Quality 20%, Management Quality 20%, Earnings and Profitability 10%, Liquidity 20%, and Sensitivity to Market Risk 10%. As a result, the CAMELS variable is obtained as follows:

3.9. CAMELS Variable Formula

$$\mathrm{CAMELS} = (0.20 * \mathrm{C}) + (0.20 * \mathrm{A}) + (0.20 * \mathrm{M}) + (0.10 * \mathrm{E}) + (0.20 * \mathrm{L}) + (0.10 * \mathrm{S})$$

In order to compute the CAMELS weighted average some steps have to be concluded. Firstly, we calculate each explained financial ratio: CAR ratio for Capital Adequacy, NPA ratio for Assets Quality, ER ratio for Management Quality, ROA and ROE ratios for Earnings and Profitability, CATA and LTD ratios for Liquidity, and VL ratio for Sensitivity to Market Risk, for each year between 2013 and 2017 and for each banking institution of the sample. To calculate the financial ratios for each year and banking institution, we consider the December's accounting information, balance sheets and income statements, published by the AEB for each banking institution. To illustrate this step, in the first section of Annex III are shown the descriptive variables resulted from calculating the financial ratios for each year and banking institution.

Secondly, once the financial ratios are calculated it has to be assigned a score ranging from 1 to 5 to each financial ratio. In order to assign a score ranging from 1 to 5 to each financial ratio, we calculate five percentiles: 20%, 40%, 60%, 80% and 100%, from the financial ratios in order to obtain five ranges. Then, we assign the scores: 1, 2, 3, 4 and 5, respectively to each obtained range. This methodology allows maintaining a coherent and consistent criterion through the different years and banking institutions. It is worth stressing that to assign the scores it is essential to consider that there are ratios with ascendant scores (the higher, the better score) and with descendent scores (the lower, the better score). To clarify this step, in the second section of Annex II are depicted the resulted percentiles and the assigned ranges for each financial ratio.

The scores ranging from 1 to 5 assigned to each financial ratio are the key of the Project and the data in which we base the regression analysis of the next section to contrast the proposed hypothesis that domestic banking institutions are less likely to go bankrupt than foreign banking institutions. Finally, to calculate the CAMELS variable, we compute the CAMELS weighted average according to the Final Rules of Large Bank Pricing with the cited standard weights. In order to calculate the CAMELS variable's parameters described by two ratios, that is, Earnings and Profitability and Liquidity, following Gikas & Hyz (2015), we compute $\frac{\frac{\text{ROA}}{\text{ROE}}}{2}$ and $\frac{\text{CATA}+\text{LTD}}{2}$, respectively. The higher the CAMELS score (the closer the CAMELS score to 5) the higher the probability of the banking institution to go bankrupt and the lower the CAMELS score (the closer the CAMELS score to 1) the lower the probability of the banking institution to go bankrupt.

3.1.3. METHODOLOGY

Concerning the methodology, the main statistical tool that we use is the regression analysis[11]. Regression analysis allows us to find the causal relationship between a dependent variable, CAMELS, and an independent variable, FOREIGN. This methodology enables us to contrast the proposed hypothesis that domestic banking institutions are less likely to go bankrupt than foreign banking institutions. In order to implement this methodology, we use the statistical software *Stata: Software for Statistics and Data Science 12.0*. Stata is a statistical software package created in 1985 by StataCorp used in research studies of different filed, such as Economics, Biomedicine or Political Sciences. Stata is a complete, integrated statistical software that provides everything we need for data analysis, data management, and graphics (Stata: Software for Statistics and Data Science, 2019).

When running the regression analysis, we want to look at the F-test, R^2 and R^2-Adjusted, and t-coefficients. Firstly, the F-test measures the significance of the model, we consider every Prob.>F below 0.1 as a significant model because it means that the model is significant at the 90%. Secondly, the R^2 and R^2-Adjusted measure the amount of the dependent variable explained by the independent variable, we disregard R^2 and R^2-Adjusted low values because the objective of the Project is not to explain the CAMELS variable but to contrast the hypothesis that domestic banking institutions are less likely to go bankrupt than foreign banking institutions. Third and lastly, t-coefficients measure the accuracy of the model, we consider a Prob.> |t| below 0.1 as an accurate model because it means that the model is accurate at the 90%.

In addition to the regression analysis, other statistical techniques are used to contrast the hypothesis that domestic banking institutions are less likely to go bankrupt than foreign banking institutions. Using Stata, we also calculate the variance inflation factor (from now on, VIF). The VIF quantifies the severity of multicollinearity and provides an index that measures how much the variance of an estimated regression coefficient has increased because of co-linearity (Gareth et al., 2017). We consider that if VIF gets values higher than 2 our analysis has to be rejected. The tables with the main statistical results obtained using the Stata software are organized in the next section. In the first tables are the descriptive results. In the second tables are the explanatory results. Also, in the following subsection we discuss those results obtained.

[11] The regression analysis is a powerful statistical method that allows you to examine the relationship between two or more variables of interest. The formula of the regression analysis is depicted in 4.1.1. Model Formula.

3.2. RESULTS

In this section we explain the results obtained from implementing the model. In the first subsection we analyze the descriptive results obtained from calculating the means, standard deviations, minimums and maximums of the dependent variable, the CAMELS variable, and each of the parameters of its acronym (Capital Adequacy, Asset Quality, Management Quality, Earnings and Profitability, Liquidity, and Sensitivity to Market Risk). In the second subsection we examine the explanatory results obtained from running the lineal regression and we contrast the proposed hypothesis that domestic banking institutions are less likely to go bankrupt than foreign banking institutions.

3.2.1. Descriptive Results

As we previously mentioned, the dependent variable of the model is the CAMELS variable and this variable is composed by six parameters represented by its acronym and defined by financial ratios: Capital Adequacy (CAR ratio), Asset Quality (NPA ratio), Management Quality (ER ratio), Earnings and Profitability (ROA and ROE ratios), Liquidity (CATA and LDT ratios), and Sensitivity to Market Risk (VL ratio). The descriptive results for the CAMELS variable and the CAMELS variable's parameters are the followings:

3.10. Table of Descriptive Results Before Assigning Scores

Variable	Obs.	Mean	Median	Std. Dev.	Min.	Max.
CAR	265	0.211	0.103	0.276	-0.004	1.000
NPA	265	0.005	0.001	0.022	-0.182	0.194
ER	265	0.598	0.574	0.409	-0.134	2.609
ROA	265	0.007	0.004	0.024	-0.120	0.173
ROE	265	0.048	0.040	0.118	-0.621	0.476
CATA	265	0.071	0.018	0.114	0.000	0.569
LTD	265	0.732	0.855	0.518	0.000	2.670
VL	265	0.127	0.012	0.200	0.000	0.867
CAMELS	265	2.773	2.842	0.605	1.238	4.150

Source: Compiled by author using the AEB's database

The data above represents the 265 observations obtained from examining the fifty-three banking institutions of the sample between the years 2013 and 2017 (53 banking institutions × 5 years= 265 observations). In this first table, we have calculated the means, medians, standard deviations, minimums and maximums for the CAMELS variable and each of the parameters of its acronym before calculating the five percentiles and assigning a score ranging from 1 to 5 to each one.

3.11. Table of Descriptive Results After Assigning Scores

Variable	Obs.	Mean	Median	Std. Dev.	Min.	Max.
CAR	265	3	3	1.42	1	5
NPA	265	3	3	1.42	1	5
ER	265	3	3	1.42	1	5
ROA	265	2.96	3	1.37	1	5
ROE	265	3	3	1.42	1	5
CATA	265	3	3	1.42	1	5
LTD	265	3	3	1.42	1	5
VL	265	3.2	3	1.17	2	5
CAMELS	265	2.77	2.85	0.60	1.24	4.15

Source: Compiled by author using the AEB's database[12]

The second table shows the same descriptive variables for the CAMELS variable and each of the parameters of its acronym. However, the calculations are made after calculating the five percentiles and assigning a score ranging from 1 to 5 to each parameter. In the following paragraphs we analyze the given descriptive results.

