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TESIS DOCTORAL:

Three essays on the use of neural networks for financial prediction

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La elaboración de la tesis ha presentado momentos la mayor parte del tiempo agradables. He tenido que aprender nuevas metodologías estadísticas, redes neuronales y otros algoritmos de *machine learning* que han resultado muy interesantes y útiles, no solamente a nivel personal, sino también en el ámbito laboral. La lectura y estudio de trabajos previos también me ha permitido encontrar la mejor forma de aplicar los nuevos conocimientos adquiridos.

Sin embargo, durante la elaboración de este proyecto, han existido momentos menos buenos. La elaboración de una tesis por compendio de varios artículos también conlleva un arduo trabajo de publicación en revistas con alto factor de impacto. La combinación de finanzas, economía y redes neuronales en los trabajos ha hecho difícil encontrar las revistas a las que se ajustaran correctamente. Nos han rechazado varias veces los artículos por no considerarse adecuados en las revistas enviadas. Aunque el tiempo empleado, la espera y los rechazos han sido fructuosos, consiguiendo publicar en mejores revistas, pero también creaban inseguridad, cansancio y frustración. Puedo considerar que Félix me ha enseñado a tener paciencia y no caer en el error de intentar ir a revistas de publicación menos exigente, sino a trabajar con más esmero y no decaer.

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1. Introduction

Several financial crises have occurred over the world over the last few decades (Laeven and Valencia, 2008; 2010; 2012), being the financial crisis arisen in 2008, the latest example and probably the worst financial crisis since the Great Depression of the 1930s (Dhameja, 2010). During these crisis periods, significant bank failures or bank liquidations have occurred. Financial regulators and Governments have been obliged to intervene in order to limit the contagion effect in the financial system and to mitigate the impact of failures on the real economy.

The consequences of financial crises depend highly on the causes and on the effectiveness of the policies applied to mitigate them. From an economic point of view, the latest financial crisis has resulted in a high number of North American and European bank failures, and in a worldwide decline in the stock markets (Altman, 2009; Fackler, 2008). These effects soon became noticeable on the real economy as well. The reduction of credit from the financial sector to the firms and households affected negatively the domestic investment and consumption demand. The international trade and growth were dramatically reduced resulting in a sharply increase of the unemployment rate in most of the developed countries. Thus, the impact of the 2008 global financial crisis on each country can be easily observed from the main macroeconomic variables related to the GDP growth, GDP per capita, total general government debt, unemployment rate, and inflation.

But the consequences have not been only economic. For most regions and income groups in developing countries, the number of people at risk of falling into poverty and exclusion is considerably higher after the crisis and the income distribution has notably worsened (Otker-Robe and Podpiera, 2013). The effects have been felt in the political scene with a replacement of the ruling political parties in favor of the opposition parties. The United States, United Kingdom or France are some examples. New political forces have emerged at the same time, blaming the traditional parties for causing the crisis. The number of anti-government demonstrations, the frequency of violent riots and general strikes have increased progressively over all the countries, mainly in the most affected countries in the European Union like Greece, Portugal, Spain, and Ireland among others. Nationalist movements and protectionist measures have acquired a greater presence as well.

As usual, the number of studies trying to explain the causes and consequences of a crisis rise considerably after a banking crisis occurs. A better comprehension of previous crises is important to prevent future ones. It is precisely this objective, preventing future crisis, the main motivation of this PhD dissertation. Our dissertation is made up of three different essays, trying to strengthen what we consider as two important mechanism that have failed during the latest years and that are closely related to the onset of the financial crisis: The assessment of the solvency of banks and the systemic risk over the time, and the detection of the macroeconomic imbalances in some countries, especially in Europe, which made the financial crisis evolve through a sovereign crisis in Europe.

Although the financial crisis was a consequence of a complex number of circumstances and there is not only a single trigger, in the following lines we outline a brief consensus of the literature. The starting point could be set in the facilities to access the credit and the low interest rates, which increased the leverage of banks, the risk taking and the housing bubble preparing the ground of the financial crisis (Meltzer, 2010; Taylor, 2013).

The progressively reduction in the interest rate was due to the fear of a possible recession in the US, especially after the recent terrorist attacks in 2001 and the bust of the dotcom bubble; and it also motivated by the "savings glut" in Europe and especially in China (Bernanke, 2005).

The effect of low interest rates in the profitability of banks is considered as positive in the short term. The reduction of interest rates usually fosters an increase in credit activity and a general recovery of the economy. However, persistently low interest rates negatively affect bank net margins (Borio, Gambacorta and Hofmann, 2017; Claessens, Coleman and Donnelly, 2018). For example, the International Monetary Fund (2003) International Monetary Fund (2003) blames the low levels of interest rates for being one of the reasons of the slow recovery of the Japanese bank's profitability in the early 2000s.

A long exposure to low interest rates represent a major concern for supervisors and policy makers too. Low interest rates result in an increase in risk taking (Acharya and Plantin, 2017; Drechsler, Savov and Schnabl, 2018; Jiménez, Ongena, Peydró and Saurina, 2014; Martinez-Miera and Repullo, 2017; Rajan, 2006). Kumhof and Rancière (2010) and Rajan (2011) argue that the rising inequality in the past years was the cause of the credit boom and the financial crisis. The US political system was not able to fairly redistribute the income through the tax income and it was necessary to keep growing the consumption levels of the middle class. The easiest way the political system found to reduce inequality was to ease the access of housing credit facilities (McCarty, Poole and Rosenthal, 2006).

These factors encouraged an aggressive increase and acceleration of the real estate market, facilitating access to mortgage loans to all types of people, even with very low income and stability in employment. Banks allowed people to take out loans for 100 percent or more of the value of their new homes. Mortgages granted to applicants with a high probability of default were named as "subprime mortgages". The mortgage loans were supported by the price of the houses themselves, which kept on rising progressively. New mortgage loans generated a high volume of income for the financial companies, and, if the loans were not paid, banks acquired the ownership of the property, whose value was higher at that time.

In 2004, the Fed started raising rates reaching the 2.25% at the end of the year, a 4.25% in 2005 and the 5.25% by June 2006. The number of non-performing loans rose because most of the mortgages had adjustable interest rates, and people with low incomes could not afford the repayment. In many cases, people tried to sell the properties as the people which had bought homes as investments did too. In 2006 the housing prices, which have increased progressively during the latest fourteen years at high rates, started falling.

But, how a US housing boom became a global financial crisis? Most of the US home loans were sold by the financial companies in the secondary market of mortgage-backed bonds, the so-called “originate-to-distribute” model. Pooled mortgages were used to back securities known as collateralized debt obligations (CDOs), which were sliced into tranches by the degree of exposure to default. The securitization of subprime mortgages into mortgage-backed securities (MBS) and collateralized debt obligations (CDOs) was a major contributing factor in the subprime mortgage crisis. The securitization process implies grouping and classifying these loans into different risk levels in the same portfolio, and subsequently selling them to investors through other corporate structures or investment funds. It became a highly profitable business, allowing financial institutions to transform liquid assets into instruments to raise funds, eliminating the risk of non-payment of their loans.

However, when the home prices started to decline, prices on mortgage-backed securities plunged, resulting in large losses for banks and other financial institutions even in the highest quality tranches. Banks had used securitization to avoid minimum-capital regulations as well, which made them more vulnerable. Losses soon spread to other asset classes, fueling a crisis of confidence in the health of many of the world's largest banks, whose the real exposure to subprime loans were unknown. Problems also affected the largest insurance companies as AIG, which have provided guarantees especially in the best quality tranches. The financial crisis reached its peak with the bankruptcy of Lehman Brothers in September 2008, which resulted in a credit freeze that brought the global financial system to the brink of complete collapse.

As a consequence of the financial turmoil, many studies have focused in the development of early warning systems (EWS) that aim to detect potential problems in banks some time before. An early identification of problematic banks is likely to reduce the expected cost of a bank failure and to avoid the contagion effect through the financial system. Despite the efforts carried out by the supervisors and the researchers, some unexpected bank failures arise in each new financial crisis.

Why did these models fail? Evidently, EWS are not perfect. In fact, 520 banks have failed in US from January 2008 to December 2016. A number of factors can affect their performance. One of the most important reasons is the evolution of the financial system worldwide. Models, which use statistics or ratios based on past relationships between debt defaults, can ignore very important factors and possibilities (Woellert and Kopecki, 2008). The update of the models to gather the new information or the new relationships do not evolve at the same pace than the new underlying risk from the banking activities. Sometimes it is also impossible to know future risks, unknown until the new crisis occurs.

In addition, the wide use of EWS can be problematic as well. If banks acquired knowledge about the ratios and how the regulator’s use them, it could increase the incentives to manage their own ratios and hide the real situation in the case of financial difficulties (Glasserman and Tangirala, 2016; Mariathasan and Merrouche, 2012). Finally, the detection of the determinants of distress is conditioned not only to individual financial ratios but also to macroeconomic variables. EWS to detect failed banks should be complemented with other macro prudential tools as stress test, but the available resources to a carry out a complete oversight are limited.

Techniques and models are becoming obsolete over time. Nevertheless, as the global financial system evolves, the models of prediction have become more sophisticated to account for the effects of financial crises or other outstanding business episodes (Mokhatab Rafiei, Manzari and Bostanian, 2011; Nassirtoussi, Aghabozorgi, Wah and Ngo, 2014).

During the most recent years, new approaches have been tested, especially in the field of machine learning algorithms. Support vector machines (Boyacioglu, Kara and Baykan, 2009; Huang, Chen, Hsu, Chen and Wu, 2004) or random forest (Tanaka, Kinkyo and Hamori, 2016) have been successfully used in this field. Moreover, the use of hybrid approaches, techniques that combine the outputs of several predictors are used to predict bank failures. The result of hybrid models displays more accuracy than techniques used separately (Kainulainen, Miche, Eirola, Yu, Frénay, Séverin and Lendasse, 2014).

Artificial neural networks (ANNs) play a prominent role in this field. These techniques have been widely used to predict bankruptcies, especially since the year 2000. There is a consensus that the ANN’s techniques are more successful than multivariate discriminant analysis (Martínez, 1996; Piramuthu, 1999; Vellido, Lisboa and Vaughan, 1999; Wu and Wang, 2000). Regardless of the methodology used, almost all the bankruptcy prediction models fail in predictions when the time horizon goes beyond the near short term, finding few models that achieve stable results over the time.

In this line, the first essay of this dissertation is our paper "Bankruptcy visualization and prediction using neural networks: A study of U.S. commercial banks". The aim of this study is twofold: descriptive and predictive. First, we describe the main characteristics of U.S. distressed banks and how bank failures have evolved from the onset of the financial crisis in 2007. The implementation of our model and the analysis of the most descriptive variables provide interesting insights about the most critical features of distressed banks relative to nondistressed banks. Second, we provide a tool to predict the probability of bank failures some time before they happen. In so doing, we define three different models that are conditional on the period before the failure. These two objectives lead to the development of a visual tool that can assess the strengths and weaknesses of a bank in the short, medium and long term by combining the outputs of the three models in a bi-dimensional map. This tool offers not only a method to detect failures but also a visual representation of when weaknesses can arise. This procedure also provides a dynamic perspective as it can assess the probability of bank failure along a period of time, unlike most previous models that are limited to a single point in time.

From this study we can tell the storyline of distressed banks in US: as a consequence of the U.S. business upturn fueled by low interest rates, financial institutions expanded rapidly to gain market share as quick as possible. The real estate boom along with low interest rates compelled banks to grant loans to construction and land development irrespective of the credit quality. Distressed banks had to pay back higher interest rates to depositors to raise money to reinvest in the real estate industry. Due to the business downturn in 2008 and 2009, along with the fall of the prices of real estate collateral, these banks faced a growing default rate, had to create more provisions, and accumulated a troublesome portfolio of real estate. The provisions impacted earnings negatively, and the solvency of the banks worsened. The liquidity crisis constrained the possibility of improving the solvency of the banks through equity issuance, and banks had to pay higher interest rates. These growing interests on deposits along with troublesome loans led to a negative margin. This vicious circle could not be maintained for long time, and finally financial authorities intervened.

The predictive power of our model was tested on a sample of U.S. banks that went bankrupt between May 2012 and December 2013. We also compared our MLP-SOM results with both traditional classification models (the discriminant and logit analyses) and with more recent techniques such as support vector machine and random forest procedures. Our model, which exhibits high predictive power, predicted one year ahead 96.15% of the 52 banks that failed between May 2012 and December 2013.

In this paper we go a step ahead in several domains. First, our model outperforms most of the previous ones in terms of predicting ability. Second, the output of our model is compared against a wider set of alternative methods than previous papers do. Third, our model is simpler and, at the same time, provide a clearer visualization of the complex temporal behaviors. We hope our procedure can be a useful tool for bank supervisors and other stakeholders to delineate the risk profile of each bank. As far as the supervisory authority is concerned, the preventive measures to correct imbalances can be different in the short, medium, or long term depending on the probability of banking failure—that is, on the group to which the bank belongs. Investors, depositors, and other participants in capital markets can assess the risk profile of their investment and, consequently, define their optimal risk-return combination.

The financial crisis evolved to the sovereign crisis in the European Union (EU). The European debt crisis started in 2009 and the effects still continue today. During these years, some of the EU members mainly Greece, Portugal, Ireland, Spain and Cyprus were unable to repay or refinance their government debt without the assistance of third parties like other Eurozone countries, the European Central Bank (ECB), or the International Monetary Fund (IMF).

What were the causes of the sovereign crisis in the EU? Could this crisis be avoided simply diagnosing the banks in troubles? Despite the name, the sovereign crisis is not directly related to the government debt ratios before the crisis. In fact, the public debt ratio of some of the most affected countries was below the euro-area average at the onset of the crisis. Moreover, some highly-indebted countries have not been affected by this crisis.

The sovereign crisis was, in part, a consequence of the financial crisis. Because of the effects of this financial crisis, some countries were unable to repay or refinance their government debt, mainly due to the uncertainty and closure in financial markets. The main problem was the sharp increase of debt levels because of the different bailouts of large banks in the financial systems in some of the member states. In some cases, these bailouts were only possible with the assistance of other Eurozone countries, the European Central Bank (ECB) or the International Monetary Fund (IMF).

This crisis can be considered as a competitiveness crisis, whose causes underlie the very definition and the foundation of the Economic and Monetary Union (EMU). According to some authors (Chang and Leblond, 2015; De Grauwe, 2016; Eichengreen, 2014; Krugman, 2013), two main types of countries could be identified in the EMU: the Northern or core countries (Austria, Belgium, Finland, Germany, the Netherlands and France) and the Southern or peripheral countries. The EMU aimed to integrate the two different growth models into a currency union without a centralized federal government. The Northern and core countries were exporting states with low inflation rates and current account surpluses. On the contrary, the Southern or peripheral countries relied heavily on the domestic markets, with generally high inflation rates and budget deficits (Regan, 2017).

At the beginning of the EMU, both Northern and Southern growth models seemed to be completely complementary. The EMU was born at a time of low global interest rates and a surplus of savings from some countries, which tunneled its investments and lending to the periphery. The later countries could find cheaper funding belonging to the eurozone. The interest rates on peripheral assets fell to levels of the German rates. In fact, the 10-years Government bond spreads remained similar for all the countries from 2000 to 2008, assuming an implicit Eurozone guarantee and similar risk all over the countries. Nevertheless, during this period, the imbalances among the countries increased. Countries like Greece, Ireland, Portugal, Italy or Spain were growing strongly but increasing their trade deficit, which was funded by a combination of public and private borrowing.

Each of the most affected countries increased the imbalances in different ways before 2008, generally resulting in excessive lending, asset price bubbles and a loss of competitiveness. For example, in Spain, the quick growth and the easy access to funding to low prices created a housing bubble and vulnerabilities in the financial sector. When the financial crisis burst, some doubts about the solvency of some of the largest banks emerged, and the Spanish Government had to bail-out some banks. The situation was even more adverse in other countries like Ireland and Greece. Defaults were glimpsed in several countries and even the continuity of the European Union itself (EU).

In 1997, the Stability and Growth Pact (SGP) was designed as a set of rules to ensure that countries in the European Union pursue sound public finances and coordinate their tax policies. Specifically, each country must keep an annual budget deficit no greater than 3% of GDP, and the public debt of any country must be lower than 60% of GDP. Although the member states have always been willing to comply with these rules, the SGP was not sufficient to keep all countries within the set limits (De Haan et al, 2004; McNamara, 2005) and even to prevent the current crisis.

As cited above, current sovereign crisis was motivated by the financial crisis but also for the latent imbalances since the foundation of the EMU. Both crises, the closure of markets and the financial instability have been difficult to predict some time before, even for the EU. This fact motivated us to carry out our second essay: "Self-organizing maps as a tool to compare financial macroeconomic imbalances: The European, Spanish and German case".

In this paper, we developed a model to anticipate and detect possible divergences among countries to prevent future crisis. The earlier the economic imbalances are detected, the easier they could be corrected. Our paper aims to contribute to the literature on national financial balance providing a complete and simple model. Most of the international comparisons until now have been based on one single indicator, which results in the lack of enough explanatory ability. Our model is based on self-organizing maps (SOM), the same technique we also used to create different profiles of banks according to their solvency. Based on this method and a set of the usual macroeconomic variables, in this paper we analyze and compare the financial situation of the European countries in 2009 to obtain groups of countries conditional on their capacity to meet their financial commitments. Our results show the existence of several groups of countries, each one of them with specific characteristics. We also find that government expenditure and the saving rate are the most influential variables affecting the macroeconomic financial imbalances.

The EU has been working on a better way to measure possible imbalances, mainly due to the weaknesses observed in the original foundations of the SGP. Thus, in 2011, the Macroeconomic Imbalance Procedure (MIP)1 was implemented. It aims "to identify, prevent and address the emergence of potentially harmful macroeconomic imbalances that could adversely affect economic stability in a particular Member State, the euro area, or the EU as a whole". Currently, this program consists of a scoreboard of 14 headline indicators covering the most relevant areas of macroeconomic imbalances, competitiveness, and adjustment issues, which are complemented by 25 auxiliary indicators.

A country may be found to have 'no imbalances', 'imbalances', 'excessive imbalances', or 'excessive imbalances with corrective actions'. Countries with imbalances may receive policy recommendations to solve this situation with a set of country-specific recommendations. In our paper, we based on many of the indicators used in the MIP scorecard too. The identification of groups of similar countries can allow discovering possible channels of financial contagion and financial turbulences propagation across countries. In the paper we detect seven different groups of countries and we describe them. For example, we find that countries currently in a troublesome situation are placed together: Greece, Hungary, Ireland, Ukraine, Latvia, Lithuania and Iceland. Another group of countries placed together are Spain, Portugal and Slovakia. These ones were countries in financial troubles but in an intermediate situation. The group formed by Holland, the Czech Republic, Belgium, Austria and Germany seems to be the more stable group.