The CAR describes the Capital Adequacy parameter of the CAMELS variable and measures the amount of risky assets that can be absorbed by the shareholders' equity of a banking institution. The CAR has a mean of 0.211 and a score of 3 for the banking institutions of the Spanish industry. These results mean that in general, disregard of whether they were domestic or foreign, the banking institutions of the Spanish industry were able to absorb the 21.1% of their risky assets with their shareholders' equity and that this 21.1% scores as a 3 which is labelled as a "fair" situation. However, the median of the CAR is 0.103 and its standard deviation is 0.276 which means that the observations are quite disperse and even though there are some banking institutions with quite low CAR values there are more banking institutions with high values. This can also be inferred if we take a look to the CAR's maximum and minimum. The minimum of -0.004 was scored by Dexia Sabadell in 2014. This banking institution was unable to absorb

[12] In order to analyze the scores of the table above, it is worth mentioning that we can distinguish five main categories of scores: **1.** Range 1.00-1.49 with description "strong", **2.** 1.50-2.49 with description "satisfactory", **3.** 2.50-3.49 with description "fair", **4.** 3.50-4.49 with description "marginal", and **4.** 4.50-5.00 with description "unsatisfactory" (Gikas & Hyz, 2015).

its risky assets with its shareholders' equity because its shareholders' equity was negative. Dexia Sabadell CAR's mean between 2013 and 2017 is quite low (Dexia Sabadell CAR's mean for the five studied years is 0.003) and it was closely followed by other domestic banking institutions such as Banco Cooperativo Español or Banco Santander**.** The maximum of 1.000 was scored by Citibank, N. A. in various years. This banking institution was able to absorb all of its risky assets with its shareholders' equity. Citibank, N. A. CAR's mean between 2013 and 2017 is slightly lower (Citibank, N. A. CAR's mean for the five studied years is 0.374), yet it was closely followed by other foreign banking institutions such as Deutsche Bank Trust Company Americas, S.E. or Citibank España. Therefore, we can assume that domestic banking institutions get lower values at the CAR ratio (meaning a worst Capital Adequacy) than foreign banking institutions.

The NPA ratio describes the Assets Quality parameter of the CAMELS variable and measures the amount of non-payed loans out of the total loans given to clients. NPA ratio has a mean of 0.005 and a score of 3 for the banking institutions of the Spanish industry. These results mean that in general the banking institutions of the Spanish industry were able to pay the 0.5% of their non-payed loans with their total loans given to clients and that this 0.5% scores as a 3 which si labelled as a "fair" situation. The median of the NPA ratio is 0.001 and its standard deviation is 0.022 which means that the observations are all close to the mean and thus, they are quite uniform. Nevertheless, if we take a look to the NPA ratio's maximum and minimum it can be inferred that there are some polarized banking institutions. The minimum of -0.182 was scored by Aresbank in 2013. This banking institution would have to pay 18.2% of its total loans to overcome its non-payed loans. Even though this is a punctual situation since Aresbank NPA ratio's mean between 2013 and 2017 is way lower (Aresbank NPA ratio's mean for the five studied years is -0.039), it has the one of the highest rates of losses due to impairment of financial assets. The maximum of 0.194 was scored by Citibank España in 2014, this banking institution did not even have losses due to impairment of financial assets. Although this was a punctual situation since the NPA ratio's mean for the years between 2013 and 2017 is actually lower (Citibank España NPA ratio's mean for the five studied years is 0.054), Citibank España has the one of the lowest rates of losses due to impairment of financial assets

The ER ratio describes the Management Quality parameter of the CAMELS variable and measures the overhead expenses made in proportion with the operating income gained by a banking institution. The ER has a mean of 0.598 and a score of 3 for the banking institution of the Spanish industry. These results mean that in general, disregard of whether they are domestic or foreign, the banking institutions of the Spanish industry were able to cover more than the half of their overhead expenses with their operating income and that this 59.8% scores as a 3 which is labelled as a "fair" situation. The median of the ER ratio is 0.574 and its standard deviation is 0.409 which means that the observation are all close to the mean and thus, they are quite uniform. However, just like in the NPA ratio, if we take a look to the ER ratio's maximum and minimum it can be inferred that there are some polarized banking institutions. The minimum of -0.134 was scored by Citibank, N. A in 2016 which could not cover any of its overhead expenses with its operating income since it was negative (Citibank, N. A.'s operating income in 2016 was -3353). Citibank, N. A was closely followed by other foreign banking institutions such as Andbank España, Deutsche Bank Trust Company Americas or Bank of America National Association, S.E. The maximum of 2.609 was scored by Banco de Albacete in 2015 which could cover the double of its overhead expenses with its operating income. Although this was an exceptional situation since Banco de Albacete ER ratio's mean for the years between 2013 and 2017 is lower (Banco de Albacete ER ratio's mean for the five studied years is 0.854), it got quite high values on average and it was closely followed by other domestic banking institutions such as Banco Europeo de Finanzas or EVO Banco, S. A. Therefore, we can assume that domestic banking institutions get higher values at the ER ratio (meaning better Management Quality) than foreign banking institutions.

The ROA and ROE describe the Earnings and Profitability parameter of the CAMELS variable and measure the profit made from the total assets and the shareholders' investment, respectively. Firstly, the ROA ratio has a mean of 0.007 and a score of 2.96 for the banking institutions of the Spanish industry. These results mean that in general the banking institutions of the Spanish industry made 0.007 euros from each euro invested on assets and that this 0.007 scores as 2.96 which is labelled as a "fair" situation (notice that even though the ROA ratio's score is within the range 2.50-3.50 with description "fair" is closer than the other ratios to the range 1.50-2.49 with description "satisfactory"). The median of the ROA ratio is 0.004 and its standard deviation is 0.024 which mean that the observations are all close to the mean and thus, they are quite uniform. Nevertheless, just like in the NPA ratio and ER ratio, if we take a look to the ROA ratio's maximum and minimum it can be inferred that there are some polarized banking institutions. The minimum of -0.120 was scored by Banco Popular Español in 2017[13], this banking institution loss 0.120 euros from each euro invested in assets. This was not an exceptional situation since the ROA ratio's mean for the years between 2013 and 2017 experienced a descendent trend (Banco Popular Español ROA ratio's mean for the five studied years is -0.269). The maximum of 0.173 was

[13] Banco Popular Español and Banco Pastor will disappear as a brand in 2019. Banco Santander will integrate Banco Popular and Banco Pastor into its systems at the end of this year and expects to operate under the same brand in June 2019. These last two brands will no longer exist in the market and will only have those of the financial entity chaired by Ana Booty (Intereconomy, 2018).

scored by Banco Industrial de Bilbao in 2016. This banking institution made 0.173 euros from each euro invested on assets. Even though this was a punctual situation since Banco Industrial de Bilbao ROA ratio's mean for the years between 2013 and 2017 is actually lower (Banco Industrial de Bilbao ROA ratio's mean for the five studied years is 0.063), it got quite high values on average.

Secondly, the ROE ratio has a mean of 0.048 and a score of 3 for the banking institutions of the Spanish industry. These results mean that in general the banking institutions of the Spanish industry returned 0.048 euros from each euro invested by shareholders in the organization and that this 0.048 scores as a 3 which is labelled as a "fair" situation. The median of the ROE ratio is 0.040 and its standard deviation is 0.118 which mean that the observations are all close to the mean and thus, they are quite uniform. However, if we take a look to the ROE ratio's maximum and minimum it can be inferred that there are some polarized banking institutions. The minimum of -0.621 was scored by Banco Pastor in 2017. This banking institution loss 0.621 euros from each euro invested by shareholders in the organization. This is not a punctual situation since Banco Pastor ROE ratio's mean for the years between 2013 and 2017 experienced a descendent trend (Banco Pastor ROE ratio's mean for the five studied years is -0.117). The maximum of 0.476 was scored by Santander Banco de Emisiones, S. A. in 2016. This banking institution made 0.476 euros from each euro invested by shareholders in the organization. Santander Banco de Emisiones, S. A. always gave a high return to its investors since its ROE ratio's mean for the years between 2013 and 2017 is almost always the same (Santander Banco de Emisiones, S. A. ROE ratio's mean for the five studied years is 0.377).

The CATA and LTD describe the Liquidity parameter of the CAMELS variable and measure the amount of current assets out of the whole amount of assets and the amount of total loans given out of the amount of granted loans, respectively. Firstly, the CATA ratio has a mean of 0.071 and a score of 3 for the banking institutions of the Spanish industry. These results mean that in general the banking institutions of the Spanish industry had 7.1% of their assets in current assets and that this 7.1% scores as a 3 which is labelled as a "fair" situation (this is consistent with the statement that the banking industry is non-liquid by nature). The median of the CATA ratio is 0.018 and its standard deviation is 0.114 which means that the observations are quite disperse and even though there are some banking institutions with quite high values there are more banking institutions with low values. This can also be inferred if we take a look to the CATA ratio's maximum and minimum. The minimum of 0.000 was scored by multiple domestic banking institutions such as, Santander Banco de Emisiones, S. A., Nuevo Micro Bank, Banco Industrial de Bilbao or Banco Occidental or Banco de Albacete all in various years. Nonetheless, the maximum of 0.569 was scored by Andbank España in 2016, this banking institution had more of half of its assets as current assets. Andbank España was closely followed by multiple foreign banking institutions such as Banco Pichincha España or JP Morgan Chase Bank. Therefore, we can assume that domestic banking institutions get lower values at the CATA ratio (meaning worst Liquidity) than foreign banking institutions.

Secondly, the LTD ratio has a mean of 0.732 and a score of 3 for the banking institutions of the Spanish industry. These results mean that in general the banking institutions of the Spanish industry had 73.2% of total loans given to clients out of the amount of granted loans and that this 73.2% scores as a 3 which is labelled as a “fair” situation. The median of the LTD ratio is 0.855 and its standard deviation is 0.518 which means that the observations are quite disperse and that is more common to observe banking institutions with higher values of given loans out of the amount of granted loans. The minimum of 0.000 was scored by almost the same banks that have a low amount of current assets according to the CATA ratio (Santander Banco de Emisiones, S. A., Banco Occidental or Banco de Albacete) in several years. The maximum of 2.670 was scored by Banco de Depósitos in 2016, this banking institution had more than the double of its total loans given to clients in granted loans. However, Banco de Depósitos was closely followed by other American banking institutions such as, JP Morgan Chase Bank or Citibank, N. A. Therefore, we can confirm the assumption made in the paragraph above, domestic banking institutions get lower values at the LTD ratio (meaning worst Liquidity) than foreign banking institutions.

The VL describes the Sensitivity to Market Risk parameter of the CAMELS variable and measures the amount of assets susceptible of experiencing changes over time from the whole amount of total assets. VL ratio has a mean of 0.127 and a score of 3.2 for the banking institutions of the Spanish industry. These results mean that in general the banking institution of the Spanish industry had 12.7% of their total assets in volatile assets and that this 12.7% % scores as 3.2 which is labelled as a “fair” situation (notice that even though the VL ratio’s score is within the range 2.50-3.50 with description “fair” is closer than the other ratios to the range 3.50-4.49 with description “marginal”). The median of the VL ratio is 0.012 and its standard deviation is 0.200 which means that the observations are quite disperse and even though there are some banking institutions with quite high values there are more banking institutions with lower values. This can also be inferred if we take a look to the VL ratio’s maximum and minimum. The minimum of 0.000 was scored by the majority of the foreign banking institutions during the years between 2013 and 2017, for example JP Morgan Chase Bank, Bank of America National Association, S. E., Credit Suisse AG, Bank of Tokyo Mitsubishi UFJ, Citibank, N. A., Deutsche Bank Trust Company Americas, S. E., or Banco de la Nación Argentina, S. E. The maximum of 0.867 was scored by EBN Banco de Negocios in 2016, this banking institution had 86.7% of its assets in volatile assets. This is EBN Banco de Negocios’s normal strategy since the VL ratio’s mean for the years between 2013 and 2017 is almost the same

(Banco Mediolanum VL ratio's mean for the five studied years is 0.777). EBN Banco de Negocios is closely followed by multiple other domestic banking institutions such as Banco Cooperativo Español or Renta 4 Banco. Therefore, we can assume that domestic banking institutions get higher values at the CATA ratio (meaning more Sensitivity to Market Risk) than foreign banking institutions.

We can conclude from the analysis of the means, medians, standard deviations, minimums and maximums of each of the parameters of the CAMELS acronym that the both categories of banking institutions of the model, domestic and foreign banking institutions, disregard of whether they were in one category or the other, perform within the range 2.50-3.50 with description "fair" which means that there are not outstanding distinctions between the two observed groups. Nonetheless, foreign banking institutions seem to follow a different pattern in Spain than domestic banking institutions. Foreign banking institutions get lower values at the ER ratio meaning worst Management Quality than domestic banking institutions, which is consistent with the reviewed literature by Berger (2005) and Sturm & Williams (2008). However, foreign banking institutions get higher values at the CAR ratio meaning better Capital Adequacy, higher values at the CATA and LTD ratios meaning more Liquidity, and lower values at the VL ratio meaning less Sensitivity to Market Risk. Better values in the CAR, CATA, LTD, and VL ratios, outweigh better values only in the ER ratio when computing the CAMELS variable formula[14]. Therefore, it seems that foreign banking institutions get better overall CAMELS variable which means less probability to go bankrupt than domestic banking institutions and is contrary to our hypothesis. In order to determine if we reject the hypothesis that domestic banking institutions are less likely to go bankrupt than foreign banking institutions we want to take a look to the overall CAMELS variable.

The overall CAMELS variable measures the probability of a banking institution to go bankrupt. CAMELS variable has a mean of 2.77 which means that the banking institutions of the Spanish industry, disregard of whether they were domestic or foreign, were in a "fair" situation with regards to the possibility of bankruptcy (notice that even though the CAMELS score is within the range 2.50-3.50 with description "fair" is close to the range 1.50-2.49 with description "satisfactory"). The median of the CAMELS variable is 2.85 and its standard deviation is 0.60 which means that the observations are slightly disperse. If we take a look to the maximum and minimum of the CAMELS variable, we can appreciate that they go all the range from 1.24 (Banco Occidental and Deutsche Bank Trust Company Americas, S.E. in 2013 scored a 1.24) to 4.15 (Banco Popular Español in 2017 scored a 4.15) meaning that some banking institutions got really low CAMELS variable's values while other banking institutions got quite high CAMELS variable's

[14] See 3.9. CAMELS Variable Formula

values. The banking institutions that got a CAMELS score closer to 1 were less likely to go bankrupt than the banking institutions that got a CAMELS score closer to 5. In the following table are confronted the five banking institutions with the lowest (the best) five years' average CAMELS scores and the five banking institutions with the highest (the worst) five years' average CAMELS scores:

3.12. Table of Lowest/Best and Highest/Worst 5-Year Average CAMELS Variable's Scores

Lowest/Best CAMELS scores	Highest/Worst CAMELS scores
1. Banco Occidental (Venezuela): 1.61	1. Deutsche Bank, S.A.E. (Germany): 3.64
2. Banco Industrial de Bilbao: 1.61	**2. Banco Popular Español: 3.51**
3. Deutsche Bank Trust Company Americas, S.E. (Germany): 1.84	**3. Bankinter: 3.51**
4. Citibank N.A. (United States): 1.92	**3. Banco Pastor, S.A.: 3.50**
5. Bank of America National Association (United States): 1.95	5. Banco Pichincha España (Ecuador): 3.40

In boldface are the domestic banking institutions

Source: Compiled by author using the AEB's database

On the one hand, it can be inferred that the lowest/best five years' average CAMELS scores were made by foreign banking institutions: Banco Occidental (Venezuela), Deutsche Bank Trust Company Americas, S. E. (Germany), Citibank N. A. (United States), and Bank of America National Association (United States). There is only one domestic banking institution within the top five banks: Banco Industrial de Bilbao. On the other hand, it is discernible that the highest/worst five years' average CAMELS scores were made by domestic banking institutions: Banco Popular Español, Bankinter and Banco Pastor, S. A.. Furthermore, as previously mentioned, Banco Popular and Banco Pastor, S. A. will disappear as a brand this year. Thus, the results of the five years' average CAMELS scores seem be more consistent with the idea that foreign banking institutions are less likely to go bankrupt than domestic banking institutions and thus, contrary to our hypothesis.