Finally, our paper also tries to go one step further: since several countries of the European Union have regions with some degree of economic and financial competences, we study the influence of the regions on the whole country. The motivation to extend the analysis of the paper on the regions came from the recently macroeconomic unbalances of the Spanish autonomous communities (AA.CC) and

[11] https://ec.europa.eu/info/business-economy-euro/economic-and-fiscal-policy-coordination/eu-economic-governance-monitoring-prevention-correction/macroeconomic-imbalance-procedure_en

their burden on the whole national public expenditure (Martínez García and Colldeforns, 2003; Ríos, López and Pérez, 2007; Sanz and Velázquez, 2001). The gap between the dramatic increments in the public expenditure of most of the AA.CC. and the objectives of Spain as a country forced the Spanish Government to pass a strict adjustment plan to cut-off the public deficit and to meet the European objectives. As in the case of countries, we train a SOM model as a tool to assess and to compare the financial situation of the AA.CC.

Results were complemented with an analogous analysis of other country, in this case with the situation of Germany and its 16 federal states or *Bundesländer*. In both cases, we find that the macroeconomic situation of the regional entities is a key determinant of the country financial (im)balance.

The two first papers are closely related to the financial crisis and the possible impact on the real economy. Nevertheless, we also are concerned about other factor that could affect the recovery of the economy after the crisis. Corruption in clearly one of these factors. Indeed, Jim Yong Kim, the president of the World Bank, at the "Speak Up Against Corruption" on December 2013, considered corruption as the "public enemy number one" for most developing economies. In the same line, Kaufmann and Bellver (2005) estimate that corruption account for some $1.1 trillion globally; and according to a recent estimate from the International Monetary Fund (2016), the annual cost of bribery reaches between $1.5 and $2 trillion (roughly two percent of global GDP).

Could corruption be a cause of the international financial crisis? Although the literature is scarce on the possible link between financial crises and corruption, crises seem to have taken place more often in countries with higher levels of corruption (Laeven and Valencia, 2013). Chen, Jeon, Wang and Wu (2015) have assessed the impact of corruption on banks' risk-taking behavior and found evidence that more severe levels of corruption are associated with higher bank risk-taking. As it was described above, in an environment of low interest rates, banks shifted towards a risk-taking behavior that finally resulted in the financial crisis.

Whether directly or indirectly related to financial crises, the corruption can interrupt or slow down the recovery in some countries. For example, Ormerod (2016) showed that the resilience of a country is considerably higher in countries with lower levels of corruption. This paper is in the line of other papers arguing that corruption can have a considerable negative impact on a country's economic development and detrimental effects on the economy (Mauro, 1998; Ortega, Casquero and Sanjuán, 2016; Salinas-Jiménez and Salinas-Jiménez, 2007; Transparency International, 2009), which may in turn lead to more corruption. Public finances in some heavily affected countries during these years have been under significant stress causing a high sacrifice for citizenship. But, at the same time, a growth of corruption has been observed in certain countries causing alarm and avoiding the recovery. Lamentably, Spain is a good example. Between 2007 and 2012, the financial wealth of Spanish households fell by €167 billion, the unemployment rate shot up from 8.8 to 26.2%, and the 2% public surplus turned into a 10.6% public deficit. Furthermore, the risk premium on Spanish treasury bonds reached a worrying 610-point peak in the summer of 2012. While tough measures to reduce government expenditure and public deficit were enforced, several political corruption cases were unearthed.

We are concerned about corruption and the difficulties to uncover it. Hence, we carry out the third paper of this thesis entitled: "Predicting Public Corruption with Neural Networks: An Analysis of Spanish Provinces".

In the paper, we develop a model of neural networks to predict public corruption based on economic and political factors. To develop our model, we use the information that comes from the corruption database gathered by El Mundo, one of the most influential newspapers in Spain. The database contains information about the criminal cases involving a politician or a public official reported in Spain since 2000. Unlike previous research, which is based on the perception of corruption, we use data on actual cases of corruption.

The output of our model is a set of SOMs, which allow us to predict corruption in different time scenarios before corruption cases are detected. Our model provides two main insights. First, we identify some underlying economic and political factors that can result in public corruption. Taxation of real estate, economic growth, and an increase in real estate prices, in the number of deposit institutions, and the same party remaining in office for a long time seem to induce public corruption. Second, our model provides different time frameworks to predict corruption. In some regions, we are able to detect latent corruption long before it emerges (up to 3 years), and in other regions our model provides short-term alerts, and suggests the need to take urgent preventive or corrective measures.

The remainder of this thesis is organized as follows. Sections 2, 3 and 4 review the three different papers developed during these years and whose motivation and background have been explained throughout the present Introduction. Finally, Section 5 concludes.

2. Bankruptcy visualization and prediction using neural networks: A study of U.S. commercial banks

2.1. Introduction

The recent financial crisis, the generalization and propagation of systemic risk in a more and more global financial environment, and the high social costs of bank failures have drawn attention to the mechanisms of control of banks solvency (Wang, Ma and Yang, 2014). The 2009 Basel Committee on Banking Supervision papers, widely known as the Basel III Accord,[2] advise banking regulators to develop capital and liquidity rules sufficiently rigorous to allow financial firms to withstand future downturns in the global financial system.

The Basel III Accord follows the capital agreement found in the 1988 accord, commonly known as Basel I. Basel I is enforced by law in the G10 and adopted by over 100 other countries. The goal of this 1988 roundtable was to minimize credit risk. However, innovation and financial changes in the world led to the need in 2004 for a more comprehensive set of guidelines known as Basel II. The purpose of this new framework was to promote greater stability in the financial system and reduce the social costs of financial instability. To fulfill this aim, the accord requires banks to classify their loan portfolio and identify the risks that they may face through their lending and investment practices to ensure that they hold enough capital reserves. Basel II put in place a broader view of financial risk that incorporated the differences among credit, operational, and market risk. In addition, the accord gave both supervisors and markets a wider range of action.

The collapse of a number of financial institutions in the United States at the beginning of the crisis in 2007 due to the emergence of new financial products and

[2] In December 2009, the Basel Committee on Banking Supervision published two consultative documents entitled "Strengthening the Resilience of the Banking Sector" and "International Framework for Liquidity Risk Measurement, Standards and Monitoring." Although these papers retain no other official designation, they have been widely dubbed Basel III.

risks, the fall of real estate prices, and biased pricing methods of real estate premises exposed Basel II's shortcomings. The industry clearly required new standards for supervision of financial intermediaries and new metrics of financial risk. Our paper joins the stream of analysis that examines the failures of U.S. banks in recent years. In so doing, we follow the recommendations of the G20 Finance Ministers and Central Bank Governors who met June 3–5, 2010, in Busan, Korea, and "[welcomed] the progress on the quantitative and macroeconomic impact studies which will inform the calibration of . . . new rules.".

We develop a hybrid neural network model to study the bankruptcy of U.S. banks by combining a multilayer perceptron (MLP) network and self-organizing maps (SOMs). With this contribution, we complement previous evidence and update the methods of risk assessment (Oreski and Oreski, 2014). Our aim is twofold: descriptive and predictive. First, we describe the main characteristics of U.S. distressed banks and how bank failures have evolved from the onset of the financial crisis in 2007. The implementation of our model and the analysis of the most descriptive variables provide interesting insights about the most critical features of distressed banks relative to nondistressed banks. Second, we provide a tool to predict the probability of bank failures some time before they happen. In so doing, we define three different models that are conditional on the period of time before the failure. These two objectives lead to the development of a visual tool that can assess the strengths and weaknesses of a bank in the short, medium and long term by combining the outputs of the three models in a bi-dimensional map using SOMs (Kohonen, 1993). This tool offers not only a method to detect failures but also a visual representation of when weaknesses can arise. This procedure also provides a dynamic perspective as it can assess the probability of bank failure along a period of time, unlike most previous models that are limited to a single point in time.

Reliability is concern for models of failure prediction when the time horizon goes beyond the near short term because few models achieve stable results over the time. Our work makes advances in three directions relative to previous research. First, we widen the selection of variables and implement better selection criteria based on the experience and performance of previous research. In this way we avoid the loss of predictive power due to single-period data. Second, we explicitly take into account the specific features of the recent crisis and measure credit risk in conjunction with the Basel accords. Finally, we provide three different time-horizon scenarios for failure prediction (up to three years before bankruptcy). We then combine the joint likelihood of default from each model into a visual SOM that allows us to create different profiles of risk and to extend the time horizon to evaluate the potential risk of bank failure.

We test the predictive power of our model on a sample of U.S. banks that went bankrupt between May 2012 and December 2013. We also compare our MLP-SOM results with both traditional classification models (the discriminant and logit analyses) and with more recent techniques such as support vector machine and random forest procedures. Our model, which exhibits high predictive power, predicted one year ahead 96.15% of the 52 banks that failed between May 2012 and December 2013.

Our results show that distressed banks were heavily concentrated on the real estate at the explosion of the mortgage bubble. Distressed banks carried out a strategy of quick expansion and had to pay back higher interest rates to raise enough money. The business downturn and the fall of the prices of real estate collateral resulted in a growing default rate. The poor quality of the loan portfolios of distressed banks relative to their counterparts required higher provisions. The liquidity crisis constrained the possibility of improving the solvency of the banks through equity issuance and led to a negative margin. This vicious circle could not be maintained for long, and finally financial authorities intervened.

The paper is divided into five sections. Section 2.2 reviews previous research on models of bankruptcy prediction. Section 2.3 describes the main characteristics of our hybrid NN model: the MLP and SOM methodologies. In Section 2.4, we provide the results. We provide descriptive results and the storyline of the failed banks. In this section we also compare the predictive power of the NN models with the output from traditional techniques and from other more recent approaches. Finally, in Section 2.5, we draw some conclusions from our results and offer some directions for future research.

2.2. Review of bankruptcy prediction models

Corporate and specially banks bankruptcy prediction is an important and widely studied topic in the business intelligence field (Chen, 2011a; Serrano-Cinca and Gutiérrez-Nieto, 2013; Sun, Li, Huang and He, 2014; Yu, Miche, Séverin and Lendasse, 2014; Zhou, 2013). Models of prediction have become more sophisticated to account for the effects of financial crises or other outstanding business episodes (Mokhatab Rafiei, Manzari and Bostanian, 2011; Nassirtoussi, Aghabozorgi, Wah and Ngo, 2014). Although a sharp line cannot be easily drawn, broadly speaking, two approaches exist to bankruptcy prediction: structural and empirical (Angelini, di Tollo and Roli, 2007). The structural approach is based on modeling the dynamics of firm characteristics and derives the default probability based on these dynamics. The empirical approach, rather than modeling bankruptcy on firm characteristics, gleans the default relation from the data (Atiya, 2001).

The foundations of the empirical approach can be traced to Davies and Bouldin (1979) and Ingaramo, Leguizamón and Errecalde (2005). Beaver (1966) pioneered the prediction of bankruptcy using financial statement data. His univariate analysis focused on the evolution of certain financial ratios such as financial leverage, return on assets, and liquidity and showed how these ratios worsened as long as firms faced bankruptcy. Altman (1968) and Ohlson (1980) use linear models that classify firms using financial ratios as inputs. These authors widened the scope of the model by introducing a multiple discriminant credit scoring analysis. Their models identify financial variables that have statistical explanatory power. They also introduced the logistic regression approach and used a novel set of financial ratios as inputs. Yin (2005) contributed further to the empirical approach by using a step-wise multiple discriminant analysis to distinguish between corporate future failures and successes.

From the late 1980s, artificial intelligence techniques, particularly rule-based expert systems, case-based reasoning systems, and machine learning techniques such as artificial neural networks (ANNs) have been successfully applied to bankruptcy prediction (Angelini, di Tollo and Roli, 2007; Atiya, 2001; Mukta and Kumar, 2009). Empirical approaches have been improved along the time, from the simplest and the most restrictive models to more flexible and recent ones. Some of these approaches are the statistical techniques, the neural networks, the random forest, the support vector machine, the genetic algorithm and, even, some hybrids techniques.

Compared to other empirical approaches to bankruptcy prediction, NNs have some advantages. First, as previously stated, NNs do not make assumptions about the distribution of the data. Second and interestingly, NNs allow a nonlinear set of relations. This allowance is especially important for bankruptcy predictions because the relation between the likelihood of default and the explanatory variables do not have to be linear. NNs are quite powerful and flexible modeling devices that do not make restrictive assumptions on the data-generating process or the statistical law relating variables of interest. Oreski and Oreski (2014) argued that a nonlinear approach outperforms linear models for two reasons: first, saturation effects can occur in the relation between financial ratios and the prediction of default. Second, multiplicative factors may become problematic.

The comparison between traditional models and NNs remains an open question within the literature and has led to mixed results (Bernhardsen, 2001; Fulmer, Moon, Gavin and Erwin, 1984; Ohlson, 1980). Furthermore, the choice of one method over another is usually based on several heterogeneous criteria, such as data availability. Nevertheless, in recent years, some authors have shown the superiority of NNs relative to other techniques (Hol, 2006; Lee and Choi, 2013; Levy-Yeyati, Martínez Pernía and Schmukler, 2010; Mokhatab Rafiei, Manzari and Bostanian, 2011). In particular, du Jardin (2010) who uses more than 500 ratios taken from approximately 200 previous papers, shows that an NN-based model that uses a set of variables selected with a criterion specifically adapted to the network leads to better results than a set chosen with criteria used in the financial literature.

A number of papers have shown that NNs provide a better performance than the purely linear models or the heuristic systems based on expert rules of thumb. Likewise, Piramuthu (1999) find that the bankruptcy predictions based on NNs are more precise that the ones based on the discriminant analysis. These studies compare the prediction accuracy of the back propagation methods with others and show the outperformance of NNs.

In the case of bank failures, Martínez (1996) compares back propagation methods with discriminant analysis, logit analysis and the *k*-nearest neighbour for a sample of Texas banks and concludes that the first set of methods outperforms. Similarly, the results of Vellido, Lisboa and Vaughan (1999) suggest that NNs are more able to predict commercial bank failures than the logit model. According to Wu and Wang (2000), the back propagation method outperforms discriminant analysis and human judgment in predicting bank failures. Also, Miguel, Revilla, Rodríguez and Cano (1993) show that the MLP is more successful than multivariate discriminant analysis, *k*-means cluster analysis, and logistic regression analysis in predicting the financial failure of Turkish banks.

Nevertheless, like some other approaches, NN also display some weaknesses: sometimes they can be seen like black boxes, being difficult the explanation of the prediction results and, on the other hand, NN can suffer from difficulties with generalization because of over fitting and they need a lot of time to train the models and to obtain the most adequate configuration.

Recently some new models have emerged, such as the random forest (Adusumilli, Bhatt, Wang, Bhattacharya and Devabhaktuni, 2013; Booth, Gerding and McGroarty, 2014; Calderoni, Ferrara, Franco and Maio, 2015) and the support vector machines (Czarnecki and Tabor, 2014; Harris, 2015; Horta and Camanho, 2013; Kurtulmuş and Kavdir, 2014). Random forest (RF) is a general data mining tool proposed by Breiman (2001), in which a set of decision trees is generated on bootstrap samples of the data and then combined by majority voting. Random forest tries to create different decision trees to get the best classification among different classes of data according to the dependent variable. In the financial domain, RF has been successfully implemented for credit card fraud detection (Whitrow, Hand, Juszczak, Weston and Adams, 2009) and banks customer churn prediction (Xie, Li, Ngai and Ying, 2009). But, similar to NN and simple decision trees, the random forest technique can suffer from over fitting and requires a great deal of data in order to deliver reliable predictions.

Support vector machines (SVM) use a linear model to implement nonlinear class boundaries by mapping input vectors into a high-dimensional feature space. In the new space, an optimal separating hyperplane is constructed. The maximum margin hyperplane gives the maximum separation between decision classes. The training examples that are the closest to the maximum margin hyperplane are called support vectors.

SVM has the advantage of being simple enough to be analyzed mathematically. As suggested by Min and Lee (2005), SVM may serve as a promising alternative by combining the strengths of theory-driven conventional statistical methods and data-driven machine learning methods. SVM has proved its usefulness in some financial domains such as credit ratings, the detection of insurance claim fraud, and corporate failure prediction (Angelini, di Tollo and Roli, 2007; Chen and Li, 2014; Chen, 2011b; Erdogan, 2012; Harris, 2013; Wu and Liu, 2007).

Despite this good performance, the question about whether this approach is the most suitable one to separate healthy and unhealthy banks still remains. Boyacioglu, Kara and Baykan (2009) evaluate four different neural network models, support vector machines and three multivariate statistical methods to the problem of predicting bank failures. Although SVMs provide satisfying prediction performance, these authors corroborate the superiority of MLP in prediction problems given the difficulties in the selection of the kernel and the slow behavior in the test phases. These assertions are consistent with Lee, Booth and Alam (2005).

Recent research has developed a hybrid intelligent model to combine the advantages of individual models and avoid their weaknesses (Sánchez-Lasheras, de Andrés, Lorca and de Cos Juez, 2012; Tsai, Hsu and Yen, 2014; Xu, Xiao, Dang, Yang and Yang, 2014; Zhou, Lai and Yen, 2012). A technique is called hybrid if several soft computing approaches are applied in the analysis and only one predictor is used to make the final prediction, or outputs of several predictors are combined, to obtain an ensemble-based prediction. The result of hybrid models might be more accurate than either of the techniques used separately (Kainulainen, Miche, Eirola, Yu, Frénay, Séverin and Lendasse, 2014). Consistent with this approach we also combine two kinds of networks (a MLP and a SOM) to predict banking failures. Detailed information on both networks is presented in Section 2.3.

2.3. Bankruptcy prediction model: Empirical design

2.3.1. The model for bankruptcy prediction

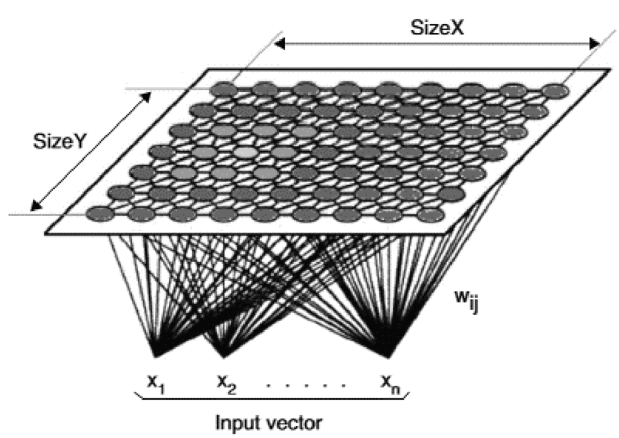
The methodology of NN is an efficient way to develop dynamic models for bankruptcy prediction because this approach takes into consideration the financial environment of firms and it offers a good tool for early warning system models (Altman, Marco and Varetto, 1994; Davis and Karim, 2008). That previous models proved unable to predict the recent wave of bank failures, primarily in the United States, does not invalidate the NN approach. Rather, it suggests the need to improve the models by considering the specific issues related to the recent global financial crisis.