Even though it seems that banking institutions' five years' average CAMELS scores show that foreign banking institutions are less likely to go bankrupt than domestic banking institutions, we want to test if exists a significant difference between the five years' average CAMELS scores. To do this, we perform a means difference t-test between the domestic and foreign banking institutions' five years' average CAMELS scores with the Stata software. The following table shows the results obtained from performing the means difference t-test:

3.13. Table of Means Difference T-Test

Category	Obs.	Mean	Std. Dev.
Domestic	145	2.869 *** (0.049)	0.595
Foreign	120	2.656 *** (0.055)	0.598
Obs.		265	
Prob.> |t|		0.0045 ***	

***, **, and * indicate significance at the 99%, 95%, and 90% confidence level, respectively

Source: Compiled by author using the AEB's database

The means difference t-test performed with the Stata software shows a five years' average CAMELS score for the domestic baking institutions of 2.869 with a standard error of 0.049 and a five years' average CAMELS score for the foreign banking institutions of 2.656 with a standard error of 0.055. The means difference is 0.211 with a standard error of 0.074. A Prob.> |t| below 0.1 means that the difference between the means is significant at the 90%, since the means difference t-test shows a Prob.> |t| of 0.0045, this explains that the difference between the means is significant at the 99%. Therefore, our means difference t-test shows a five years' average CAMELS score better for foreign banking institutions (the lowest score, the better: 2.656) than for domestic banking institutions (the highest score, the worst: 2.896) and that this means difference is statistically significant. We can conclude that this t-test seem to be contrary to our hypothesis that domestic banking institutions are less likely to go bankrupt than foreign banking institutions.

3.2.2. Explanatory Results

In this subsection, as previously mentioned, we examine the explanatory results obtained from performing the most relevant statistical method of our analysis, the regression analysis, and we finally resolve whether we accept or reject the proposed hypothesis that domestic banking institutions are less likely to go bankrupt than foreign banking institutions. The following table shows the results obtained from running the regression:

3.14. Table of Explanatory Results

	CAMELS
FOREIGN	-0.211 *** (0.074)
Constant	2.912 *** (0.089)
Year variables	Yes
Obs.	265
F-test	0.088 *
Adjusted R-squared	0.017
VIF	1.480

***, **, and * indicate significance at the 99%, 95%, and 90% confidence level, respectively

Source: Compiled by author using the AEB's database

As previously mentioned, when running the regression, we want to look at the F-test, R^2 and R^2-Adjusted, t-coefficients and also at the variance inflation factor. Firstly, the F-test measures if the model is statistically significant, we consider every Prob.>F below 0.1 as a significant model because it means that the model is significative at the 90%. The F-test calculated with the Stata software got a Prob.>F = 0.088. Therefore, we can infer that our model is significant at the 90%.

Secondly, the R^2 and R^2-Adjusted measure the amount of the dependent variable explained by the independent variable. The R^2 and R^2-Adjusted results obtained are 0.036 and 0.017, respectively. This R^2 and R^2-Adjusted's results are quite low because they mean that the FOREIGN variable explains the CAMELS variable at the 3.6% and at the 1.7%, respectively. However, as we previously mentioned, we disregard R^2 and R^2-Adjusted low values because the objective of the Project is not to fully explain the CAMELS variable, yet to assess if the CAMELS variable depends on the FOREIGN variable. Evidently, there are many other factors influencing the likelihood of a banking institution of going bankruptcy apart from its ownership, we even add the year variables to the model in order to control the influence of the years in the probability of bankruptcy. Nevertheless, we still consider this model applicable since it shows the existence of a causal relationship between the CAMELS variable and the FOREIGN variable which is, indeed, the final purpose of this regression analysis.

Thirdly, t-coefficients measure the accuracy of the model, we consider every Prob.> |t| below 0.1 as an accurate model because it means that the model is accurate at the 90%. The t-coefficients calculated with the Stata software got a Prob.> |t| = 0.005. Therefore, we can infer that our model is accurate at the 99% because it has a Prob.>F below 0.1. Finally, we also want to take a look at the variance inflation factor (also known as VIF). We consider every VIF<2 to qualify the analysis as adequate. The VIF calculated with the Stata software got a VIF= 1.480. Therefore, we can infer that our model can be accepted.

It is clear that the model is significant, accurate, and shows a causal relationship between the FOREIGN variable and the CAMELS variable. Nonetheless, probably the most important outcome of the regression analysis is the FOREIGN variable coefficient's sign. A positive independent variable's coefficient shows a positive correlation between the independent variable (FOREIGN in the model) and the dependent variable (CAMELS in the model), whereas a negative independent variable's coefficient shows a negative correlation between these two variables. The FOREIGN variable coefficient's sign of the model is negative (FOREIGN= -0.211) meaning that the FOREIGN variable has a negative causal relationship with the CAMELS variable.

This negative causal relationship implies that when the FOREIGN variable takes bigger values (value 1 which means that the banking institution is foreign instead of value 0 which means that the banking institution is domestic), the CAMELS variable gets lower values (value 1 which means that the banking institution is less likely to go bankrupt instead of value 5 which means that the banking institution is more likely to go bankrupt). Therefore, the regression analysis is contrary to the proposed hypothesis that domestic banking institutions are less likely to go bankrupt than foreign banking institutions. From all the performed statistical analysis (the analysis of the descriptive results of the CAMELS variable and each of the parameters of its acronym, the means difference t-test, and the regression) we determine to reject the proposed hypothesis that domestic banking institutions are less likely to go bankrupt than foreign banking institutions.

IV. CONCLUSIONS AND FURTHER IMPLICATIONS

As defined in the introduction, the purpose of the Project is to determine if domestic banking institutions are less likely to go bankrupt than foreign banking institutions. In order to achieve this objective, we selected as a sample the fifty-three banking institutions from the Spanish industry operative between the years 2013 and 2017. Out of the fifty-three banking institutions, twenty-nine were domestic and twenty-four were foreign. Then, we proposed a model where the dependent variable was the variable that measures banking institutions' probability to go bankrupt (CAMELS variable) and the independent variable was the variable that represents the type of ownership of the observed banking institution (FOREIGN variable). After this, we implemented the methodology of the Project which consisted on developing several statistical methods to test the proposed hypothesis, being the regression analysis the most relevant one.

The results obtained allows us to conclude that foreign banking institutions follow a pattern that differs from the one followed by domestic banking institutions in the Spanish industry. Foreign banking institutions get lower values at the ER ratio meaning worst Management Quality, which is consistent with the reviewed literature by Berger (2005) and Sturm & Williams (2008). However, foreign banking institutions get higher values at the CAR ratio meaning better Capital Adequacy, higher values at the CATA and LTD ratios meaning more Liquidity, and lower values at the VL ratio meaning less Sensitivity to Market Risk. Better values in the CAR, CATA, LTD, and VL ratios, outweigh better values in only the ER ratio when computing the CAMELS variable formula[15]. Therefore, foreign banking institutions get better overall CAMELS scores which means less probability to go bankrupt than domestic banking institutions. Contrary to expectations, foreign banking institutions are less likely to go bankrupt than domestic banking institutions.