In a NN application, some main issues must be defined, including the network structure and the learning and the optimization algorithm, among others. Whereas the most used network structures are layered and completely connected, the three typologies of learning mechanisms are supervised learning, unsupervised learning, and reinforced learning. Supervised learning is applied when the network must learn to generalize some given examples. Unsupervised learning is used for tasks in which regularities are sought from a large amount of data. Reinforced learning algorithms are applied to train adaptive systems that perform a task composed of a sequence of actions.

We use two kinds of networks: a MLP and a SOM. The MLP networks, which have shown their ability to predict financial distress better than other methods (Vellido, Lisboa and Vaughan, 1999), are supervised networks that assign a probability of failure at one, two, and three years ahead of the current balance information. MLPs, which usually consist of one input, one hidden layer, and one output layer, create a classificatory and pattern detection process. For the hidden layer to serve any useful function, multilayer networks must have nonlinear activation functions for the multiple layers. The backpropagation algorithm is one of the most widely applied methods to layered feedforward networks (Huang, Li and Xiao, 2015; Wang, Zeng and Chen, 2015). Learning occurs in the perceptron by changing connection weights after each piece of data is processed, based on the amount of error in the output compared to the expected result.

The SOM, which is an unsupervised network, creates a visual representation of banks according to their profile of risk in different periods of time. In this kind of network, neurons learn in an unsupervised way because the network is not required to provide a specific objective. Thus, the network must discover the common patterns among the inputs; in other words, the neurons must self-organize conditional on the outside data. SOMs are competitive networks so that the neurons compete to provide the right answer, with only one neuron (or one node of neurons) becoming activated when a data pattern is presented.

Figure 1. SOM graphical representation



As shown in Figure 1, in the SOM the neurons of the input layer are connected with all the neurons of the output layer through synaptic weights. Thus, it is possible to establish in a bi-dimensional map different zones such as failing and non-failing regions and create bankruptcy trajectories (Chen, Ribeiro, Vieira and Chen, 2013;

Chen, Ribeiro, Vieira, Duarte and Neves, 2011; Kiviluoto, 1998; Serrano-Cinca, 1996). Nour (1994) summarizes a SOM learning algorithm as follows:

1. As the first step, in t=0 $W_i(t)$ is set randomly. In this moment the maximum number or possible iterations in the training phase of the network (T) is defined.

2. Present an input vector X to the network, and compute the distance (similarity) D using the Euclidean metric to find the closest matching unit c, to each input vector.

$$d_{i,j,(t)} = \sqrt{\sum_{h=1}^{k} \left(W_{i,j,h} - X_k\right)^2}$$

3. Update the weight vector according to the following rule:

$$W_{jik}(t+1) = W_{jik}(t) + \alpha \cdot \left[X_k(t) - W_{jik}(t)\right]$$

   where α is the learning ratio, $X_k(t)$ is the input pattern in t and $W_{jik}(t)$ is the synaptic weight that connects the k input with the (j,i) neuron in *t*. The neighborhood function allows actualizing the weights of the winning neuron and of the neighbor neurons to localize similar patterns too. The neighborhood radio decreases with the number of iterations of the model to achieve a better specialization for each neuron.

4. The process goes on an iterative way until *t* reaches the maximum number of iterations T and then it jumps back to step 2.

We use the MLP to create three different prediction models of failure depending on the time horizon that we cover. First we develop a model with the most predictive ratios to detect failures one year before the failure happens. Then, we iterate the procedure with information from two and three years before the bankruptcy, respectively. We combine the output of all these models (i.e., the default likelihood of each bank in each year) to build a SOM. Our aim is to identify failing and non-failing areas to create a bi-dimensional map that enhances the study of different risk profiles.

This map provides a visual representation of the risk profile of each bank and can be a useful tool for supervisor authorities who may take preventive measures in a weak bank some time before the failure arises.

2.3.2. Empirical design of the model

We obtain our data from the Federal Deposit Insurance Corporation (FDIC). All U.S. banks must report their financial statements quarterly in the Uniform Bank Performance Report so that the information then becomes publicly available. For each bank, this report includes information about the bank's loans portfolio, default rate, capital composition, liquidity, and so on. We select a set of 32 variables that are potentially explanatory for bankruptcy risk. Most of these variables have been previously used by other authors, which enhances the comparability of our results (Hammer, Kogan and Lejeune, 2012; Lin, Liang and Chen, 2011; Martínez, 1996; Nour, 1994). Consistent with du Jardin (2010), we also add some variables suitable to control for specific features of the current global financial crisis. These variables are selected with a criterion adapted to the network to improve the results of the model. We report the name and definition of the all initial variables in Table 1. Ratios are grouped into five different sets of variables: Ratios 1–14 measure the bank's earnings, ratios 15–21 assess the asset structure of each bank, ratios 22–25 go deeper on the assets and assess the loan portfolio, ratios 26–29 measure risk concentration, and ratios 30–32 are related to solvency. This approach is close to the CAMEL rating system established by the FDIC to conduct banking supervision.

Table 1: List of variables and definition

Classification	Name	Calculation
Performance	INC	Interest income/Average assets
Performance	EXP	Interest expense/Average assets
Performance	NET_INC	Net interest income/Average assets
Performance	NON_INC	Noninterest income/Average assets
Performance	NON_EXP	Noninterest expense/Average assets
Performance	PROV	Provision for loans and leases receivables losses/Average assets
Performance	EASST	Average earning assets/Average assets
Performance	LNLCR	Gross loans and lease charge-off less gross recoveries/Average total loan and leases
Performance	EFFCY	Efficiency ratio (Average total costs/Total assets)
Performance	ASST	Average assets per employee (millions)
Performance	YLD_LNLS	Yield of total loans and lease/Average total loans
Performance	YLD_DOM	Yield of interest and fees on domestic office loans secured primiraly by real state/Average domestic real state loans
Performance	MBS_YLD	Interest on mortgage backed securities (MBS)/ Average MBS
Performance	HIGH_INT	Cost of interest on deposits higher $100,000/Average deposits higher $100,000
Asset structure	BAL	On average, all interest-bearing balances due from depository institutions/Total assets
Asset structure	NLLA	The sum of the averages for net loans and lease-financing receivables, held-to-maturity and available-for-sale securities, interest-bearing balances due from depository institutions, federal funds sold and resold, and trading-account securities/Average total assets.
Asset structure	FIX	Average of bank premises,furniture,equipment and others/Total assets
Asset structure	PREM	Average real estate owned other than bank premises/Average total assets
Asset structure	MMDA	Average money market deposit account/Average total assets
Asset structure	DEP	Total deposits as a percent of average assets
Asset structure	TMDEP	The sum of the averages for time certificates of deposit of $100,000 or more and other time deposits in amounts of $100,000 or more/Average total assets
Loan portfolio	LNLL	Gross loan and lease losses/Average total loans and leases
Loan portfolio	LNLR	Gross loan and lease recoveries/Average total loans and leases
Loan portfolio	OFCR	Credit to the bank’s executive officers, main shareholders as of the report date/Total loans
Loan portfolio	OFCR_ASST	Credit to the bank’s executive officers, main shareholders/total assets
Concentration	CONS	Construction, land development and other land loans plus closed end loans secured by family residential properties first liens plus revolving open-end loans plus loans secured by farmland plus secured by nonfarm nonresidential propertiesas a percentage of total capital
Concentration	CMID	Commercial and industrial loans to U.S. addressees in domestic offices plus commercial and industrial loans to non-U.S. addressees in domestic offices as a percentage of total capital
Concentration	CARDO	Credit card plans in domestic offices plus other revolving credit plans in domestic offices plus other consumer loans in domestic offices as a percentage of total capital

Concentration	REAL	Real estate loans 90+ day past due
Capital	LNEQ	Number of times net loans and lease-financing receivables exceed equity capital
Capital	NET_INCEQ	Net income/Average total equity capital
Capital	RISK	Total risk-based capital/Risk-weighted assets.

Our training sample covers the period from December 2002 to May 2012. We test the predictive power of our model by applying it to banks that actually went bankrupt between May 2012 and December 2013. Between 2003 and 2013, the FDIC reported 516 U.S. banks failures. However, given our set of variables, the necessary information was available for only 386 banks. This sample size of distressed banks is consistent with previous research (Bernhardsen, 2001; Chen, 2011b; Ingaramo, Leguizamón and Errecalde, 2005; Moro, Cortez and Rita, 2015).

To isolate the main drivers of bankruptcy, we select a random sample among the remaining U.S. FDIC member banks. In bankruptcy analyses, it is a common practice to use one-to-one match of failure and non-failure cases (Davies and Bouldin, 1979; Kurtulmuş and Kavdir, 2014; Wu and Liu, 2007). Consequently, our training sample is made up of 386 failed and 386 non-failed banks. Since most of our explanatory variables are ratios, it is expected that these variables may have fat tails with large positive and negative values, so that outliers can have a negative influence on the model performance. We follow the procedure suggested by Van Gestel, Baesens, Van Dijcke, Garcia, Suykens and Vanthienen (2006) for outliers handling. The boundaries are defined using the winsorized mean procedure, where the maximum (and minimum) allowed values are defined by median $(x) \pm 3 \cdot \sigma$, with $\sigma = \mathrm{IQR}(x)/2 \times 0.6745$ and IQR is the interquartile range. The sample test is made up of 52 banks that went bankrupt between May 2012 and December 2013 and other 52 non-failed banks. Table 2 reports some descriptive statistics of our sample. Table 2 also displays the Kolmogorov–Smirnov normality test. Because several of the variables are not normally distributed, the Mann–Whitney U test is more reliable than the *t*-Student test to compare the differences between failed and non-failed banks. We denote with a number suffix if the variable is reliable to compare failed banks and non-failed banks one, two and three years before the fail. As we can see, variables (e.g., BAL and MMDA) display noticeable changes in discriminant power across time.

Table 2: Descriptive analysis of the sample

Mean, standard deviation, minimum, maximum, percentiles, the Kolmogorov–Smirnov (significance) test of normality and the U Mann–Whitney tests. See Table 1 for variable definitions.

Variable	Mean	Std. Dev.	Min	Max	25%	50%	75%	Z K-S	U1	U2	U3
INC	5.23	1.16	1.39	17.31	4.53	5.11	5.86	1.59 (0.01)	0.00	0.07	0.00
EXP	2.15	0.88	0.00	4.75	1.50	2.09	2.72	1.16 (0.13)	0.00	0.00	0.00
NET_INC	3.08	1.14	–0.24	17.30	2.41	3.11	3.75	1.74 (0.01)	0.00	0.00	0.15
NON_INC	0.88	5.61	–7.01	131.78	0.14	0.42	0.78	10.82 (0.00)	0.00	0.00	0.00
NON_EXP	3.87	5.60	0.33	123.85	2.60	3.18	3.96	8.85 (0.00)	0.00	0.92	0.92
PROV	2.17	2.40	–0.35	17.09	0.33	1.22	3.54	4.86 (0.00)	0.00	0.00	0.00
EASST	92.38	5.51	35.72	103.88	90.48	93.31	95.73	3.25 (0.00)	0.06	0.06	0.00
LNLCR	2.34	2.89	–0.53	32.00	0.27	1.25	3.69	5.48 (0.00)	0.00	0.00	0.00
EFFCY	129.20	258.94	–916.43	5,812.00	64.85	85.05	137.81	9.47 (0.00)	0.00	0.00	0.05
ASST	4.99	2.98	0.24	42.60	3.32	4.36	5.77	4.30 (0.00)	0.00	0.00	0.00
YLD_LNLS	6.46	2.57	3.24	69.20	5.55	6.24	6.97	5.88 (0.00)	0.00	0.04	0.00
YLD_DOM	6.45	2.58	3.07	69.20	5.54	6.22	6.96	5.85 (0.00)	0.00	0.05	0.00
MBS_YLD	4.40	1.72	0.00	29.72	3.80	4.54	5.12	3.77 (0.00)	0.49	0.34	0.12
HIGH_INT	3.21	1.11	0.00	6.74	2.33	3.21	4.02	1.09 (0.18)	0.00	0.00	0.00
BAL	3.68	5.37	0.00	49.12	0.16	1.61	5.03	6.85 (0.00)	0.00	0.27	0.74
NLLA	90.47	4.67	27.30	98.47	88.39	91.25	93.51	2.76 (0.00)	0.00	0.41	0.01
FIX	2.03	1.67	0.00	14.31	0.84	1.63	2.82	3.13 (0.00)	0.26	0.34	0.32
PREM	1.60	2.47	0.00	16.66	0.08	0.59	2.03	7.16 (0.00)	0.00	0.00	0.00
MMDA	12.49	10.23	0.00	66.91	5.26	9.98	17.23	3.12 (0.00)	0.16	0.74	0.05
DEP	63.18	11.93	0.00	87.74	56.67	64.17	70.81	1.70 (0.01)	0.00	0.00	0.00
TMDEP	19.33	10.21	0.00	61.53	11.73	17.97	25.21	2.02 (0.00)	0.00	0.00	0.00
LNLL	2.45	2.97	0.00	32.71	0.33	1.33	3.77	5.66 (0.00)	0.00	0.00	0.02
LNLR	0.12	0.34	0.00	7.67	0.01	0.04	0.12	10.17 (0.00)	0.00	0.01	0.00
OFCR	2.00	2.56	0.00	25.27	0.29	1.33	2.79	6.01 (0.00)	0.01	0.46	0.49
OFCR_ASST	1.34	1.54	0.00	13.12	0.18	0.89	1.95	5.32 (0.00)	0.28	0.31	0.02
CONS	2,040.21	27,258.56	–27,045.46	750,687.50	408.11	668.86	1,240.75	12.48 (0.00)	0.00	0.00	0.00
CMID	311.88	3,548.07	–2,786.49	91,968.75	50.45	97.36	181.84	12.30 (0.00)	0.00	0.00	0.09
CARDO	61.22	514.37	–761.54	13,466.67	8.76	22.23	52.76	12.05 (0.00)	0.00	0.00	0.00
REAL	9.04	9.56	0.00	53.79	1.36	5.66	14.59	4.76 (0.00)	0.00	0.00	0.00
LNEQ	35.84	413.11	0.00	11,071.42	6.39	9.19	17.80	12.76 (0.00)	0.00	0.00	0.00
NET_INCEQ	–40.67	67.34	–563.79	98.03	–74.86	–14.62	6.77	4.38 (0.00)	0.00	0.00	0.00
RISK	766,183.98	8,222,516.17	1,493.80	222,501,589.20	64,683.53	142,636.65	340,695.63	12.86 (0.00)	0.00	0.00	0.00

Table 3: Power predictive of each variable and means in each model

	1 year before the failure			*2 years before the failure*			*3 years before the failure*		
Variable	*Non-failed*	*Failed*	*Gini index (%)*	*Non-failed*	*Failed*	*Gini index (%)*	*Non-failed*	*Failed*	*Gini index (%)*
INC	5.24	4.87	26.74	5.90	6.09	7.33	6.31	6.86	30.49
EXP	1.70	2.41	43.48	2.12	2.88	45.71	**2.34**	**3.09**	**50.22**
NET_INC	3.63	2.50	66.44	3.78	3.20	39.30	3.97	3.76	12.12
NON_INC	0.92	0.41	43.72	1.04	0.59	33.67	0.87	0.59	29.70
NON_EXP	3.26	3.78	18.28	3.51	3.53	6.36	3.62	3.71	0.15
PROV	**0.69**	**3.46**	**76.20**	**0.53**	**1.97**	**62.42**	**0.37**	**1.06**	**45.90**
EASST	92.47	91.80	7.14	93.22	93.17	2.56	93.37	94.00	10.75
LNLCR	0.80	3.84	74.97	0.68	1.72	44.01	0.36	0.80	22.96
EFFCY	74.46	179.89	66.60	75.75	101.75	34.43	74.77	93.46	13.40
ASST	4.38	5.51	30.41	4.19	5.32	34.73	4.08	5.00	32.94
YLD_LNLS	6.71	5.98	43.57	7.25	7.10	8.50	7.71	7.94	12.87
YLD_DOM	6.70	5.98	42.89	7.24	7.10	8.21	7.70	7.94	13.46
MBS_YLD	4.58	4.31	31.71	4.69	4.83	38.73	4.92	5.47	39.36
HIGH_INT	2.84	3.23	17.68	3.67	4.02	18.05	4.11	4.41	22.48
BAL	3.72	4.33	10.23	2.40	1.94	3.66	1.74	1.12	1.26
NLLA	91.40	89.17	31.98	91.55	90.98	6.66	91.85	92.08	6.53
FIX	1.78	2.20	8.67	1.83	2.18	6.85	1.86	2.11	4.57
PREM	0.62	3.06	62.27	0.40	1.43	43.45	0.23	0.60	22.00
MMDA	13.41	11.98	6.47	13.09	12.70	0.82	12.85	13.56	5.65
DEP	66.37	63.12	1.38	65.94	59.86	26.72	**66.15**	**58.15**	**41.00**
TMDEP	16.26	21.51	44.78	16.38	21.86	34.84	15.52	22.39	40.21
LNLL	0.89	4.00	74.06	0.78	1.80	40.70	0.44	0.84	16.74
LNLR	0.09	0.15	8.08	0.09	0.08	14.86	0.08	0.04	23.40
OFCR	2.03	1.80	4.54	2.09	2.19	2.86	2.29	4.45	3.08
OFCR_ASST	1.28	1.31	0.13	1.34	1.62	7.91	1.39	1.80	10.16
CONS	**463.10**	**3675.16**	**80.14**	**450.83**	**789.10**	**66.21**	**431.64**	**658.04**	**56.11**
CMID	90.23	547.60	42.45	91.57	119.33	15.30	91.23	102.90	7.81
CARDO	36.90	79.42	11.51	38.66	22.40	35.52	41.44	20.75	40.70
REAL	**145.97**	**244.74**	**80.17**	**2.33**	**8.11**	**60.30**	1.49	3.92	33.32
LNEQ	**6.56**	**66.94**	**89.61**	**6.44**	**10.48**	**60.09**	**6.32**	**8.41**	**42.37**
NET_INCEQ	**2.42**	**–83.74**	**91.26**	**5.16**	**–20.18**	**58.55**	7.85	–1.55	27.64
RISK	411,159.76	506,968.28	24.01	405,422.65	545,675.16	30.55	378,166.09	540,985.14	31.96

Note: See Table 1 for variable definitions.