Since domestic banking institutions are more likely to go bankrupt than foreign banking institutions, it makes as much if not more sense to recommend the Bank of Spain and the European Banking Authority setting greater requirements for domestic banking institutions. Firstly, in order to outcome the inadequate Capital Adequacy of domestic banking institutions, the Bank of Spain and the European Banking Authority could set higher capital requirements for domestic banking institutions. Secondly, to outcome the lack of Liquidity of domestic banking institutions these supervisory authorities could set either a regulated by law minimum amount of current assets for domestic banking institutions or a maximum amount of total loans given for these banking institutions. Lastly, to outcome the high Sensitivity to Market Risk, the Bank of Spain and the European Banking Authority could establish a maximum amount of volatile liabilities for domestic banking institutions.

If the recommendations are carried out, we belief that a less devastating panorama appears for the domestic banking institutions of the Spanish industry and that many, if not the majority, of them could save themselves from the effects of bankruptcy. Nevertheless, there is a long way to walk for these domestic banking institutions that have to overcome the “to big to fall” foreign banking institutions which have better Capital Adequacy, more Liquidity, are less Sensitive to Market Risk, and have learnt the role they have to play in the Spanish banking sector in order to success in general.

[15] See 9.3. CAMELS Variable Formula

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ANNEX I: SAMPLE OF BANKING INSTITUTIONS

The following table gathers the fifty-three banking institutions of the sample grouping them between the two categories: domestic banking institutions and foreign banking institutions. It is attached next to the foreign banking institutions the country where they are headquartered.

Domestic Banking Institutions (0)	Foreign Banking Institutions (1)
1. Banco Santander	1. Deutsche Bank, S.A.E. (Germany)
2. Banco Bilbao Vizcaya Argentaria	2. Banco Caixa Geral (Portugal)
3. Banco de Sabadell	3. Citibank España (United States)
4. Banco Popular Español	4. Targobank (Germany)
5. Bankinter	5. RBC Investor Services España (Portugal)
6. Santander Consumer Finance	6. Banco Mediolanum (Italy)
7. Banca March	7. UBS Bank (Suisse)
8. Santander Banco de Emisiones, S.A.	8. Banco Cetelem (France)
9. Open Bank	9. BNP Paribas España (France)
10. Banco Cooperativo Español	10. Banco Finantia Sofinloc (Portugal)
11. Santander Investment	11. Ares Bank (Arabia)
12. Dexia Sabadell	12. Self-trade Bank (Germany)
13. Bankoa	13. Privat Bank Degroof (Germany)
14. Banco Caminos	14. Banco Pichincha España (Ecuador)
15. Banca Pueyo	15. Banque Marocaine du Commerce Exterieur Internal (Morocco)
16. Banco Inversis	16. Banco Occidental (Venezuela)
17. Popular Banca Privada	17. Andbank España (Andorra)
18. Bancofar	18. JP Morgan Chase Bank (United States)
19. EBN Banco de Negocios	19. Bank of America National Association, S.E. (United States)
20. Renta 4 Banco	20. Credit Suisse AG (Suisse)
21. Banco de Depósitos	21. Bank of Tokyo Mitsubishi UFJ (Japan)
22. Allfunds Bank	22. Citibank, N.A. (United States)
23. Nuevo Micro Bank	23. Deutsche Bank Trust Company Americas, S.E. (German)
24. Banco Alcalá	24. Banco de la Nación Argentina, S.E. (Argentina)
25. Banco Europeo de Finanzas	
26. Banco Industrial de Bilbao	
27. Banco Pastor, S.A.	
28. Banco de Albacete	
29. EVO Banco, S.A.	

ANNEX II: CAMELS VARIABLE'S CALCULATIONS

In the first section of Annex II are shown the descriptive variables resulted from calculating the financial ratios for each year and banking institution. In the second section are shown the resulted percentiles and the assigned ranges for each financial ratio.

1. CAMELS VARIABLE'S FINANCIAL RATIOS DESCRIPTIVE RESULTS BY YEARS

1. Year 2013

		Mean	Median	Std. Dev.	Minimum	Maximum
C	CAR	0.21	0.11	0.26	0.01	1.00
A	NPA	0.01	0.00	0.03	-0.18	0.14
M	ER	0.54	0.57	0.27	0.04	1.12
E	ROA	0.01	0.00	0.03	-0.03	0.17
E	ROE	0.05	0.03	0.10	-0.19	0.36
L	CATA	0.05	0.01	0.09	0.00	0.42
L	LTD	0.94	1.00	0.46	0.00	1.86
S	VL	0.11	0.00	0.19	0.00	0.81

2. Year 2014

		Mean	Median	Std. Dev	Minimum	Maximum
C	CAR	0.23	0.12	0.28	0.00	1.00
A	NPA	0.01	0.00	0.03	-0.02	0.19
M	ER	0.55	0.53	0.35	0.02	1.93
E	ROA	0.02	0.01	0.04	-0.03	0.22
E	ROE	0.08	0.06	0.14	-0.47	0.48
L	CATA	0.06	0.01	0.14	0.00	0.74
L	LTD	0.91	1.03	0.47	0.00	2.17
S	VL	0.13	0.01	0.20	0.00	0.84

3. Year 2015

		Mean	Median	Std. Dev.	Minimum	Maximum
C	CAR	0.21	0.09	0.28	0.00	1.00
A	NPA	0.00	0.00	0.01	-0.01	0.03
M	ER	0.65	0.59	0.38	0.00	2.61
E	ROA	0.01	0.00	0.00	-0.03	0.08
E	ROE	0.05	0.04	0.09	-0.12	0.39
L	CATA	0.05	0.02	0.08	0.00	0.31
L	LTD	0.90	0.97	0.20	0.00	0.83

S	STM	0.13	0.03	0.20	0.00	0.83

4. Year 2016

		Mean	Median	Std. Dev.	Minimum	Maximum
C	**CAR**	0.21	0.09	0.29	0.00	1.00
A	**NPA**	0.00	0.00	0.01	-0.02	0.04
M	**ER**	0.63	0.63	0.40	-0.13	1.91
E	**ROA**	0.01	0.00	0.03	-0.09	0.17
E	**ROE**	0.04	0.04	0.12	-0.39	0.47
L	**CATA**	0.18	0.06	0.26	0.00	0.57
L	**LTD**	0.69	0.73	0.60	0.00	2.67
S	**VL**	0.13	0.02	0.22	0.00	0.87

5. Year 2017

		Mean	Median	Std. Dev	Minimum	Maximum
C	**CAR**	0.20	0.10	0.27	0.00	1.00
A	**NPA**	0.00	0.00	0.02	-0.03	0.10
M	**ER**	0.65	0.61	0.43	0.00	1.64
E	**ROA**	0.02	0.00	0.14	-0.12	0.99
E	**ROE**	0.00	0.20	0.30	-0.62	1.03
L	**CATA**	0.17	0.07	0.23	0.00	0.97
L	**LTD**	0.83	0.74	0.54	0.00	2.55
S	**VL**	0.13	0.02	0.20	0.00	0.79