Once we test the ability of the initial variables to detect differences between failed and non-failed banks, we have two possibilities for the selection of the most relevant variables. First, we can choose a set of ratios with low variation in their predictive ability across time. Second, we can use the most predictive ratios for each time horizon and design different models conditional on the time horizon considered. We balance both alternatives and opt for designing specific models for each time horizon and at the same time use the ratios with a certain stable predictive power. In any case, the complexity of such a process and the fact that the variables are not normally distributed advice the implementation of complex computational methods such as NNs (Lin, Shiue, Chen and Cheng, 2009).

We complement the information from the Mann–Whitney test with the Gini index to assess the predictive power of the variables. This index is one of the most widely used tools for calibration and a metric of the model's ability to classify correctly the dependent variable. It provides a relative metric of how close an actual model or a variable is to the ideal model of prediction. The highest score is 100%, and the lower the index, the worse the predictive power of the model. To some extent, this process is a univariate predictive analysis that allows us to accomplish one of our objectives, namely, the identification of the characteristics of the banks likely to go bankrupt. By calculating the individual predictive power of each variable, we can assess its relative impact and its evolution across time. Depending on its degree of influence, this variable can be reinforced or dropped from the calibration process.

In Table 3 we report the predictive power for each variable and model, along with the Gini test for the differences between failed and non-failed banks. We select the variables with the highest predictive power for each period of time. The number of selected variables (in grey shadow and bold font) is, to some extent, an ad-hoc decision that must balance the advantages and disadvantages of choosing many variables. Too few variables can result in poor predictive power of the model;

conversely, too many variables can lead to an overly complex model, with redundant information, higher computational costs, and the loss of some observations. Accordingly, we order the variables according to the Gini index and the Mann–Whitney test and select the variables with low correlation.[3]

Each MLP model is implemented using PASW20 software. The dependent variable is a dummy variable that equals 1 if the bank has gone bankrupt, and zero otherwise. The model's output is a set of relations among variables that explains bank defaults. Each model tries to predict bankruptcy for a different time horizon prior to the event. The MLP1 model predicts bank failures one year ahead; MLP2, two years ahead; and MLP3, three years ahead. Obviously, the shorter the difference between the year analyzed and the bankruptcy, the better the performance of the model is. The next step is to gather the output of each model in a SOM to define different risk profiles of banks depending on the areas of the map.

The prediction model is a set of three MLPs (MLP1, MLP2, and MLP3, depending on the time horizon for the bankruptcy prediction). Nine different variables are included in the three models (five in MLP1, four in MLP2, and five in MLP3). In Table 4, we provide the Pearson correlation coefficients among the most predictive variables included in the MLP1 model.[4]

Table 4: Correlation matrix in the MLP1 model

Variable	*NET_INCEQ*	*LNEQ*	*CONS*	*EFFCY*	*PREM*
NET_INCEQ	1	–0.152	–0.056	–0.233	–0.355
LNEQ	–0.152	1	–0.003	0.029	0.017
CONS	–0.056	–0.003	1	–0.062	0.163
EFFCY	–0.233	0.029	–0.062	1	0.237
PREM	–0.355	0.017	0.163	0.237	1

Note: MLP1 = multilayer perceptron model for one year ahead bank failures. See Table 1 for variable definitions.

When designing a multilayer network, two decisions are key. First, we must choose the right number of layers to maximize the accuracy and the precision of the

[3] Two variables with high predictive power cannot be chosen simultaneously if they are highly correlated.

[4] All the correlations matrix are available on request for each model.

model. Lee, Booth and Alam (2005) and Zhang, Hu, Patuwo and Indro (1999) show that models with one hidden layer can deal with most of the classification problems. The second decision concerns the number of neurons or units in the hidden layer. This number is an important part of the overall NN architecture and must balance two counteracting effects: Too many units can result in a problem of over fitting, and too few units can lead to an under fitting network (Khashman, 2010). Comparable research such as Sharda and Wilson (1996) and Tam and Kiang (1992) uses one hidden layer with 10 nodes, whereas Boritz and Kennedy (1995) use a single hidden layer with 9 nodes. The optimal number of nodes must provide the highest classification accuracy in the hold-out sample. This number can be chosen by trial-and-error tests or according to the formula 0.75i where i = 1,. . . , I represents the number of variables under consideration (Harris, 2015; Olmeda and Fernández, 1997). We implement both procedures, and both suggest using four nodes in the MLP1 model, three nodes in MLP2, and four nodes in the MLP3 model. The change of scale to activate the hidden layer and to obtain the output layer is a sigmoid function.

The network must go through a learning process, which can be either online, batch, or stochastic. Although it requires more memory capacity, we use the batch learning because it yields a much more stable descent to the optimal adjust to the patterns. The rest of parameters are similar to the ones used in previous literature, with initial lambda of 0.0000005, initial sigma of 0.00005, the center of the interval fixed around zero, and displacement of +/–5. The optimization algorithm is the scaled conjugated gradient.

2.4. Results

This section reports the main results of our empirical analysis. First, we analyze the evolution of failed banks before the failure according to the variables considered in this study. Second, we describe the results of the models using the MLP. Then, we combine the MLP output with the SOM model and show the results. We also compare our models with some common approaches in the literature such as the discriminant analysis, the logistic regression, support vector machines and random forest.

2.4.1. The storyline of distressed banks

As previously stated, in Table 3 we report the predictive power of the 32 initial variables for each year according to the Gini index. Significant differences exist among their predictive power. The table provides some interesting insights about the evolution of distressed and non-distressed banks up to three years before bankruptcy. These results contribute to our first objective concerning the identification of the main characteristics of defaulted banks prior to their bankruptcy.

The shadowed cells are the five most significant variables one, two, and three years before the failure. We can differentiate three kinds of variables. The first group includes the variables with high predictive power both in the near future (one year) and in the medium-long term (two or three years). These variables are PROV (the importance of provisions), CONS (risk concentration on the construction industry), and LNEQ (equity support to loans). According to these variables, failed banks relative to the profile of non-failed banks have higher provisions (likely as a consequence of riskier loans), are more concentrated on financing construction and residential properties, and have less equity relative to loans. Furthermore, the differences increase as the bank failure approaches. For instance, whereas the provision ratio (PROV) for failed banks is 2.86 times the ratio for non-failed banks (1.06 to 0.37) three years ahead, this proportion increases to 5.01 (3.46 to 0.69) the year before the financial distress. The same can be said for the concentration on the construction industry and for the equity.

The second group of variables includes the ones whose relative predicting power decreases as the bank failure approaches. These variables are EXP (interest expenses) and DEP (deposits). Table 3 shows that failed banks consistently pay higher interests than their non-failed counterparts over time, despite the decrease in the predicting power. Similarly, the proportion of deposits over total assets is initially lower in failed banks so that these banks are more leveraged.

The third group of variables includes the ones whose predicting power increases one or two years before the failure, namely, REAL (overdue real estate loans) and NET_INCEQ (income to equity). Once again, remarkable differences exist between both kinds of banks: Specifically, failed banks have more overdue loans to the real estate industry and receive lower income (even scaled by equity).

Taken together, these results provide a clear portrait of the crisis of U.S. banks in recent years. As a consequence of the U.S. business upturn fueled by low interest rates, financial institutions expanded rapidly to gain market share as quick as possible. The real estate boom along with low interest rates compelled banks to grant loans to construction and land development irrespective of the credit quality. Distressed banks had to pay back higher interest rates to depositors to raise money to reinvest in the real estate industry. Due to the business downturn in 2008 and 2009, along with the fall of the prices of real estate collateral, these banks faced a growing default rate, had to create more provisions, and accumulated a troublesome portfolio of real estate. The provisions impacted earnings negatively, and the solvency of the banks worsened. The liquidity crisis constrained the possibility of improving the solvency of the banks through equity issuance, and banks had to pay higher interest rates. These growing interests on deposits along with troublesome loans led to a negative margin. This vicious circle could not be maintained for long time, and finally financial authorities intervened.

2.4.2. The MLP model to predict failures

The predictions about possible future bankruptcies are done through models MLP1 to MLP3, and the results are reported in Table 5. This table provides more detailed information on the comparison among models. We measure the power of the models through receiver operating characteristic (ROC) curves. The ROC curves convey the same information as the confusion matrix but in a more visual, intuitive, and robust way (Lee and Choi, 2013). The accuracy of the test depends on how well the model separates failed and non-failed banks. The area below the ROC curve is 1 when the model has a complete discriminatory power and 0.5 when the model has no discriminatory power. As shown in Table 5, the performance of all our models is quite acceptable, and it increases as the bank moves closer to the failure date: that is, the closer the bank is to failure, the lower the training and trial squared errors are and the higher the area is below the ROC curve.

Table 5: Performance of each model

Model	*Training squared errors*	*Trial squared errors*	*Area below ROC*
MLP3	106.978	7.738	0.87
MLP2	90.097	5.660	0.91
MLP1	60.403	2.500	0.95

Note: ROC = receiver operating characteristic. MLP1 (MLP2; MLP3) = multilayer perceptron model for one (two; three) year ahead bank failures.

To assess the performance of NNs as banking failure prediction methods, we compare the discriminatory power with the output of two traditional techniques (the discriminant analysis and the logistic regression) and with two more recent and flexible models (support vector machines and random forest). Table 6 shows the correct classification rates of the five methods. Three main issues arise from this table. First, there are two models (MLP and SVM) with better performance than the other ones. Both form non-failed banks and for failed banks irrespective of the time framework, MLP and SVM deliver higher correct classification rates. Second, for non-failed banks, MLP usually outperforms SVM. Third, for failed banks, MLP outperforms SVM in the short term (one year before failure) but SVM outperforms in the medium-long term (two and three years before failure). Taken together, these results corroborate the superiority of the flexible and emerging techniques over the traditional methods and a certain outperformance of MLP. These results are consistent with previous research (Chen, Ribeiro, Vieira and Chen, 2013).

Table 6: Models comparison

Correct classification rates for alternative models: discriminatory analysis (DA), logit regression (LR), random forest (RF), multilayer perceptron (MLP) and support vector machine (SVM).

	Years before failure		
Method	*1 (%)*	*2 (%)*	*3 (%)*
Non-failed banks			
DA	78.85	76.92	71.15
LR	82.69	84.62	76.92
RF	88.46	76.92	75.00
MLP	92.31	86.54	84.62
SVM	90.38	88.46	82.69
Failed banks			
DA	76.92	71.15	69.23
LR	80.77	78.86	73.08
RF	86.54	80.77	76.92
MLP	94.23	84.69	80.77
SVM	88.46	86.54	82.69

NNs have sometimes been criticized for being like black boxes because the manner in which they receive the inputs and provide the output is not very transparent. The complexity of the mathematical and algorithmic elements makes the flow of information through the net difficult to understand. One of the most widely used methods to cope with this criticism is the so-called sensitivity analysis (Garson, 1991; Hunter, Kennedy, Henry and Ferguson, 2000; Rambhia, Glenny and Hwang, 1994; Zurada, Malinowski and Cloete, 1994). The sensitivity analysis is based on measuring the observed effect on an output Y_j due to the change in an input X_i: the bigger the effect, the more sensitive. Figures 2 to 4 show the results of each sensitivity analysis. The importance of an independent variable is a measure of how much this variable affects the probability of distress. As shown in Figure 3, for the predictions one year ahead of bankruptcy, the most important variable is net income as a percentage of total capital, followed by the efficiency ratio and total loans to construction and real estate. Figures 4 and 5 show that during the years prior to bankruptcy the most determinant variables of the possibility of banking failure are provisions and interest expenses.

Figure 2: Sensibility analysis one year before the failure (MLP1 model)

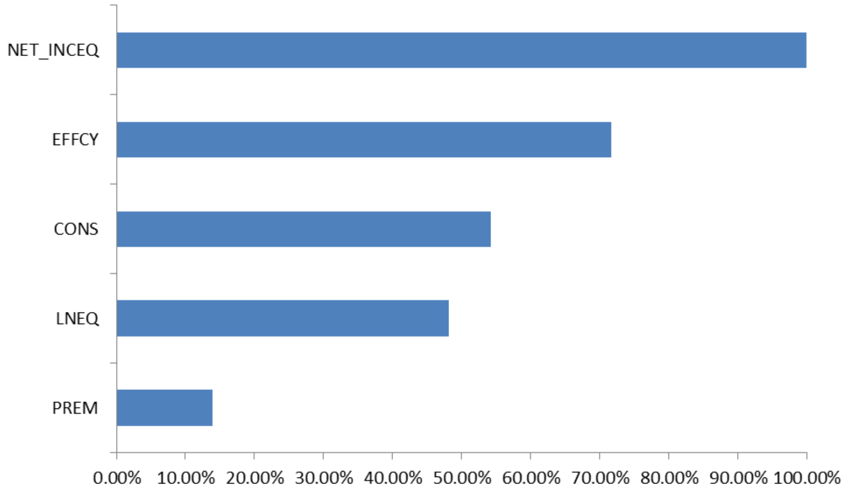


Figure 3: Sensibility analysis two years before the failure (MLP2 model)

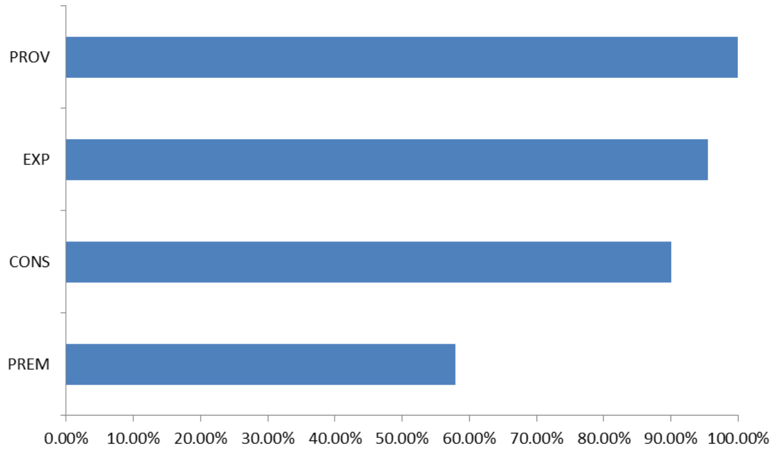


Figure 4: Sensibility analysis three years before the failure (MLP3 model)

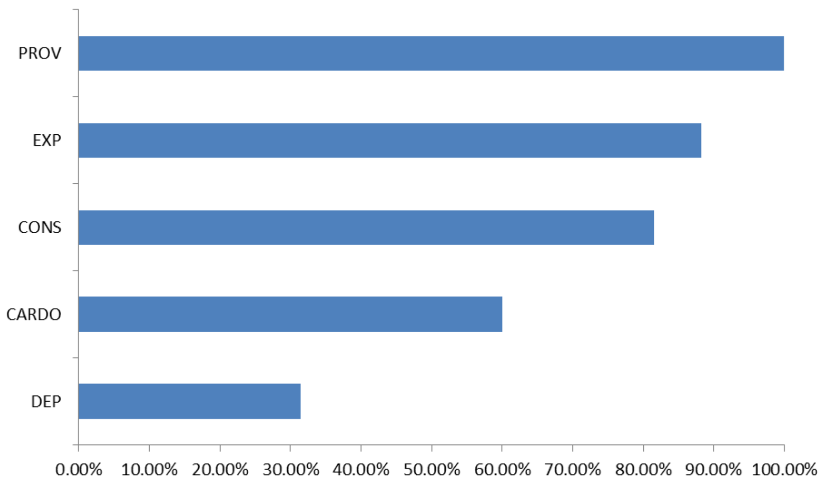
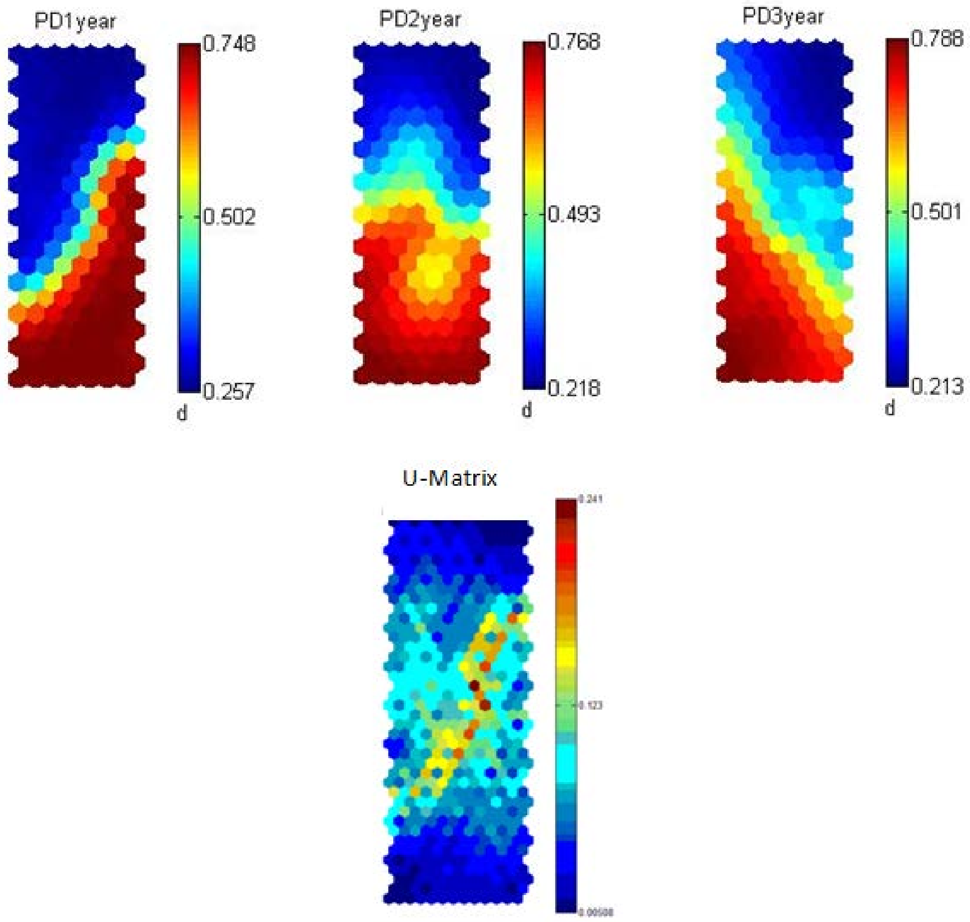


Figure 5: Learning results of SOM



2.4.3. SOM to monitor potential bank risk

Once we have checked the validity of the MLP method for bankruptcy prediction, we gather the output of the models to create a visual tool to detect the risk of bank failure. Similar to other prediction models that provide a dichotomous output (i.e., failing vs. non-failing entities), SOM models give a wide range of intermediate possibilities. In this sense, SOMs are an interesting tool for decision-making due to their capability to project multidimensional data onto a less dimensional output space. We first combine the output of the MLP models (i.e., the likelihood of default one, two, and three years ahead) to create a map in which healthy banks are displayed clearly away from unhealthy banks. We then differentiate more groups inside the unhealthy banks area to assess dynamically the solvency and the potential risks of each bank across time. In so doing, the model provides a time framework with information about how long before the bankruptcy the threats arise, so that correctional measures can be taken to reverse the situation and avoid the failure.