2. Financial Ratio's Percentiles and Ranges

CAR

0.00	5
0.05	4
0.08	3
0.12	2
0.26	1

NPA

-0.18	1
0.00	2
0.00	3
0.002	4
0.01	5

ER

-0.13	1
0.28	2
0.50	3
0.67	4
0.95	5

ROA

-0.12	5
0.00	4
0.0003	3
0.006	2
0.13	1

ROE

-0.62	5
0.00	4
0.02	3
0.05	2
0.11	1

CATA

0.00	1
0.0003	2
0.01	3
0.03	4
0.16	5

LDT

0.00	1
0.26	2
0.78	3
1.01	4
11.29	5

STM

0.00	1
0.00	2
0.00	3
0.06	4
0.24	5

ANNEX III: FINAL DATABASE

1. Year 2013

FINANCIAL ENTITY	C	A	M	E	E	L	L	S	CAMELS
BANCO SANTANDER	3	5	3	4	4	5	3	4	3,45
BANCO BILBAO VIZCAYA ARGENTARIA	3	5	3	3	3	5	3	4	3,45
BANCO DE SABADELL	4	5	2	4	3	3	3	4	3,27
BANCO POPULAR ESPAÑOL	4	5	2	4	3	3	3	4	3,27
BANKINTER	5	4	2	3	2	4	3	4	3,38
SANTANDER CONSUMER FINANCE	1	1	1	1	2	1	5	3	1,53
BANCA MARCH	4	5	3	4	4	4	3	4	3,55
DEUTSCHE BANK S.A.E.	4	5	4	5	5	3	4	3	3,65
SANTANDER BANCO DE EMISIONES, S.A.	5	2	1	4	4	1	1	2	2,05
OPEN BANK	5	3	5	4	4	2	4	2	3,45
BANCO COOPERATIVO ESPAÑOL	5	3	1	4	1	5	3	5	3,30
SANTANDER INVESTMENT	5	1	1	2	1	1	4	2	2,20
BANCO CAIXA GERAL	4	4	5	5	5	3	3	4	3,65
CITIBANK ESPAÑA	3	5	3	5	5	3	4	3	3,25
TARGOBANK	2	4	3	2	2	2	4	3	2,75
DEXIA SABADELL	5	4	4	5	5	2	2	5	3,55
BANKOA	4	4	4	3	3	3	4	3	3,45
BANCO CAMINOS	3	5	2	3	3	4	2	5	3,15
BANCA PUEYO	3	5	3	4	3	3	2	5	3,27
BANCO INVERSIS	4	5	4	4	4	3	2	5	3,65
POPULAR BANCA PRIVADA	4	3	3	2	2	1	2	5	2,85
BANCOFAR	4	4	2	2	1	1	4	2	2,80
RBC INVESTOR SERVICES ESPAÑA	3	1	5	5	5	2	5	2	2,75
BANCO MEDIOLANUM	2	3	2	1	2	2	1	5	2,23
EBN BANCO DE NEGOCIOS	5	5	2	4	4	5	1	4	3,45
UBS BANK	4	3	4	2	1	2	4	2	3,10
RENTA 4 BANCO	4	1	4	2	2	1	2	5	2,65
BANCO CETELEM	3	2	1	1	1	1	5	2	2,05
BNP PARIBAS ESPAÑA	2	4	5	4	4	2	4	2	3,05
BANCO FINANTIA SOFINLOC	2	5	3	2	3	2	1	5	2,83
ARESBANK	1	1	4	1	1	2	5	2	2,15
BANCO DE DEPÓSITOS	2	3	2	3	4	2	5	2	2,34
ALLFUNDS BANK	1	2	2	1	1	2	5	3	2,05
NUEVO MICRO BANK	1	5	1	1	1	1	5	3	2,35
SELF TRADE BANK	1	4	4	2	3	2	3	4	2,73
BANCO ALCALÁ	2	2	5	4	4	1	2	2	2,35
BANCO EUROPEO DE FINANZAS	1	2	4	3	4	1	5	2	2,24
BANCO INDUSTRIAL DE BILBAO	1	2	1	1	4	1	5	3	1,71
PRIVAT BANK DEGROOF	2	3	5	4	4	2	4	2	2,85
BANCO PICHINCHA ESPAÑA	4	2	4	3	3	4	2	4	3,05
BANQUE MAROCAINE DU COMMERCE	2	5	2	1	2	3	5	2	2,83
BANCO PASTOR, S.A.	5	1	3	4	4	2	4	2	2,65
BANCO OCCIDENTAL	1	2	2	3	4	1	1	2	1,44
BANCO DE ALBACETE	1	2	2	3	4	1	5	4	2,04
ANDBANK ESPAÑA	2	4	5	5	5	2	5	2	3,15
EVO BANCO S.A.	5	3	1	5	5	2	3	2	2,55
JP MORGAN CHASE BANK NATIONAL	1	1	3	1	3	2	5	2	1,92
BANK OF AMERICA NATIONAL ASSOCIATION	1	4	1	1	3	2	5	2	2,12
CREDIT SUISSE AG	2	4	4	1	2	4	5	2	3,13
THE BANK OF TOKYO-MITSUBISHI UFJ, LTD	4	4	1	1	1	3	4	2	2,75
CITIBANK, N.A.	2	2	1	1	1	5	2	2	1,95
DEUTSCHE BANK TRUST COMPANY AMERICAS	1	2	5	5	5	3	5	2	2,65
BANCO DE LA NACIÓN ARGENTINA	2	5	2	4	4	4	5	3	3,05

2. Year 2014

FINANCIAL ENTITY	C	A	M	E	E	L	L	S	CAMELS
BANCO SANTANDER	3	4	3	3	3	5	3	4	3,25
BANCO BILBAO VIZCAYA ARGENTARIA	3	4	3	3	3	5	3	4	3,25
BANCO DE SABADELL	4	5	2	3	2	3	3	4	3,28
BANCO POPULAR ESPAÑOL	4	5	2	3	3	3	3	4	3,25
BANKINTER	5	4	2	2	1	5	4	4	3,60
SANTANDER CONSUMER FINANCE	1	2	1	1	3	1	5	3	1,72
BANCA MARCH	4	4	3	2	1	3	3	4	3,30
DEUTSCHE BANK S.A.E.	4	5	4	5	5	3	4	3	3,65
SANTANDER BANCO DE EMISIONES, S.A.	5	3	1	1	1	1	3	2	2,45
OPEN BANK	5	3	4	4	3	2	4	2	3,27
BANCO COOPERATIVO ESPAÑOL	5	3	1	4	1	5	2	5	3,20
SANTANDER INVESTMENT	3	2	1	2	2	2	4	2	2,05
BANCO CAIXA GERAL	3	4	4	3	3	3	3	3	3,15
CITIBANK ESPAÑA	1	5	2	1	1	3	1	3	2,35
TARGOBANK	2	4	3	2	3	3	4	3	2,83
DEXIA SABADELL	5	4	1	5	2	2	3	4	3,03
BANKOA	4	4	4	3	3	2	4	4	3,45
BANCO CAMINOS	4	5	3	3	3	4	2	5	3,55
BANCA PUEYO	3	5	3	3	3	3	2	5	3,25
BANCO INVERSIS	5	1	4	2	1	4	1	5	3,10
POPULAR BANCA PRIVADA	3	4	2	1	1	2	2	5	2,75
BANCOFAR	3	5	1	5	5	2	4	2	2,65
RBC INVESTOR SERVICES ESPAÑA	3	1	4	5	5	2	5	2	2,55
BANCO MEDIOLANUM	3	4	3	2	2	3	1	5	2,95
EBN BANCO DE NEGOCIOS	5	5	2	2	1	5	1	4	3,50
UBS BANK	4	3	4	2	1	2	4	2	3,10
RENTA 4 BANCO	5	3	4	3	1	1	2	5	3,35
BANCO CETELEM	2	2	1	1	1	1	5	2	1,85
BNP PARIBAS ESPAÑA	2	3	5	4	4	4	4	3	3,15
BANCO FINANTIA SOFINLOC	2	5	2	1	2	2	1	5	2,63
ARESBANK	1	1	3	1	2	3	5	2	2,03
BANCO DE DEPÓSITOS	2	1	2	3	3	2	5	2	1,95
ALLFUNDS BANK	2	3	2	1	1	2	5	3	2,45
NUEVO MICRO BANK	1	5	1	1	1	1	5	2	2,25
SELF TRADE BANK	2	1	5	3	4	2	4	3	2,54
BANCO ALCALÁ	3	2	4	4	4	3	2	2	2,55
BANCO EUROPEO DE FINANZAS	1	2	5	5	5	1	5	2	2,45
BANCO INDUSTRIAL DE BILBAO	1	2	1	1	2	1	5	5	1,93
PRIVAT BANK DEGROOF	2	3	5	4	4	2	4	2	2,85
BANCO PICHINCHA ESPAÑA	5	2	3	2	1	5	2	5	3,30
BANQUE MAROCAINE DU COMMERCE	2	4	2	1	2	3	5	2	2,63
BANCO PASTOR, S.A.	5	4	3	4	3	3	4	3	3,47
BANCO OCCIDENTAL	1	2	1	3	4	1	1	2	1,24
BANCO DE ALBACETE	1	2	3	4	4	1	5	4	2,25
ANDBANK ESPAÑA	1	3	5	5	5	2	4	4	2,85
EVO BANCO S.A.	5	5	5	5	5	2	2	5	3,95
JP MORGAN CHASE BANK NATIONAL	1	1	2	1	2	2	5	2	1,73
BANK OF AMERICA NATIONAL ASSOCIATION	1	1	1	1	2	2	5	2	1,53
CREDIT SUISSE AG	2	3	4	1	1	4	4	2	2,85
THE BANK OF TOKYO-MITSUBISHI UFJ, LTD	4	4	1	2	2	2	4	2	2,65
CITIBANK, N.A.	2	2	1	1	1	5	2	2	1,95
DEUTSCHE BANK TRUST COMPANY AMERICAS	1	2	1	3	4	1	1	2	1,24
BANCO DE LA NACIÓN ARGENTINA	2	5	2	4	4	3	5	2	2,85