To build the map we use the same training and test samples as in the previously reported models. The first layer of the net has three input patterns, and the output layer is a bi-dimensional 21×7 map. The size of the map follows the recommendations of Kohonen (1993) and Kaski and Kohonen (1994). The results of the training phase are shown in Figure 5. In the so-called U-matrix we display the distances among the neurons by training the model. Different colors represent the varying distances: light colors for short distances and dark colors for long distances. Given the bi-dimensional nature of the map, the differences and distances among neurons can proxy possible groups of neurons or clusters. Thus, the U-matrix can be a useful tool for visualizing clusters in the input data without any a priori information about these clusters.

The other three figures in Figure 5 show the density function of the bankruptcy probability for each year. They enhance the visualization of the cluster structure and the correlation among the input variables. The bottom areas comprise the banks with the highest default probabilities, and the upper areas comprise the most solvent banks. Figure 6 complements Figure 5; in Figure 6 we display the neurons distribution on the map and draw a line to differentiate the solvency zone (blue area) and the bankruptcy zone (red area). We use the proportion of failed and non-failed banks in the sample to label each neuron as failed or non-failed.

The bankruptcy area is bigger than the solvency area and accounts for 58.5% of the cells. If we apply this map to the test sample, the model predicts 98.08% of the bank failures one year ahead. This result means that the Type I error is 1.52%. In addition, the model correctly classifies 94.23% of the non-failed banks, so the Type II error is 5.77%.

Chen (2011b) suggests some advanced metrics to assess the quality and to compare different classification models. In Table 7 we report the performance of our hybrid model and the comparison with the other techniques. The overall accuracy is the percentage of correctly classified instances. Precision is defined as the number of classified positive or abnormal instances that actually are positive instances. Sensitivity measures how well a classifier can recognize abnormal records. Specificity refers to how well a classifier can recognize normal records.

Table 7: Classification results by model

Performance (in percentage) of the classification models. The overall accuracy is the percentage of correctly classified instances. Precision is the number of classified positive or abnormal instances that actually are positive instances. Sensitivity is how well a classifier can recognize abnormal records. Specificity is how well a classifier can recognize normal records. Discriminatory analysis (DA), logit regression (LR), random forest (RF), multilayer perceptron (MLP) and support vector machine (SVM) are compared.

	Overall accuracy			Precision			Sensitivity			Specificity		
	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
DA	77.88	74.04	70.19	78.43	75.51	70.59	76.92	71.15	69.23	78.85	76.92	71.15
LR	81.73	81.73	75.00	82.35	83.67	76.00	80.77	78.85	73.08	82.69	84.62	76.92
RF	87.50	78.85	75.96	88.24	77.78	75.47	86.54	80.77	76.92	88.46	76.92	75.00
MLP	93.27	85.58	82.69	92.45	86.27	84.00	94.23	84.62	80.77	92.31	86.54	84.62
SVM	89.42	87.50	82.69	90.20	88.24	82.69	88.46	86.54	82.69	90.38	88.46	82.69
MLP-SOM	96.15	90.38	84.62	94.44	92.00	87.50	98.08	88.46	80.77	94.23	92.31	88.46

We note a gap between the performance of MLP, SVM and our hybrid MLP-SOM model and the performance of the random forest and the traditional techniques (DA and LR). As expected, the performance of all the models deteriorates as long as the time before failure increases. Nevertheless, the decline of the MLP, SVM and MLP-SOM models is lower than the alternative models[5]. More interestingly, our hybrid method usually outperforms even the MLP and SVM procedure. In addition, the MLP-SOM model has a high and stable predictive power over the time, reaching a balance between Type I and Type II errors.

[5] For instance, in terms of overall accuracy, RF correctly classifies 87.5% of banks one year before, but only 78.85% of banks two years before. Similar results hold for other metrics and models.

2.4.4. Creating several groups of risk in the SOM

Along with the prediction on bankruptcy likelihood, another relevant output of the model is the time horizon in which a bank may fail. To improve the predictive power of the model, further clusters might be identified within the two initial groups of banks (failed vs non failed). We use k-means to create different zones in the original map displayed in Figure 6. Although several methods can be used to determine the optimal number of groups, one of the most widely used algorithms in SOM is the Davies–Bouldin index (Lin, et al., 2011). This index is a function of the within-cluster variation to the between-cluster variation ratio (Ingaramo, et al., 2005). According to this index, the optimal number of groups is six, as shown in Figure 7. Based on this classification, in Table 8 we report the mean value of the failure likelihood for each group one, two, and three years ahead.

Table 8: Probability of distress by group

Group	*Proportion of failed banks (%)*	*Mean of P.1year (%)*	*Mean of P.2years (%)*	*Mean of P.3years (%)*
Group 1	96.28	73.83	73.55	74.56
Group 2	89.87	73.12	63.01	48.64
Group 3	86.67	71.23	32.28	36.30
Group 4	57.81	33.84	68.09	71.91
Group 5	14.29	30.83	45.66	48.70
Group 6	2.30	27.02	25.34	26.46

In the same vein, Table 9 reports the values of the main variables by group. The comparison of these probabilities with the actual rate of bankruptcy provides some interesting insights on the timing of the bankruptcy symptoms. Banks in group 1 have important weaknesses over the entire period, both in the short and long term. Banks in groups 2 and 3 are examples of short-term concerns but not long-term concerns: although they have high rates of failure, these bankruptcies are difficult to predict three years ahead. Banks in group 4 are in the opposite situation: the probability of distress decreased across time so that failures are difficult to predict one year prior to bankruptcy. Finally, banks in groups 5 and 6 have the lowest rate of predicted failure, and, in fact, their actual rate of failure is lower than their predicted rate for both the short and the long term.

Table 9: Average of the main variables by group

Group	*REAL*	*EXP*	*CONS*	*LNEQ*	*NET_INCEQ*	*DEP*	*PROV*
1	95.53	2.80	2,179.76	36.69	–43.05	60.51	2.48
2	100.83	2.68	1,034.75	17.78	–31.51	62.12	2.10
3	24.59	2.51	710.85	11.33	–23.92	62.24	1.41
4	14.85	2.91	712.36	9.09	–5.01	56.96	1.26
5	3.07	2.53	575.20	7.70	6.00	60.13	0.80
6	64.31	1.88	381.71	5.84	8.55	68.08	0.29

Note: See Table 1 for variable definitions.

The proportion of bank failures inside each group is complemented by the mean of the most predictive variables as previous discussed (Table 3). The differences between groups 1, 2, and 6 are considerable for all the variables; namely, group 6 has lower level of expenses, construction exposure, provisions, and real state past due and a higher level of deposits compared to the other two groups. However, banks that are clearly identifiable as "safe" or "non-safe" are not a big challenge to regulators and policymakers. They are more likely interested in the intermediate groups—that is, groups 3, 4, and 5—because they may be a threat in a short or medium term. The first two groups (groups 3 and 4) are very close; however, in group 4 all the variables improve slightly, particularly real state past due and net income to total equity. As noted previously, these slight differences contribute to change in the risk profile across time. Threats in group 4 are derived of high levels of construction loans and an increase in the level of expenses of provisions. The probability of default is moved to two or three years ahead considering potential worsening of the economy and the increase in past due loans. Also the importance of deposits in the financial structure of the banks is lower than the other groups. These results suggest that regulators should place their highest priority on group 3 and their next level of priority on group 4.

2.5. Summary and conclusions

The recent financial crisis and the globalization process have accelerated the obsolescence of bankruptcy prediction models and emphasized the need of reformulation. We develop a model of neural networks to study the bankruptcy of U.S. banks, taking into account the specific features of the current financial crisis.

We combine multilayer perceptrons and self-organizing maps to provide a tool that displays the probability of distress up to three years before bankruptcy occurs.

Previous research has proposed many statistical and intelligent methods to predict corporate bankruptcy, although there is no overall best method that has been used (Chen, Ribeiro, Vieira and Chen, 2013; Fedorova, Gilenko and Dovzhenko, 2013; Lee and Choi, 2013; Xu, Xiao, Dang, Yang and Yang, 2014). We build on this previous research and go a step ahead in several domains. First, our model outperforms most of the previous ones in terms of predicting ability. Second, the output of our model is compared against a wider set of alternative methods than previous papers do. Third, our model is simpler and, at the same time, provide a clearer visualization of the complex temporal behaviours.

Our procedure can be a useful tool for bank supervisors and other stakeholders to delineate the risk profile of each bank. As far as the supervisory authority is concerned, the preventive measures to correct imbalances can be different in the short, medium, or long term depending on the probability of banking failure—that is, on the group to which the bank belongs. Investors, depositors, and other participants in capital markets can assess the risk profile of their investment and, consequently, define their optimal risk-return combination.

This study has three limitations. First, as many other hybrid techniques, our model needs multiple calculations to deliver all the output and a complete visualization. Second, in spite of the fact that we consider some features of the financial crisis, we do not control for macroeconomic factors potentially affecting the banks propensity to fail. Third, we focus on commercial banks, so there may be some concerns about whether our results can be applied to large investment banks, whose failure has more far-reaching consequences.

Although our hybrid model performs better than the existing methods for bankruptcy prediction, there is still room for improvement. One direction for future research is the extension of our model to the international framework to determine to what extent different national regulations address credit risk and to identify the best performing regulations. Another application may be the assessment of whether the wave of mergers and acquisitions among banks reduces the risk of bankruptcy and reinforces the solvency of financial institutions. Given the support to hybrid models that our research lends, another meaningful future work could be combining alternative sets of techniques to achieve an optimal balance between prediction accuracy and interpretation simplicity.

3. Self-organizing maps as a tool to compare financial macroeconomic imbalances: The European, Spanish and German case

3.1. Introduction

The current financial crisis, although initially a bank-level crisis, has resulted in a situation of generalized illiquidity in financial markets and financial instability. Whereas in the first months the crisis had a microeconomic impact over the firms and the financial intermediaries, it later reached macroeconomic dimensions and the solvency of some countries became under discussion.

The switch from microeconomic financial distress to macroeconomic distress can be verified from 2010 in after. At the beginning of 2010, the European Union (EU), the International Monetary Fund (IMF) and the European Central Bank (ECB) granted 110 billion of euros credit to Greece given the inability of this country to serve its public debt. Some days later, a permanent fund for ransom of 750 billion was created due to the threat of international contagion and in order to reinforce the international reliability of the European currency. Some months later, in November 2010, Ireland received 87 billion of euros as financial help to refinance the public debt. In April 2011, Portugal asked and received from the EU and the IMF financial help amounting to 78 billion of euros. In addition, the implausibility of Greece to serve the interest of the public debt after the first bailout casted new doubts about the stability of the euro area after May 2011. From April 2012, the main European concern has focused on Spain, which has received 100 billion of euros credit line from the EU[6]. More recently, in March 2013, a 10 billion of euros bailout was announced for Cyprus.

In a financial environment so globalized as the current one, the national financial distresses can be transmitted to other countries, be a threat for the global economic recovery and lead to a generalized collapse of the credit flow to the real economy. In spite of the fact that in July 2011 the European Banking Authority

[6] A more in detail presentation of the main yardsticks throughout the financial crisis can be found in the ECB website http://www.ecb.int/ecb/html/crisis.es.html.

(EBA) published the results of the stress tests of the financial institutions[7] with an acceptable result in general terms, financial markets did not rely completely on the States and Governments. In fact, the credit rating of the United States and of many European countries worsened in the summer of 2011.

An implication of these facts is that Europe should have some tools to assure the effective comparability among countries as a means to assure the efficiency of the correctional policies. In addition, early warning systems in the European financial system could alleviate the asymmetric impact of the financial crisis among countries and avoid the threat of “two speed Europe” that could put in danger the common currency.

The model we propose is a step forward to have such a tool for the detection and management of divergences among countries to anticipate this danger. The analysis within countries can also provide interesting insights since the regions or the states with economic autonomy can contribute significantly to the (in)stability and growth of the whole country. The earlier the economic unbalances among regions are detected, the easier they could be corrected.

Spain is an interesting case to test our model given the financial problems that it is going through, and the special regional configuration of the Public Administration. The Spanish regional governments (Autonomous Communities or AA.CC. hereinafter) have high levels of financial leverage that cast doubts on the ability of Spain to meet its financial engagements. This is the view of the rating agencies, which have systematically downgraded the credit rating of the AA.CC., and the view of the EU, which has required the Spanish Government to control the financial deficit of the AA.CC. In order to enable the comparability of our model, we apply our model to Germany. Although the German states (*Bundesländer*) are considered NUTS-1 and the Spanish AA.CC. are considered NUTS-2 according to

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[7] http://www.eba.europa.eu/EU-wide-stress-testing/2011/2011-EU-wide-stress-test-results.aspx

the European classification[8], both kinds of institutions are comparable in terms of political and economic competences. In addition, the quite different financial situation of Germany and Spain allows us to test the "virtuous or vicious circle" effect of regions on the country as a whole.

Our paper aims to contribute to the literature on national financial balance providing a complete and simple model. Most of the international comparisons until now have been based on one single indicator, which results in the loss of explanatory ability. Our model is self-organizing maps (SOM), a technique based on neural networks (NN) that enables complex international classifications by combining several variables.

Although NN have been widely used in business and finance domains, the analysis of country financial issues is a relatively unexplored field and has promising avenues for research (Herrero et al., 2011; Yim and Mitchell, 2005). The SOM method has been previously used to classify regions (Alfaro Cortés et al., 2003). These authors show the validity of the SOM method for the socio-economic classification of the European NUTS-2 regions. Unlike these authors' research, which focuses on social issues, our paper is concerned with financial and economic factors.

Our objective is twofold. First, we use the SOM method to perform a classification of the European countries depending on their solvency using the most common variables in the literature. The identification of the similarities and differences among countries is relevant information to detect imbalances in order to take correcting measures to avoid the propagation of financial crises. Our second aim is to relate the financial situation of the country as a whole with the financial situation of its regions. Recent concerns about the impact of the financial situation of the regions on the solvency of the whole country advices for a more in-depth

8 http://ec.europa.eu/eurostat/ramon/nomenclatures/index.cfm?TargetUrl=LST_NOM_DTL&StrNom=NUTS_33&StrLanguageCode=EN&IntPcKey=&StrLayoutCode=HIERARCHIC

analysis. Accordingly, we perform a classification analysis of the German and Spanish regions. Germany and Spain are two countries with an analogous territorial organization but with diametrically different financial situation, so that our analysis can cast some light on to which extent the national distress is due to the regional macroeconomic imbalance.

Our paper is divided into six sections. After the introduction, in the second Section we present the foundations of the neural networks as methods for financial analysis and prediction; we also describe the SOM methodology. In Section 3.3 we apply our model to the European countries in order to have an international classification and to identify the most determinant variables of the financial situation. We compare our results with the ones from previously used techniques as the *K*-means and the Factor/*K-means* clustering procedures In Sections 3.4 and 3.5 we reply an analogous analysis for the Spanish AA.CC. and the German *Länder*. In Section 3.6 we conclude with the most remarkable ideas and we point out some applications of our model for the design of economic policies.

3.2. The neural network method

3.2.1. Foundations of neural networks in business and finance

NN are one the most widely used models among the intelligence techniques. They have mathematical and algorithmic elements that mimic the biological neural networks of the human nervous system, so that they have similarities with the functioning of the human brain (Kohonen, 1993). NN take into account the relations among different groups of artificial neurons and processes the information about them using a so-called connectionist approach, in which network units are connected by a flow of information.

Neural networks are a powerful set of algorithms whose objective is to find a pattern of behavior (Moreno and Olmeda, 2007) and that have two main advantages compared to more traditional multivariate statistical techniques. First, NN do not require any kind of assumption about the statistical distribution of the data. Second, NN are not limited by linear specifications as many of the traditional techniques. So, a successful NN implementation generates a system of relationships that has been learnt from observing past examples and is able to generalize these lessons to new examples.

As shown by Vellido et al. (1999) and Wong and Selvi (1998), NN have been profusely used in several domains of business, management, marketing and production. These applications usually involve the interaction of many diverse variables that are highly correlated, frequently assumed to be nonlinear, unclearly related, and too complex to be described by a mathematical model.

The use of neural networks in finance applications has been previously investigated in a number of areas such as loan segmentation, country investment risk, forecasting market movement, and credit scoring (Baesens et al., 2005; Becerra-Fernandez et al., 2002; Falavigna, 2012; Huang et al., 2005). NN have been used even in accounting issues to examine the occurrence of earnings management in various contexts (Höglund, 2012). By far, the main application of NN is bankruptcy and insolvency prediction, which accounts for around 30 percent of contributions (Vellido et al., 1999).

The general outcome of such works is that in the credit industry, neural networks have been considered to be accurate tool for credit analysis (Min and Lee, 2008). Similarly, Guresen et al. (2011) show that in most of the cases NN models give better result than other methods in forecasting stock markets movements.

Dutta and Shekhar (1988) pioneered the use of NN for corporate bond ratings. According to their results, the predictive success rate of NN was 88.3% compared to 64.7% for the regression model. Such significant results motivated further implementations of NN for bond ratings. Surkan and Singleton (1990) compare the NN against the multivariate discriminant analysis and find that the former perform significantly better. Kim et al. (1993), Lee and Choi (2013) and Maher and Sen (1997) also compare the performance of the regression analysis, the multivariate discriminant analysis, the logistic regression and the rule-based methods with NN for the classification of debt ratings. In all the cases the highest percentage of correctly classified bonds was achieved with NN. Likewise, Ravi Kumar and Ravi (2007) comprehensively review the methods developed to predict bank failures and conclude that the traditional statistical techniques are all outperformed by the NN. The results of Mokhatab Rafiei et al. (2011) also show that NN models achieved 98.6% accuracy rates in predicting financial health of Iranian companies, whereas multiple discriminant analysis reached 80.6%.

In the international arena Nag and Mitra (1999) rely on NN to predict some Far East currency crises, and Franck and Schmied (2003) improve the prediction of the currency crisis contagion by using NN. Interestingly, Bennell et al. (2006) use a 70 countries sample to demonstrate that NN represent a superior technology for calibrating and predicting sovereign ratings relative to the ordered probit modeling, which had been considered until recently the most successful approach (Trevino and Thomas, 2001).

As a possible explanation of all these results, Brockett et al. (1994) and Wong and Selvi (1998) suggest that NN have lower-prediction risk and less variance in their errors than the other statistical techniques because they not only accumulate and recognize patters of knowledge based on experience, but also constantly adapt to new environmental situations by permanent retraining and relearning. Kim and Kang (2010) and Shin and Lee (2002) underline the widespread use of NN as an alternative methodology for bankruptcy prediction and show that the artificial intelligence techniques are less vulnerable to the restrictive assumptions on data than the conventional statistical methods. These arguments are consistent with Fioramanti (2008), who focuses on the recent financial crisis. As stated by this author, the indicators of debt, currency crises, and systemic crises are non-linearly related. Since NN are non-parametric models that allow the violation of the rigid assumptions on the data distribution, NN have a say in predicting the contagion of the financial crisis episodes.

Despite these facts, to be honest one has to acknowledge that NN should not be viewed as a panacea, since they also present various weaknesses. They are like black boxes and one can never know their internal working. In addition, NN are a family of models with many members to choose from. Thus, NN can be *ad-hoc* tailored, so that the results could be affected by the design of the net. Likewise, a design good for solving one problem might not be as good for solving some other problem. As Gonzalez (2000) suggests, NN should be considered as a powerful complement to standard econometric methods, rather than a substitute.

3.2.2. The self-organizing maps (SOM)

There are two types of neural networks: the supervised and the non-supervised networks. The supervised networks require the definition of a set of input and output data, so that the network progressively adjusts the results to the expected output. The non-supervised networks are especially suited for exploratory analyses and are a suitable method for data clustering and efficient grouping.

In this latest kind of networks, neurons learn in an unsupervised way since there is not an objective output that the network has to provide. Consequently, there is not a pattern to let the network know whether it works properly. Thus, the network has to discover on its own the common patterns among the inputs. Therefore, the neurons have to self-organize conditional on the data from outside.

Non-supervised networks can be classified into two types: non-competitive and competitive networks. In the competitive networks, nodes compete for the right respond to a subset of the input data. The aim of this training is that, facing an input pattern, only one neuron (or a node of neurons) is activated. The other neurons are annulled. The result of this process is the network classifying the inputs into different homogeneous clusters. One of the best examples of competitive networks is the SOM, which has been used to predict currency crises and debt crises (Arciniegas Rueda and Arciniegas, 2009).

As shown in Figure 1, in the SOM the neurons of the input layer are connected with all the neurons of the output layer through synaptic weights. Consequently, the information provided by each neuron of the input layer is transmitted to all the neurons of the output layer. All the neurons of the output layer receive the same set of inputs from the input layer.

The objective of a competitive network is to find the neuron of the output layer with the most similar synaptic weights to the values of the input layer neurons. To do so, each neuron calculates the difference between the input pattern and the set of synaptic weights of each output neuron. Conditional upon this calculation, the winning neuron is the one with the least difference or the shortest Euclidean distance between its weights and the set of inputs. The Euclidean distance is not the only measure to calculate the distance, but it is the most metric.

The distance between the neurons of the output layer and the vector of input patterns is calculated according to this equation:

$$d_{i,j,(t)} = \sqrt{\sum_{h=1}^{k} \left(W_{i,j,h} - X_k\right)^2}$$

where X_k is the input of the k-input neuron and $d_{i,j,(t)}$ is the Euclidean distance of the (i,j) neuron in t relative to the input pattern for a network with i x j neurons in the output layer and k neurons in the input layer. The winning neuron is the one with the shortest Euclidean distance computed as:

$$g_{i,j}=\mathrm{Min}(\forall d_{i,j})$$

After determining the winning neuron, all the neurons in the network receive an output equal to zero but the winning neuron, which receives an output equal to one. Later, the weights of the winning neuron are adjusted with a learning rule to proxy these weights to the input pattern that has made the neuron win. In this way, the neuron whose weights are the closest ones to the input pattern is updated to become even closer. The result is that the winning neuron has more chances to win the competition in the next data entry for a similar input vector and has fewer chances for the competition if the input vector is different. It means that the neuron has specialized in this input pattern.

The equation that proxies the weights of the wining neuron and of the neighborhood function neurons is the next one, where α is the learning ratio, $X_k(t)$ is the input pattern in t and $W_{jik}(t)$ is the synaptic weight that connects the k input with the (j,i) neuron in t:

$$W_{jik}(t+1) = W_{jik}(t) + \alpha \cdot \lfloor X_k(t) - W_{jik}(t) \rfloor$$

The neighborhood function allows actualizing the weights of the winning neuron and of the neighbor neurons to localize similar patterns too. The neighborhood radio decreases with the number of iterations of the model to achieve a more and better specialization of each neuron.

3.3. The country classification model

3.3.1. Empirical design of the model

The model for an international classification requires a sample as big as possible to assure the significance of the model. Thereby we have collected information from 84 countries for the 1997-2009 period. We use the data until 2008 to train the model and then test the model classifying countries with information of the year 2009.

Our two basic sources of information are the *World Development Indicators & Global Development Finance* published by the World Bank and Eurostat. In some cases we have complemented these data with information from other institutions such as the Organization for the Economic Cooperation and Development, United Nations Data, the International Monetary Fund, the CIA World Factbook and some newspapers.

The final sample is described in Table 10, where we report the period for which the information from each country is available. Regarding the variables, we have tried to be consistent with previous analogous research (Armstrong et al., 1998; Dreisbach, 2007; Manasse and Roubini, 2009; Yim and Mitchell, 2005). We have also taken into account the variables usually employed by the rating agencies Euromoney, Moody's, Standard and Poors and Fitch to assess the sovereign risk.

In Table 11 we present the list of our variables, in Table 12 we provide the definition of each variable and in Table 13 we show a descriptive analysis. Based on the correlation matrix reported in Table 14, we have selected the variables with the lowest correlation coefficient among them in order to keep the sample as big as possible[9]. The list of the chosen variables is reported in Table 15.

To soften the information, to get a more continuous distribution and to moderate the effect of outliers, we make a logistic transformation[10] of the data (Pyle, 1999). This transformation scales all possible values between 0 and 1. The transformation is more-or-less linear in the middle range (around mean value), and has a smooth nonlinearity at both ends which ensures that all values are within the range. Then we process the information from 1997-2008 (our training sample) with the *Matlab Som Toolbox tool*. The first layer of the model has 588 input patterns (all countries in the sample) and the output layer is a bidimensional map of 12x10. The size of the map follows the recommendations of Kohonen (1993) and Kaski and Kohonen (1994). Thus, the number of connections or weights is 840 (7 variables multiplied by the size of the map).

[9] Although multicollinearity is not a big issue in SOM models, since not all the variables are available for all the countries throughout the analyzed period, by focusing on a selection of variables we manage to keep as many countries as possible.

[10] The logistic transformation is also known as a *softmax* transformation.

Table 10: Sample composition

Country	Initial date	End date	Country	Initial date	End date
Argentina	2002	2004	Luxembourg	1999	2009
Armenia	2003	2004	Macedonia	2005	2008
Australia	1999	2008	Madagascar	2000	2005
Austria	1997	2009	Malaysia	1997	2003
Azerbaijan	1999	1999	Mali	2004	2004
Bangladesh	2003	2005	Islas Mauricio	1997	2008
Belgium	2002	2009	Mexico	1997	2000
Belize	1997	1997	Moldavia	1999	2008
Benin	2002	2002	Morocco	2002	2008
Bolivia	2002	2002	Namibia	2004	2004
Brazil	2006	2006	Netherlands	1997	2009
Bulgaria	2008	2008	New Zealand	2001	2004
Cambodia	2004	2004	Nicaragua	2000	2001
Canada	1997	2004	Norway	2000	2008
China	2005	2006	Pakistan	1997	2007
Croatia	1997	2009	Panamá	1997	2001
Cyprus	1999	2009	Papua N. G.	2000	2000
Czech Republic	1997	2009	Paraguay	2007	2008
Denmark	1997	2009	Peru	1997	2007
Dominican Republic	2004	2007	Philippines	2000	2008
Egypt	1997	2008	Poland	2001	2009
El Salvador	2002	2006	Portugal	1997	2009
Estonia	1997	2009	Romania	2002	2009
Finland	1997	2009	Russia	2002	2008
France	1997	2009	Slovak Republic	2006	2009
Georgia	1998	2007	Slovenia	1997	2009
Germany	1997	2009	South Africa	2000	2008
Greece	1997	2009	Spain	1997	2009
Guatemala	2001	2006	Sweden	1997	2009
Honduras	2003	2006	Switzerland	1997	2007
Hungary	1997	2009	Thailand	2003	2008
Iceland	1998	2009	Trinidad Tobago	2001	2005
India	1997	2004	Tunisia	1997	2005
Indonesia	1998	2004	Turkey	2006	2008
Ireland	1997	2009	Uganda	2003	2003
Italia	1997	2009	Ukraine	1999	2009
Jordan	2008	2008	United Kingdom	1997	2009
Kazakhstan	1997	2004	United States	2001	2009
Korea, Rep.	1997	2008	Uruguay	1997	2008
Kyrgyz Republic	2006	2006	Venezuela	1997	2004
Latvia	1997	2009	Yemen, Rep.	1999	1999
Lithuania	2000	2009	Zambia	1998	1998

Table 11: List of variables

Code	Variable
V1	Agriculture value added (%GDP)
V2	Agriculture, value added (annual growth)
V3	Cash surplus/deficit (% GDP)
V4	Current account balance (% GDP)
V5	GDP growth (annual growth)
V6	PIB per capita (constant 2000 US$)
V7	GDP per capita growth (annual %)
V8	General government final consumption expenditure (% GDP)
V9	Gross domestic savings (% GDP)
V10	Gross fixed capital formation (annual % growth)
V11	Gross fixed capital formation (constant 2000 US$)
V12	Gross savings (% GDP)
V13	Household final consumption expenditure (annual % growth)
V14	Industry, value added (% GDP)
V15	Industry, value added (annual growth)
V16	Inflation, consumer prices (annual %)
V17	Population aged 65 and above (% total population)
V18	Population growth (annual %)
V19	Population, total
V20	Unemployment, total (% of total labor force)

Table 12: Definition of variables

Code	Variable	Definition
V1	Agriculture value added (%GDP)	The share of the country's GDP derived from agriculture
V2	Agriculture, value added (annual growth)	Annual growth rate for agricultural value added based on constant local currency
V3	Cash surplus/deficit (% GDP)	Revenue (including grants) minus expense, minus net acquisition of non-financial assets. In the 1986 GFS manual nonfinancial assets were included under revenue and expenditure in gross terms. This cash surplus or deficit is close to the earlier overall budget balance (still missing is lending minus repayments, which are now a financing item under net acquisition of financial assets)
V4	Current account balance (% GDP)	Sum of net exports of goods, services, net income and net current transfers
V5	GDP growth (annual growth)	Annual percentage growth rate of GDP at market prices based on constant local currency
V6	GDP per capita (constant 2000 US$)	GDP divided by midyear population. Aggregates are based on constant 2000 U.S. dollars
V7	GDP per capita growth (annual %)	Annual percentage growth rate of GDP per capita based on constant local currency
V8	General government final consumption expenditure (% GDP)	General government final consumption expenditure (formerly general government consumption) includes all government current expenditures for purchases of goods and services (including compensation of employees). It also includes most expenditures on national defense and security, but exclude government military expenditures that are part of government capital formation
V9	Gross domestic savings (% GDP)	Gross domestic savings are calculated as GDP less final consumption expenditure (total consumption)
V10	Gross fixed capital formation (annual % growth)	Average annual growth of gross fixed capital formation based on constant local currency. Aggregates are based on constant 2000 U.S. dollars
V11	Gross fixed capital formation (constant 2000 US$)	Gross fixed capital formation (formerly gross domestic fixed investment) includes land improvements (fences, ditches, drains, and so on); plant, machinery and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings. According to the 1993 SNA, net acquisitions of valuables are also considered capital formation. Data are in constant 2000 U.S. dollars
V12	Gross savings (% GDP)	Gross savings are calculated as gross national income less total consumption, plus net transfers

Code	Variable	Definition
V13	Household final consumption expenditure (annual % growth)	Annual percentage growth of household final consumption expenditure based on constant local currency. Aggregates are based on constant 2000 U.S. dollars. Household final consumption expenditure (formerly private consumption) is the market value of all goods and services, including durable products (such cars, washing machines, and home computers), purchased by households. It excludes purchases of dwellings but includes imputed rent for owner-occupied dwellings. It also includes payments and fees to governments to obtain permits and licenses. Here, household consumption expenditure includes the expenditures of nonprofit institutions serving households, even when reported separately by the country.
V14	Industry, value added (% GDP)	Industry corresponds to ISIC division 10-45 and includes manufacturing (ISIC divisions 15-37). It comprises value added in mining, manufacturing (also reported in separated subgroup), construction, electricity, water and gas. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. It is calculated without making deductions of depreciation of fabricated assets or depletion and degradation of natural resources. The origin of value added is determined by the International Standard Industrial Classification (ISIC)), revision 3. Note: For VAB countries, gross value added at factor cost is used as the denominator
V15	Industry, value added (annual growth)	Annual growth rate for industrial value added on constant local currency
V16	Inflation, consumer prices (annual %)	Annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. The Laspeyres formula is generally used.
V17	Population ages 65 and above (% total population)	Exponential rate of growth of midyear population from year t-1 to t, expressed as a percentage
V18	Population growth (annual %)	Annual growth rate for population by country
V19	Population, total	Total population is based on the facto definition of population, which counts all residents regardless of legal status or citizenship-except for refuges not permanently settled in the country of asylum, which are generally considered part of population of their country of origin. The values shown are midyear estimates.
V20	Unemployment, total (% of total labor force)	Share of the labor force that is without work but available for and seeking employment. Definitions of labor force and unemployment differ by country.

Table 13: Descriptive analysis

Variable	Mean	Std. Dev.	Q1	Q2	Q3
V1	7.03	6.72	2.50	4.35	9.43
V2	1.66	8.50	-2.52	1.93	5.25
V3	-0.80	3.31	-2.76	-1.18	0.79
V4	-1.49	6.82	-5.79	-1.95	2.31
V5	4.13	3.28	2.36	4.01	5.89
V6	12,499	12,235	2,340	6,323	23,038
V7	3.45	3.45	1.61	3.31	5.04
V8	16.70	4.75	12.52	17.44	19.67
V9	21.70	9.64	15.96	22.33	26.45
V10	6.53	11.82	1.00	5.94	11.56
V11	8.26E+10	2.47E+11	4.02E+09	1.87E+10	5.38E+10
V12	21.65	6.51	17.06	21.31	24.92
V13	4.30	5.02	2.16	3.73	6.07
V14	29.93	7.06	25.81	29.15	33.29
V15	4.16	5.49	1.24	3.87	6.77
V16	7.10	43.88	2.09	3.40	6.46
V17	11.87	4.84	6.56	13.55	15.89
V18	0.62	0.95	0.05	0.56	1.25
V19	4.13E+07	1.20E+08	4.44E+06	1.02E+07	4.38E+07
V20	8.46	5.06	5.00	7.60	10.40

Table 14: Correlation matrix

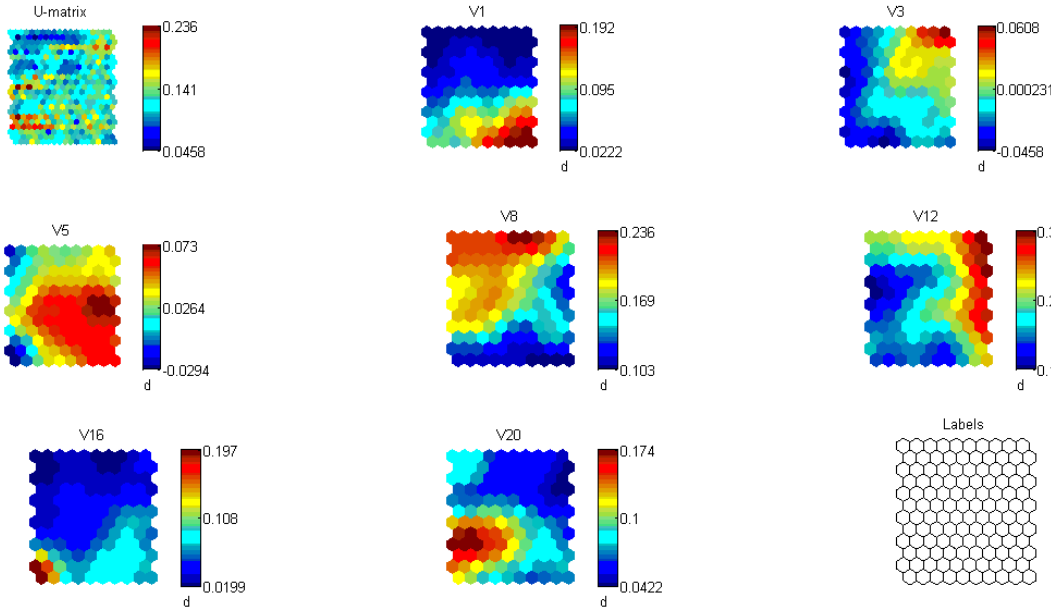
	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19
V2	.136																		
V3	-.205	-.032																	
V4	-.192	-.008	.332																
V5	.125	.148	.127	-.180															
V6	-.605	-.136	.401	.410	-.241														
V7	.061	.145	.132	-.213	.961	-.241													
V8	-.498	-.074	.197	.033	-.146	.458	-.052												
V9	-.446	-.047	.362	.605	.019	.408	-.013	.051											
V10	.104	.008	.132	-.167	.604	-.138	.582	-.005	-.024										
V11	-.204	-.017	-.062	.011	-.117	.325	-.118	.049	-.029	-.082									
V12	-.146	.014	.397	.683	.096	.160	.071	-.018	.704	.020	-.074								
V13	.071	.022	.132	-.213	.659	-.214	.642	-.088	-.108	.406	-.076	-.028							
V14	-.079	.024	.204	.341	.133	-.232	.128	-.216	.473	.071	-.129	.523	.077						
V15	.124	.037	.053	-.098	.747	-.215	.726	-.136	.075	.494	-.107	.118	.486	.199					
V16	.165	.167	-.008	.025	-.140	-.089	-.119	-.083	-.049	-.091	-.030	-.060	-.125	.023	-.138				
V17	-.546	-.079	.134	-.058	-.145	.504	.037	.591	.067	-.044	.115	-.098	-.103	-.263	-.109	-.005			
V18	.158	-.011	-.048	.178	-.071	.067	-.337	-.304	.178	-.048	.036	.083	-.094	.040	-.077	-.054	-.610		
V19	.182	.052	-.095	.097	.076	-.078	.038	-.149	.108	.039	.397	.201	.080	.079	.144	-.007	-.187	.128	
V20	.103	.051	-.209	-.132	.027	-.390	.078	.039	-.269	.018	-.112	-.231	.022	.049	.031	.059	-.089	-.183	-.105

Table 15: Final selected variables

Code	Variable
V1	Agriculture value added (%GDP)
V3	Cash surplus/deficit (% GDP)
V5	GDP growth (annual growth)
V8	General government final consumption expenditure (% GDP)
V12	Gross savings (% GDP)
V16	Inflation, consumer prices (annual %)
V20	Unemployment, total (% of total labor force)

The results of the training of the model are shown in Figure 7. We can note the so-called *U-Matrix*, with which we determine the different distances among the neurons through the training of the model. In the U-Matrix, the distance is reported by colors: light colors for short distances and dark colors for long distances. The other figures show the density function of the variables. For each variable we show the whole map of neurons and the value distribution in the map.