3. Year 2015

FINANCIAL ENTITY	C	A	M	E	E	L	L	S	CAMELS
BANCO SANTANDER	3	4	3	3	3	5	2	4	3,15
BANCO BILBAO VIZCAYA ARGENTARIA	3	4	3	2	2	5	3	4	3,25
BANCO DE SABADELL	4	5	2	4	3	3	3	4	3,27
BANCO POPULAR ESPAÑOL	4	5	2	4	4	3	3	4	3,25
BANKINTER	4	4	2	2	2	4	4	4	3,25
SANTANDER CONSUMER FINANCE	1	3	1	2	3	3	5	3	2,13
BANCA MARCH	4	4	3	2	1	4	3	4	3,40
DEUTSCHE BANK S.A.E.	4	4	4	3	2	4	4	3	3,58
SANTANDER BANCO DE EMISIONES, S.A.	3	1	5	5	5	2	3	3	2,65
OPEN BANK	5	3	5	4	4	3	3	2	3,45
BANCO COOPERATIVO ESPAÑOL	5	3	2	4	2	5	2	5	3,30
SANTANDER INVESTMENT	3	3	5	5	5	2	3	2	2,95
BANCO CAIXA GERAL	3	4	3	3	2	2	3	4	2,98
CITIBANK ESPAÑA	1	5	5	5	5	3	5	3	3,35
TARGOBANK	2	4	3	2	3	4	4	3	2,93
DEXIA SABADELL	5	3	4	5	4	2	4	3	3,36
BANKOA	4	4	4	3	3	3	3	4	3,45
BANCO CAMINOS	4	3	3	3	3	3	2	5	3,05
BANCA PUEYO	4	5	2	3	2	3	2	5	3,28
BANCO INVERSIS	4	3	4	2	1	4	2	5	3,40
POPULAR BANCA PRIVADA	4	3	4	2	1	2	2	5	3,20
BANCOFAR	3	4	3	4	3	3	4	2	2,97
RBC INVESTOR SERVICES ESPAÑA	5	1	4	4	3	4	3	2	2,97
BANCO MEDIOLANUM	3	3	3	2	2	2	1	5	2,65
EBN BANCO DE NEGOCIOS	5	1	3	3	2	5	1	5	2,98
UBS BANK	4	3	4	2	2	4	3	2	3,15
RENTA 4 BANCO	5	3	4	2	1	2	2	5	3,40
BANCO CETELEM	2	2	1	1	1	1	5	2	1,85
BNP PARIBAS ESPAÑA	3	3	5	4	4	3	4	2	3,15
BANCO FINANTIA SOFINLOC	2	5	2	1	1	2	1	5	2,65
ARESBANK	1	1	4	2	4	4	5	2	2,33
BANCO DE DEPÓSITOS	2	3	2	3	4	2	5	2	2,34
ALLFUNDS BANK	2	3	2	1	1	1	5	3	2,35
NUEVO MICRO BANK	2	5	1	1	1	1	5	3	2,55
SELF TRADE BANK	3	1	5	5	5	2	4	3	2,75
BANCO ALCALÁ	2	3	5	4	4	3	2	2	2,75
BANCO EUROPEO DE FINANZAS	1	2	5	4	4	1	5	2	2,45
BANCO INDUSTRIAL DE BILBAO	1	2	1	1	3	1	1	4	1,42
PRIVAT BANK DEGROOF	2	5	5	5	5	2	3	4	3,35
BANCO PICHINCHA ESPAÑA	5	5	4	5	5	2	2	5	3,75
BANQUE MAROCAINE DU COMMERCE	2	5	1	1	1	3	5	2	2,65
BANCO PASTOR, S.A.	5	4	3	3	2	3	4	3	3,48
BANCO OCCIDENTAL	1	2	2	4	4	1	1	2	1,45
BANCO DE ALBACETE	1	2	5	5	5	1	5	2	2,45
ANDBANK ESPAÑA	1	1	5	3	4	3	2	5	2,44
EVO BANCO S.A.	5	4	5	5	5	1	2	5	3,65
JP MORGAN CHASE BANK NATIONAL	1	4	4	4	4	5	5	2	3,05
BANK OF AMERICA NATIONAL ASSOCIATION	5	2	1	4	5	1	1	2	2,04
CREDIT SUISSE AG	3	3	3	2	2	4	4	2	2,85
THE BANK OF TOKYO-MITSUBISHI UFJ, LTD	3	1	2	2	2	3	4	2	2,15
CITIBANK, N.A.	1	4	1	1	2	1	5	2	2,03
DEUTSCHE BANK TRUST COMPANY AMERICAS	1	2	1	3	4	1	1	2	1,24
BANCO DE LA NACIÓN ARGENTINA	2	1	3	2	3	3	4	2	2,13