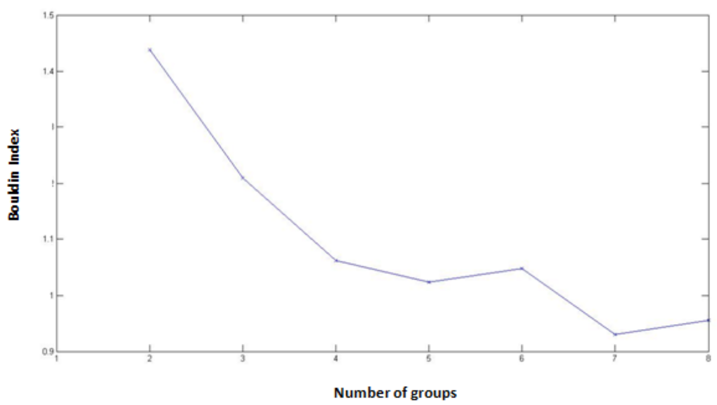
Figure 7: Learning results of the SOM net (Countries)



If we analyze the overlapping and compare the different figures we can see the logic of the model from a mathematical point of view. For instance, High values of public deficit are linked to low values of the saving rate related to the GDP, high unemployment rates and low inflation rate. According to Figure 7, all the variables are significant, which corroborates the selection of variables.

After training the model, we have to introduce and to process the information from 2009 in order to sort the countries out (Khashman, 2010). A key decision is the one concerning the number of groups given that a too low number of groups would lead to internally too heterogeneous groups whereas a too high number of groups could result in the insufficient identification of common characteristics to several countries. The ideal number of groups is the one that maximizes intra-groups homogeneity whereas maximizes inter-groups heterogeneity. The *K*-means non-hierarchical clustering function is used to find an initial partitioning. *K*-means is the least sensitive to outliers (Hair et al., 1999) and has been also used in other works like Moreno et al. (2006) to classify the Spanish mutual funds with SOM. There are some methods to determine the optimal number of groups (Fraley and Raftery, 1998), although in SOM one of the most widely used algorithms is the Davies-Bouldin index (Davies and Bouldin, 1979). This index is a function of the ratio within cluster variation to between cluster variations (Ingaramo et al., 2005). The smaller the index, the better the partition is. According to this index, the optimal number of groups of countries is seven as shown in Figure 8.

Figure 8: Bouldin Index and selection of optimal number of groups



We focus on the situation of the Euro-27 countries and, thus, in Figure 9 we report the results for these countries[11]. We include Iceland because it was the first country deeply affected by the financial crisis in Europe and formally applied for EU membership in 2009. We also include Croatia because it will join the EU in July 2013 and Ukraine because of the strategic ties and the agreement signed with the EU to create a free trade area in 2013. Results are shown in Tables 16, 17 and 18.

Figure 9: Classification of the countries in 2009

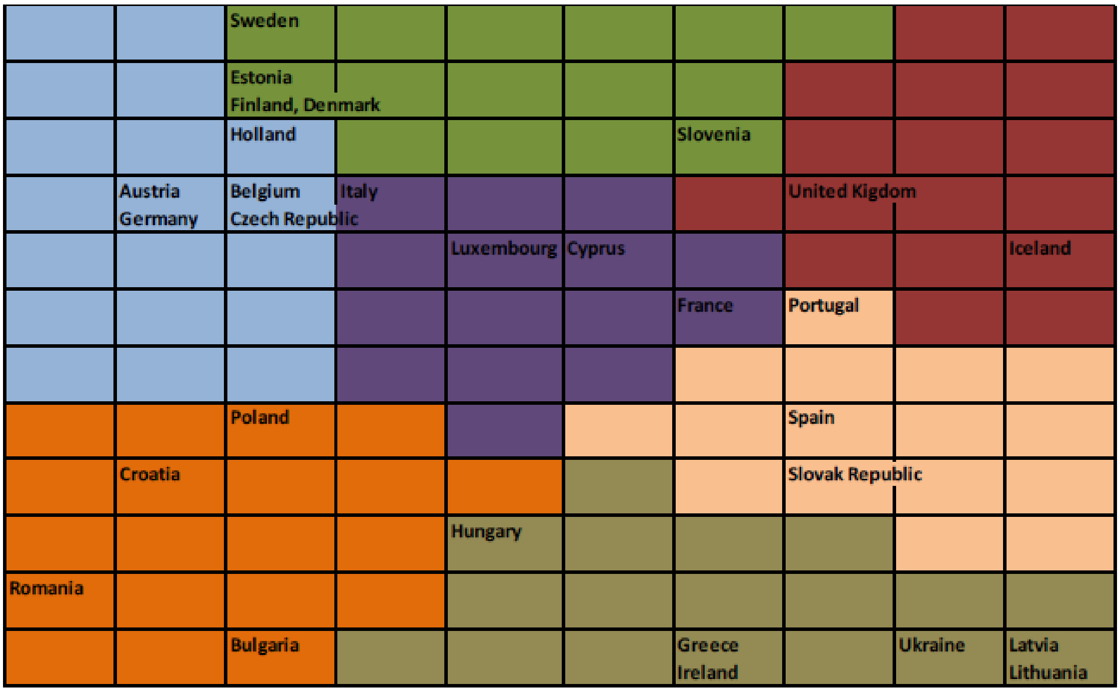


Table 16: Mean values for each group of countries

Group	Agriculture value added (%GDP)	Cash surplus/deficit (% GDP)	GDP growth (annual growth)	Government expenditure (% GDP)	Gross savings (% GDP)	Inflation, consumer prices (annual %)	Unemployment, total (% of total labor force)
1	1.40%	-4.74%	-3.93%	21.32%	24.37%	0.60%	6.44%
2	6.11%	-6.15%	-4.41%	14.60%	21.52%	3.66%	8.45%
3	2.06%	-2.72%	-7.88%	23.45%	24.63%	0.36%	9.40%
4	1.48%	-4.88%	-3.19%	19.26%	13.38%	0.40%	7.35%
5	3.96%	-10.77%	-10.67%	14.16%	14.08%	4.57%	12.93%
6	2.73%	-6.83%	3.62%	16.81%	21.50%	6.84%	8.51%
7	2.50%	-9.43%	-4.17%	19.84%	19.37%	0.13%	14.53%

[11] Malta was excluded because the information was not available.

Table 17: Main characteristics of each group of countries

Group	Characteristics
1	Low importance of agriculture and low unemployment rates
2	High importance of agriculture
3	Lower public deficit, higher saving rate and government expenditure
4	Lower saving rate
5	Higher deficit and GDP decreases, and less public expenditure
6	Higher GDP growth and inflation
7	Higher unemployment rate

Table 18: Comparison of the classification models

This table provides the F-statistics and the *p*-value of the most important variables. We also report the within groups variance of the three classification models

Variable\Model	SOM		K-means		Factor/K-means	
	F-Stat	p-Value	F-Stat	p-Value	F-Stat	p-Value
Agriculture value added (%GDP)	127.80	0.000	98.92	0.000	117.01	0.000
Cash surplus/deficit (% GDP)	74.56	0.000	49.70	0.000	69.28	0.000
GDP growth (annual growth)	49.23	0.000	82.57	0.000	125.61	0.000
Government expenditure (% GDP)	181.13	0.000	261.74	0.000	107.06	0.000
Gross savings (% GDP)	96.80	0.000	128.40	0.000	52.82	0.000
Inflation, consumer prices (annual %)	15.98	0.000	18.49	0.000	110.68	0.000
Unemployment, total (% of total labor force)	93.24	0.000	106.80	0.000	97.59	0.000
Within groups total variance	61.89		63.08		69.22	

3.3.2. Results

The main indicators of each country are reported in Table 16 and Figure 9. In order to summarize the information of this table, in Table 17 we present the main characteristics of each group.

As shown in Figure 9, the first group is made up by Holland, the Czech Republic, Belgium, Austria and Germany. Broadly speaking, this group of countries is Central-Europe nations. The second group includes the Western Europe countries recently joining or waiting for the EU membership. The third group is also quite geographical since is made up by the Nordic countries and some other close countries such as Estonia or Slovenia (although Slovenia is also near to other groups, which is consistent with the geographical distance from the Nordic countries). Group 4 includes Luxembourg and a number of Mediterranean countries such as Italy, Cyprus and France. It is a relatively heterogeneous group since whereas Italy is close to the first group, France and Cyprus are near to countries such as Spain and Portugal.

The fifth group includes the countries in the most difficult situation: Greece, Hungary, Ireland, Ukraine, Latvia and Lithuania. Ireland was intervened by the EU in 2010 and the very adverse Greek situation is widely known. Ukraine, Latvia and Lithuania are in recession, and Hungary has suffered from severe problems on the public account that led the IMF to investigate a possible intentional manipulation and that resulted in a restatement of the public deficit from 4.5% to 7.5 percent. In the Group 6 we find the UK and Iceland. Although their unemployment rate, economic growth and public deficit is close to Greece or Ireland, their economic and financial characteristics, the large size of UK, and their good perspectives, they are likely to push them out of the crisis sooner than other countries. Nevertheless, there are some troublesome issues such as the overleveraged. The last group would include Spain, Portugal and Slovakia. These are countries in financial troubles as shown by the international intervention in Portugal. 2010 has been a key year to assess the evolution of these countries: Portugal has move closer to Greece and Ireland, and Spain is under huge European pressure to give unequivocal signs of public expenditure cut-offs and to dissipate the financial uncertainty.

3.3.3. Assessment of the model

To assess the goodness of the model, we need further tests. We compare our output with two clustering techniques: *K*-means cluster and a two-step factor analysis/*K*-means procedure. These methods have been used before to compare some unsupervised networks (Kiang, 2001; Kiang et al., 2006, Mingoti and Lima, 2006). *K*-means is one of the most best-known unsupervised algorithms since it is a robust and easy-to-implement method. The two-step factor analysis/*K*-means procedure consists of the application of the factor analysis to reduce the data dimensions before applying the *K*-means clustering method.

The optimal model is the one that maximizes intra-groups homogeneity and inter-groups heterogeneity. It can be assessed by comparing the within cluster total variance. For a given number of clusters, the smaller the within cluster variance, the more homogenous the clusters. Given the sensitivity of the cluster analysis to initial seeds (Milligan and Cooper, 1980), in the *K*-means procedure we use the same inputs than the SOM. In the factor/cluster method, we use a factor analysis with varimax rotation. In a first step we obtain three factors, which are the inputs in a *K*-means procedure. Table 18 shows the within-groups variance of the three methods. As reported, the F-statistic and the *p*-value of the most important variables are highly consistent across all the methods. Interestingly, SOM outperforms the *K*-means and the factor/cluster procedures according to the within-cluster variance.

Finally, an interpretation about the weights of the network can be done with the so-called sensitivity analysis (Garson, 1991; Hunter et al., 2000; Rambhia et al., 1994; Zurada et al., 1994). Because of the complexity to determine the importance (or relation) of each input variable with the output of the model, the sensitivity analysis allows us to identify the most relevant variables. The ANOVA with the results of SOM model are reported in Table 11. We use four indicators to analyze the significance of the differences: Wilk's Lambda, Pillai's Trace, Hotelling's Trace and the Roy's Largest Root. All the indicators show that there are significant differences among the variables across the groups. High values of the first indicator or low values of the last three indicators point at differences among groups. As shown in Table 18, the mean of each group is significantly different.

The sensitivity analysis is based on measuring the observed effect on an output Y_j due to the change in an input X_i. The bigger the effect is, the more sensitivity. Results reported in Table 19 show that the most influential variables are the public expenditure (as a proportion of GDP) and the saving rate (also as a proportion of GDP). The following variables in importance are the rate of GDP growth, the public deficit and the unemployment. On the contrary, the inflation rate and the importance of agriculture in GDP are the least significant variables.

Table 19: Sensitivity analysis of the countries classification

Variable	Importance	Normalized importance
Agriculture value added (%GDP)	0.15	85.66%
Cash surplus/deficit (% GDP)	0.15	86.67%
GDP growth (annual growth)	0.16	91.46%
General government final consumption expenditure (% GDP)	0.17	100.00%
Gross savings (% GDP)	0.17	98.27%
Inflation, consumer prices (annual %)	0.06	34.98%
Unemployment, total (% of total labor force)	0.15	85.78%

3.4. The classification of the Spanish regions

The Spanish AA.CC. are regional entities with wide range of political and financial autonomy that show big differences in terms of financial balance. Although it has not been until recently that the macroeconomic unbalance of AA.CC. has drawn the attention of politicians and mass-media, academia had thoroughly studied their budgetary ability and their contribution to the whole national public expenditure (Martínez García and Colldeforns, 2003; Ríos et al., 2007; Sanz and Velázquez, 2001). The gap between the dramatic increments in the public expenditure of most of the AA.CC. and the objectives of Spain have forced the Spanish Government to pass a strict adjustment plan to cut-off the public deficit and to meet the European objectives.

In this Section we explore the financial differences across AA.CC. to identify the ones that should make the most effort to balance their public accounts and to assure their solvency. We aim to provide a tool to assess and to compare the financial situation of the AA.CC., in order to focus the effort on the most troublesome regions and to implement the necessary corrective policies.

As in the countries classification, the SOM method is a suitable way to identify the main similarities and differences across AA.CC. Peralta et al. (2000) and Alfaro Cortés et al. (2002) have utilized the SOM method for a socio-economic classification of the European regions, and Moreno and Olmeda (2007) and Jaráiz Cabanillas et al. (2012) do the same for the Valence region and for the central area of the Iberia Peninsula respectively. Our research goes a step forward not only in the variables we use but also in the objective since we do not intend a socio-economic classification but to identify the financial unbalances and the AA.CC. solvency threats. Thus, we focus on the economic variables to which the EU gives priority and we base in the conclusions, methods and recommendations of the above mentioned literature.

3.4.1. Empirical design of the model

Unlike the national accounts of Section 3.3, macroeconomic information about Spanish AA.CC. is not so profuse. We have used the information available at the Spanish National Statistical Institute, the Statistical Institute of each AA.CC., Eurostat and the reports on the economic situation from the Saving Banks Foundation (FUNCAS) and the Bank of Spain. The variables have been selected consistently with previous research (Fernández Llera, 2006), with the rating agencies and with the EU recommendations (Table 20). In Table 21 we report the correlation matrix.

The model has been developed with the *Matlab Som Toolbox*, based on the information on the AA.CC. from 2001 to 2009. Then, we test the model with the information for 2010. As previously, after loading all the variables in the model, we perform a logistic normalization to smooth the information and to increase the data continuity.

Table 20: Variables considered in the Spanish regions classification

Code	Variable	Definition
V1	Unemployment rate	Share of the labor force that is without work but available for and seeking employment.
V2	GDP per capita growth (annual %)	Annual percentage growth rate of GDP per capita based on constant local currency
V3	Population growth (annual %)	Annual growth rate for population by region
V4	Gross debt to total GDP ratio	Amount of national debt as a percentage of total GDP by region. A low rate indicates and economy that produces a large number of goods and services and probably profit enough to pay the debt interest
V5	Inflation, consumer prices (annual %)	Annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. The Laspeyres formula is generally used.

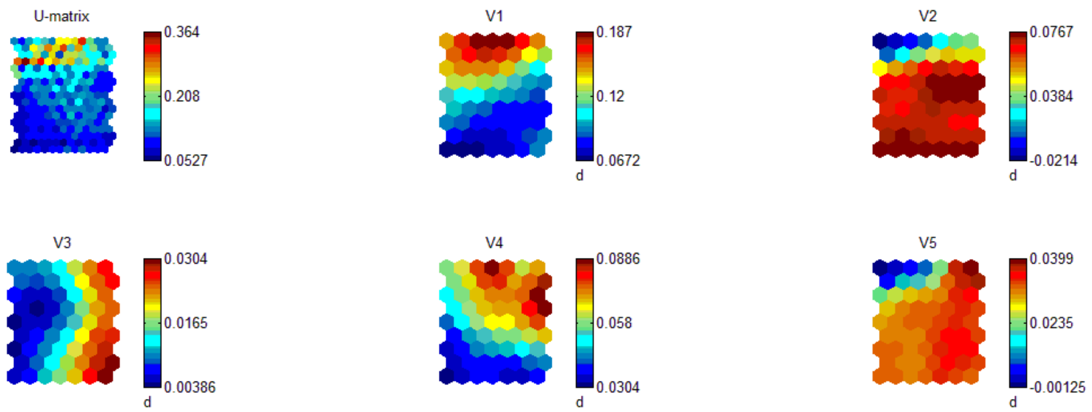
Table 21: Correlation matrix (Spanish classification)

	Unemployment rate	GDP per capita growth (annual %)	Population growth (annual %)	Gross debt to total GDP ratio
GDP per capita growth (annual %)	-0.635			
Population growth (annual %)	-0.203	0.161		
Gross debt to total GDP ratio	0.497	-0.416	-0.016	
Inflation, consumer prices (annual %)	-0.523	0.783	0.233	-0.314

Since the model is a competitive network, it has only two layers: the input one and the output one. The input layer is made of 162 input patterns from the data of the 17 AA.CC. for nine years and nine more observations from Spain as a whole. The neurons of the input layer are connected through synaptic weights with all the neurons of the output layer. Thus, the information provided by each neuron from the input layer is sent to every neuron of the output layer. Likewise, each neuron of the output layer receives the same set of inputs from the input layer. The number of units of the output layer is a two-dimension map of 9x7; therefore, the number of connections or weight is 441.

The results of the model training are shown in Figure 10. We present the U-Matrix that determines the distances among the neurons through training step, and the density functions of the six variables that we finally use. As in the country classification model, the colors of the U-Matrix represent the distance among the neurons, so that strong colors are representative of long distances and clear colors of lower distance among the neurons. For each variable the Figure 10 shows the whole map of neurons and their density functions. By overlapping and comparing the different figures we can note the logic of the model from an economic point of view. For example, high values of unemployment are matched with low or even negative variation of GDP, high debt levels and stagnation of the total population. All the variables considered are statistically significant.

Figure 10: SOM learning results (Spanish AA.CC.)



Concerning the ideal number of groups, we again use the Davies-Bouldin index. The optimal number of clusters that maximizes the within-groups homogeneity and the between-groups heterogeneity is six. In Tables 22-24 and in Figure 11 we provide the results of the model for 2010.