4. Year 2016

FINANCIAL ENTITY	C	A	M	E	E	L	L	S	CAMELS
BANCO SANTANDER	2	4	3	3	3	5	2	4	2,95
BANCO BILBAO VIZCAYA ARGENTARIA	3	4	3	3	3	5	3	4	3,25
BANCO DE SABADELL	4	4	3	4	3	4	3	4	3,37
BANCO POPULAR ESPAÑOL	4	5	4	5	5	3	3	4	3,65
BANKINTER	5	4	3	2	1	4	4	4	3,70
SANTANDER CONSUMER FINANCE	2	1	1	1	2	1	5	3	1,73
BANCA MARCH	3	1	3	2	1	4	2	4	2,50
DEUTSCHE BANK S.A.E.	4	3	4	4	4	4	5	3	3,45
SANTANDER BANCO DE EMISIONES, S.A.	4	1	2	2	2	5	1	4	2,45
OPEN BANK	5	1	4	4	3	4	3	2	2,97
BANCO COOPERATIVO ESPAÑOL	5	1	2	3	2	5	2	5	2,88
SANTANDER INVESTMENT	4	1	5	4	4	2	3	2	2,75
BANCO CAIXA GERAL	3	3	3	3	2	3	3	4	2,88
CITIBANK ESPAÑA	1	2	4	2	4	4	1	3	2,23
TARGOBANK	4	5	5	5	5	4	3	3	3,85
DEXIA SABADELL	5	2	1	4	5	1	1	2	2,04
BANKOA	4	1	4	3	3	3	3	4	2,85
BANCO CAMINOS	4	4	2	3	3	4	2	5	3,15
BANCA PUEYO	3	3	3	3	2	4	2	5	2,98
BANCO INVERSIS	3	1	4	2	2	5	1	5	2,75
POPULAR BANCA PRIVADA	4	1	4	4	4	4	2	5	2,95
BANCOFAR	3	4	3	4	3	4	4	2	3,07
RBC INVESTOR SERVICES ESPAÑA	5	2	1	4	5	1	1	2	2,04
BANCO MEDIOLANUM	3	1	4	2	1	4	1	5	2,70
EBN BANCO DE NEGOCIOS	3	5	3	2	2	2	1	5	3,05
UBS BANK	5	2	1	4	5	1	1	2	2,04
RENTA 4 BANCO	4	1	3	1	1	5	1	5	2,75
BANCO CETELEM	2	5	1	1	1	4	4	2	2,65
BNP PARIBAS ESPAÑA	3	1	5	2	2	4	4	3	2,95
BANCO FINANTIA SOFINLOC	2	1	2	1	2	3	1	5	1,93
ARESBANK	2	3	5	2	3	5	4	3	3,23
BANCO DE DEPÓSITOS	1	1	2	1	3	2	5	2	1,72
ALLFUNDS BANK	2	1	2	1	1	5	2	3	2,05
NUEVO MICRO BANK	2	5	1	1	1	1	5	3	2,55
SELF TRADE BANK	4	3	5	5	5	5	2	3	3,45
BANCO ALCALÁ	3	1	5	4	4	5	1	3	2,75
BANCO EUROPEO DE FINANZAS	1	5	5	4	4	5	5	2	3,45
BANCO INDUSTRIAL DE BILBAO	1	2	1	1	1	1	1	4	1,45
PRIVAT BANK DEGROOF	2	1	5	5	5	5	3	3	2,75
BANCO PICHINCHA ESPAÑA	4	5	4	5	5	2	3	4	3,55
BANQUE MAROCAINE DU COMMERCE	2	5	2	2	2	5	2	3	2,85
BANCO PASTOR, S.A.	5	5	4	5	5	3	4	3	3,85
BANCO OCCIDENTAL	1	2	4	4	4	1	1	2	1,85
BANCO DE ALBACETE	1	2	5	5	5	5	1	2	2,45
ANDBANK ESPAÑA	2	1	5	5	5	5	1	4	2,65
EVO BANCO S.A.	5	1	5	3	2	3	2	5	3,28
JP MORGAN CHASE BANK NATIONAL	1	1	5	2	3	5	3	2	2,43
BANK OF AMERICA NATIONAL ASSOCIATION	5	2	1	4	5	1	1	2	2,04
CREDIT SUISSE AG	3	1	4	2	2	4	4	2	2,65
THE BANK OF TOKYO-MITSUBISHI UFJ, LTD	3	1	2	1	1	4	4	2	2,25
CITIBANK, N.A.	1	2	1	5	5	5	1	2	1,65
DEUTSCHE BANK TRUST COMPANY AMERICAS	5	2	1	4	5	1	1	2	2,04
BANCO DE LA NACIÓN ARGENTINA	2	3	2	1	2	5	2	2	2,33

5. Year 2017

FINANCIAL ENTITY	C	A	M	E	E	L	L	S	CAMELS
BANCO SANTANDER	2	4	3	2	3	5	2	4	2,93
BANCO BILBAO VIZCAYA ARGENTARIA	3	4	3	3	3	5	3	4	3,25
BANCO DE SABADELL	4	5	3	3	3	4	3	3	3,45
BANCO POPULAR ESPAÑOL	5	5	5	5	5	4	3	4	4,15
BANKINTER	5	4	3	2	1	4	3	4	3,60
SANTANDER CONSUMER FINANCE	1	4	1	2	3	1	5	3	2,13
BANCA MARCH	3	3	3	3	2	4	3	4	2,98
DEUTSCHE BANK S.A.E.	4	4	5	4	4	4	5	3	3,85
SANTANDER BANCO DE EMISIONES, S.A.	4	1	2	2	2	5	1	4	2,45
OPEN BANK	5	1	5	4	4	5	1	2	3,05
BANCO COOPERATIVO ESPAÑOL	4	3	2	3	2	5	2	5	3,08
SANTANDER INVESTMENT	3	2	2	1	1	4	3	2	2,35
BANCO CAIXA GERAL	3	4	3	3	3	2	3	5	3,05
CITIBANK ESPAÑA	1	2	5	5	5	4	1	3	2,45
TARGOBANK	3	5	5	5	5	4	4	2	3,65
DEXIA SABADELL	5	2	1	4	5	1	1	2	2,04
BANKOA	4	3	4	3	2	3	3	3	3,18
BANCO CAMINOS	4	3	3	3	3	4	2	5	3,15
BANCA PUEYO	3	1	3	2	2	4	2	4	2,45
BANCO INVERSIS	5	2	5	1	1	5	2	5	3,65
POPULAR BANCA PRIVADA	4	1	5	5	5	5	1	5	3,15
BANCOFAR	3	3	4	3	3	4	4	2	3,05
RBC INVESTOR SERVICES ESPAÑA	5	2	1	4	5	1	1	2	2,04
BANCO MEDIOLANUM	3	3	4	2	2	4	2	5	3,15
EBN BANCO DE NEGOCIOS	2	4	5	5	5	3	1	5	3,15
UBS BANK	5	2	1	4	5	1	1	2	2,04
RENTA 4 BANCO	4	2	4	1	1	5	1	5	3,15
BANCO CETELEM	2	5	1	1	1	4	4	2	2,65
BNP PARIBAS ESPAÑA	3	1	4	3	3	4	4	2	2,65
BANCO FINANTIA SOFINLOC	2	4	2	1	2	4	1	5	2,63
ARESBANK	1	1	3	3	4	4	4	3	2,14
BANCO DE DEPÓSITOS	1	3	2	2	4	5	5	3	2,53
ALLFUNDS BANK	2	2	2	1	1	5	2	2	2,15
NUEVO MICRO BANK	2	5	1	1	1	1	5	3	2,55
SELF TRADE BANK	4	3	5	5	5	4	2	4	3,45
BANCO ALCALÁ	3	3	5	4	4	5	2	3	3,25
BANCO EUROPEO DE FINANZAS	1	1	4	4	4	5	5	2	2,45
BANCO INDUSTRIAL DE BILBAO	1	2	1	1	1	1	1	5	1,55
PRIVAT BANK DEGROOF	2	1	5	5	5	5	3	3	2,75
BANCO PICHINCHA ESPAÑA	3	5	4	4	4	3	3	4	3,45
BANQUE MAROCAINE DU COMMERCE	3	4	2	2	2	5	2	2	2,75
BANCO PASTOR, S.A.	5	5	5	5	5	4	3	3	4,05
BANCO OCCIDENTAL	1	2	5	4	4	1	1	2	2,05
BANCO DE ALBACETE	1	2	3	4	4	3	1	2	1,85
ANDBANK ESPAÑA	2	3	5	5	5	5	2	3	3,05
EVO BANCO S.A.	5	3	5	5	5	3	2	5	3,65
JP MORGAN CHASE BANK NATIONAL	1	3	4	4	4	5	4	2	2,75
BANK OF AMERICA NATIONAL ASSOCIATION	5	2	1	4	5	1	1	2	2,04
CREDIT SUISSE AG	3	3	4	3	3	5	3	2	3,05
THE BANK OF TOKYO-MITSUBISHI UFJ, LTD	5	1	2	3	1	3	4	2	2,65
CITIBANK, N.A.	5	2	1	4	5	1	1	2	2,04
DEUTSCHE BANK TRUST COMPANY AMERICAS	5	2	1	4	5	1	1	2	2,04
BANCO DE LA NACIÓN ARGENTINA	1	5	2	2	3	5	2	2	2,53

UNIVERSIDAD
DE BURGOS