Table 22: Spanish regions classification

Group	Components
1	Aragón, Asturias, Cantabria, Castile and Leon, La Rioja, Basque Country
2	Madrid, Navarre
3	Extremadura, Galicia
4	Andalusia, Castile La Mancha, Balearic Island, Murcia, Spain
5	Catalonia
6	Valencia Community , Canary Island

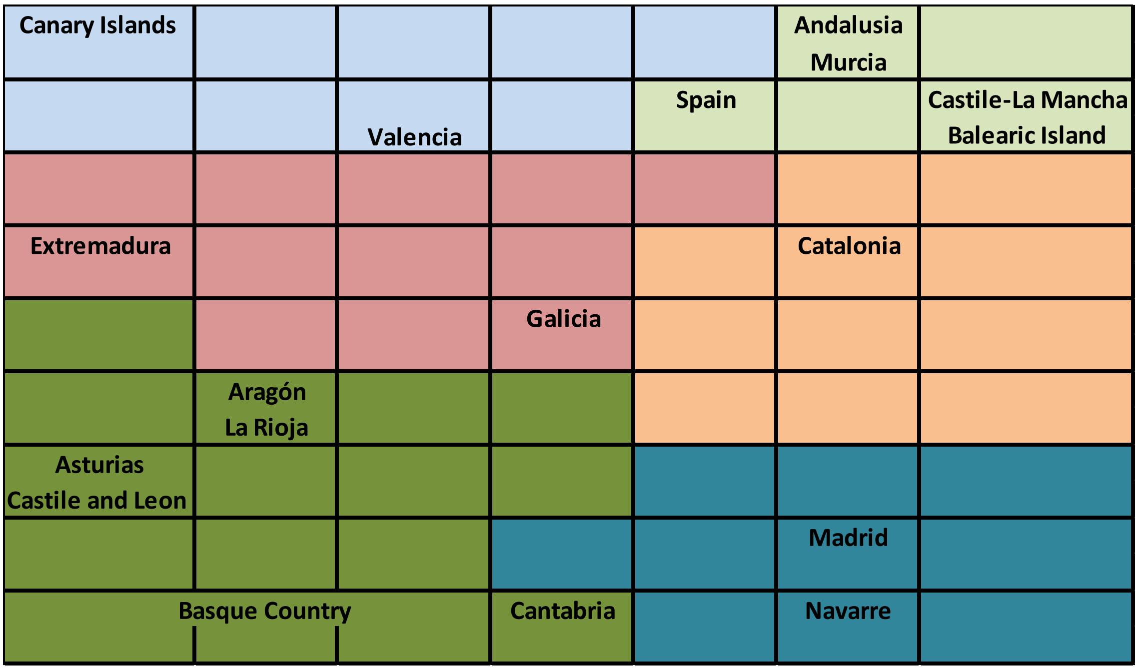
Table 23: Mean values for each AA.CC.

Group	Unemployment rate	GDP per capita growth (annual %)	Population growth (annual %)	Gross debt to total GDP ratio	Inflation, consumer prices (annual %)
1	8.68%	6.64%	0.73%	4.08%	3.02%
2	8.81%	6.77%	2.60%	4.10%	3.35%
3	14.08%	6.73%	0.45%	6.83%	3.08%
4	19.02%	2.24%	2.08%	8.86%	3.25%
5	9.31%	7.37%	2.34%	8.68%	3.29%
6	18.16%	-2.79%	1.13%	8.02%	-0.25%

Table 24: Main characteristics of each group of AA.CC.

Group	Main feature
1	Lower unemployment and lower debt to GDP ratio
2	Higher population growth and inflation
3	Lower population growth
4	Higher unemployment rate and debt to GDP ratio
5	Higher GDP per capita growth
6	Decrease of the GDP per capita and lower inflation

Figure 11: Classification of the Spanish AA.CC. in 2010



3.4.2. Results and assessment of the model

At the end of 2010, the AA.CC. with the best situation were Asturias, Aragón, Castile and Leon, La Rioja, the Basque Country and Cantabria. This group is characterized for an unemployment rate lower than the other groups, reduced debt level and a widespread increase of their GDP and inflation during 2010. Nevertheless, there are some differences inside the group. The Basque Country is the region with the best economic situation in Spain. Cantabria can also be considered in an economic recovery stage. Asturias and Castile and Leon are better placed than the national average but they show higher unemployment rates and less GDP growth. In spite of being included in this first group, Aragón and La Rioja have common characteristics with the Group 3. Group 2 is made of Madrid and Navarre. They show higher population growth in 2010.

Groups 3 and 4 are in an intermediate position. Inside the group 3, Extremadura is close to the group 1, being only different in terms of unemployment. Galicia is a rather peculiar case. It occupies a central position and relatively far from the other AA.CC., which means that it has some characteristics in common with several groups and it is not easy to include it into a specific group.

The next group by solvency and financial quality is the Group 5, formed only by Catalonia. This region is one of the most leveraged and during 2010 it issued a great amount of debt increasing the proportion of debt to GDP from 11. 9 percent to 16.2 percent. Since the Catalonia GDP only increased in 1.16 percent in 2010, these data give a clear idea of its over-leverage. Nonetheless, the population of Catalonia grows yearly and the unemployment rate is under the Spanish average.

Groups 6 and 4 have in common a worrying feature since the unemployment rate is nearby 20 percent. The situation of group 6 is even worse, with Valencia and the Canary Islands having worse growth in GDP, population and inflation than Andalusia, Castile-La Mancha, Balearic Island and Murcia.

As in the countries analysis, we test the significance of the model through the ANOVA analysis and we analyze the importance of each variable through the sensitivity analysis. The ANOVA analysis reported in Table 25 corroborates the heterogeneity among groups and the homogeneity within groups.

Table 25: Analysis of variance (ANOVA) of the Spanish AA.CC. classification

		Value	F-test	D.F. hypothesis	G.l. error	p-value	Partial Eta^2	No centrality parameter	Observed potency
Intersection	Pillai's trace	.983	1815.892	5	160	.000	.983	9079.460	1.000
	Wilks' lambda	.017	1815.892	5	160	.000	.983	9079.460	1.000
	Hotelling's Trace	56.747	1815.892	5	160	.000	.983	9079.460	1.000
	Roy's largest root	56.747	1815.892	5	160	.000	.983	9079.460	1.000
Group	Pillai's trace	2.314	28.260	25	820	.000	.463	706.499	1.000
	Wilks' lambda	.021	43.552	25	595.876	.000	.538	693.866	1.000
	Hotelling's Trace	7.852	49.752	25	792	.000	.611	1243.804	1.000
	Roy's largest root	4.369	143.310	5	164	.000	.814	716.551	1.000

Table 26 reports the comparison among the SOM results and both the *K*-means and the factor/cluster procedures. Similarly to the country classification model, the significance of the main variables is comparable and SOM provides the lowest variance among groups.

Table 26: Comparison of the AA.CC. classification models

Variable/Model	SOM		K-means		Factor/K-means	
	F-Stat	p-Value	F-Stat	p-Value	F-Stat	p-Value
Unemployment rate	40.460	0.000	47.083	0.000	23.220	0.000
GDP per capita growth (annual %)	127.097	0.000	80.797	0.000	92.239	0.000
Population growth (annual %)	82.480	0.000	68.509	0.000	62.897	0.000
Gross debt to total GDP ratio	51.411	0.000	74.438	0.000	41.645	0.000
Inflation, consumer prices (annual %)	123.888	0.000	116.213	0.000	120.348	0.000
Within groups total variance	8.737		9.419		11.341	

The sensitivity analysis reported in Table 27 shows that the debt-to-GDP ratio is the most significant variable. Our analysis shows the different situation of the macroeconomic situation of several Spanish AA.CC. It is not surprising that on September 2011 the Fitch rating agency downgraded the debt of Andalusia, Canary Island, Catalonia, Murcia and Valencia (the AA.CC. in the worst groups in our classification) and on October, 2011 Moody's downgraded the long-term debt rating of ten AA.CC., with a specially impact on Catalonia, Valencia and Castile-La Mancha. This generalized downgrading is likely to have affected the rating of the Spanish debt, which has been downgraded in 2011 and 2012.

Table 27: Sensitivity analysis of the AA.CC classification

	Importance	Normalized importance
Unemployment rate	0.18	70.92%
GDP per capita growth (annual %)	0.18	73.64%
Population growth (annual %)	0.22	89.51%
Gross debt to total GDP ratio	0.25	100.00%
Inflation, consumer prices (annual %)	0.16	64.58%

3.5. The German states classification model

3.5.1. Empirical design of the model

The classification of the Spanish AA.CC. and the study of their influence on the whole Spanish solvency can be complemented with an analogous analysis of other countries with a similar regional structure. Thus, we now present the results of our model for Germany and its 16 federal states or *Bundesländer*. With this analysis, we can test to which extent the situation of each regional entity impacts on the financial situation of the whole country. The choice of Germany has not been casual. Although German states have the consideration of NUT-1 and the AA.CC. have the consideration of NUT-2 according to the Nomenclature of the Territorial Units Statistics used by the EU, Spanish AA.CC. and German states play actually a comparable role. Likewise, the different economic situation of Germany in comparison with Spain allows testing the positive or negative effect for the whole country of the macroeconomic regional situation.

The variables we use are displayed in Table 28[12]. The information sources are Eurostat, the OECD, and the *Statistisches Bundesamt* (German National Institute of Statistics). Although data sources are not exactly the same than the Spanish ones, we develop a model with a comparable explanatory capacity. We have information for all the 16 German states between 1996 and 2009. As previously, the model is built with

[12] The variable "Licenses for construction of residential buildings" may seem weird but it is a variable with high historical importance in the German economy since the end of the World War II.

information until 2008 (training sample) and we use the information from 2009 to perform the classification of the states (test sample).

Table 28: Variables considered in the German states classification

Code	Variable	Definition
V1	GDP per capita growth (annual %)	Annual percentage growth rate of GDP per capita based on constant local currency
V2	Agriculture value added (%GDP)	The share of the each state's GDP derived from agriculture
V3	Licenses for residential building (annual growth)	Annual percentage growth rate of the number of licenses for residential building
V4	Population growth (annual %)	Annual growth rate for population by region
V5	Unemployment rate	Unemployment refers to the share of the labor force that is without work but available for and seeking employment.

In Table 29 we provide the correlation matrix among the five variables we use. One can note the low correlation among them, so that multicolinearity is not a relevant concern in our analysis. The resulting German map is reported in Figures 12 and 13, with an ideal number of five groups. In Table 30 we detail the composition of every group of states.

Table 29: Correlations matrix (Germany classification)

	GDP per capita growth (annual %)	Agriculture value added (%GDP)	Licenses for residential building (annual growth)	Population growth (annual %)
Agriculture value added (%GDP)	0.161			
Licenses for residential building (annual growth)	-0.286	-0.086		
Population growth (annual %)	-0.166	-0.26	0.189	
Unemployment rate	0.229	0.411	-0.031	-0.607

Figure 12: Classification of the German states in 2009

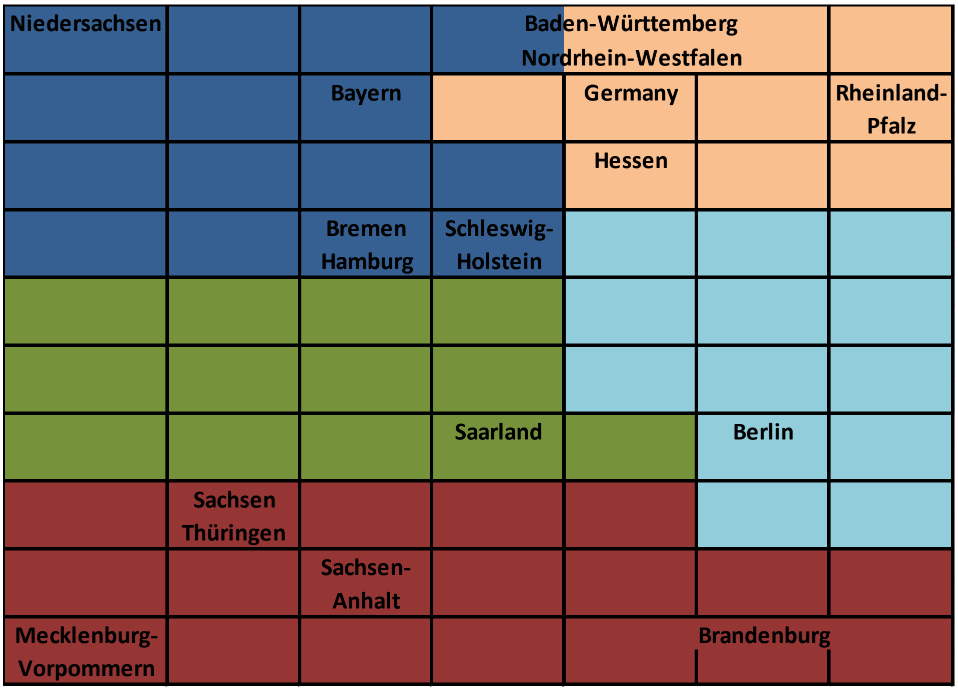


Figure 13: Geographical distribution of the German states

Table 30: Classification of the German states

Group	Components
1	Niedersachsen, Bayern, Bremen, Hamburg, Schleswig-Holstein
4	Baden-Württemberg, Nordrhein-Westfalen,Hessen, Rheinland-Pfalz
2	Saarland
3	Mecklenburg-Vorpommern, Sachsen-Anhalt, Sachsen, Thüringen, Bradenburg
5	Berlin

3.5.2. Results and assessment of the model

Our results show that nine States included in groups 1 and 2 -the most solvent ones- come from the former Federal Republic of Germany (Tables 30-32 and Figure 13). On the contrary, the six states included in the groups 4 and 5 –the ones with the lowest solvency- are located in the Eastern side of the country. This shows that, after the process of reunification of the country in the 90's, the efforts of the EU and of the German Government have not managed still to bridge the gap of development across the states. This result is coherent with Kronthaler (2003), who show the persistence of differences between both zones of Germany in terms of GDP growth and unemployment rate.

Table 31: Mean values for each group (German states)

	GDP per capita growth (annual %)	Agriculture value added (%GDP)	Licenses for residential building (annual growth)	Population growth (annual %)	Unemployment rate
1	1.03%	1.17%	7.10%	0.23%	8.41%
2	1.26%	1.04%	-12.25%	0.17%	6.88%
3	1.28%	0.33%	2.64%	-0.31%	14.64%
4	2.76%	2.30%	-8.32%	-0.64%	17.16%
5	3.78%	0.73%	-17.39%	-0.09%	8.83%

Table 32: Main characteristics of each group (German States)

Group	Characteristics
1	Lower GDP growth, more importance of the construction and the population
2	Lower unemployment rate
3	Low importance of the agricultural sector
4	High importance of the agricultural sector and higher unemployment rate
5	Higher GDP per capita growth

The Saarland state is in an intermediate position. This small state, located between the French Lorraine and Luxembourg, suffers from 2008 in after from a substantial increase of unemployment, partially due to the fall of public and residential construction. It has been the German state with the highest GDP decrease in 2009. The sensitivity analysis (Table 33) shows that the most relevant variable is the licenses for residential buildings, followed by the unemployment rate, the value added by the agriculture to the GDP, the population growth and, finally, the GDP annual growth.

Table 33: Sensitivity analysis of the German states classification

Variable	Importance	Normalized importance
GDP per capita growth	0.15	66.90%
Agriculture value added	0.19	82.40%
Licenses for residential building	0.23	100.00%
Population growth	0.17	73.40%
Unemployment rate	0.22	95.30%

The results of the ANOVA analysis (Table 34) corroborate the discriminatory power of the model and show significant differences among the groups. Again, the comparison with some more traditional techniques such as cluster analysis or factor analysis (Table 35) shows that SOM provides consistent results.

Table 34: Analysis of variance (ANOVA) of the classification of German states

		Value	F-test	D.F. hypothesis	G.l. error	p-value	Partial Eta^2	No centrality parameter	Observed potency
Intersection	Pillai's trace	.948	789.358	5	215	.000	.948	3946.791	1.000
	Wilks' lambda	.052	789.358	5	215	.000	.948	3946.791	1.000
	Hotelling's Trace	18.357	789.358	5	215	.000	.948	3946.791	1.000
	Roy's largest root	18.357	789.358	5	215	.000	.948	3946.791	1.000
Group	Pillai's trace	1.686	31.776	20	872	.000	.422	635.519	1.000
	Wilks' lambda	.065	45.753	20	714.024	.000	.495	700.933	1.000
	Hotelling's Trace	5.495	58.656	20	854	.000	.579	1173.119	1.000
	Roy's largest root	4.045	176.356	5	218	.000	.802	881.782	1.000

Table 35: Comparison of the German States classification models

Variable/Method	SOM		K-means		Factor/K-means	
	F-Stat	p-Value	F-Stat	p-Value	F-Stat	p-Value
GDP per capita growth (annual %)	35.931	0.000	26.824	0.000	37.309	0.000
Agriculture value added (%GDP)	60.114	0.000	126.382	0.000	24.847	0.000
Licenses for residential building (annual growth)	42.667	0.000	35.289	0.000	72.362	0.000
Population growth (annual %)	71.110	0.000	117.948	0.000	66.893	0.000
Unemployment rate	187.150	0.000	131.463	0.000	105.936	0.000
Within groups total variance	22.343		21.255		24.410	

Unlike Spain, Germany as a whole country would be included during 2009 in the group of states with the best financial situation. During that year the GDP per capita, the population, and the licenses for residential building have increased in Germany, and the unemployment rate has fallen.

Thus, in spite of the differences across the German states, our results show that the German regions are in a significantly better economic situation than their Spanish counterparts. Consequently, whereas the aggregation effect on the whole country is positive in Germany, the troublesome situation of Spain can be attributed, at least partially, to the financial weakness of its AA.CC.

3.6. Concluding remarks

Self-organizing maps are a very useful tool for the classification of countries and regions based on their economic indicators. Using this method and a set of the usual macroeconomic variables, in this paper we analyze and compare the financial situation of the European countries in 2009 to obtain groups of countries conditional on their capacity to meet their financial commitments. Our results show the existence of several groups of countries, each one of them with specific characteristics. We also find that Government expenditure and the saving rate are the most influential variables on the macroeconomic financial imbalances.

We also study the influence of the macroeconomic situation of each Spanish AA.CC. and German states on the national situation. We find that the macroeconomic situation of the regional entities is a key determinant of the country financial (im)balance. Therefore, the identification of the regions that need the most demanding economic and social policies could alleviate the incidence of the current financial crisis.

Our research provides interesting insights for policymakers. The debate around the role played by the rating agencies in the financial crisis requires more and better methods of processing country-level information. From this perspective, our paper provides a complementary method to analyze the international macroeconomic financial situation. Yet, the identification of groups of similar countries can allow discovering possible channels of financial contagion and financial turbulences propagation across countries. Thus, our model could serve as an early warning system for some countries when the counterpart countries get into financial troubles.

In the same vein, the enlargement of the EU can be eased through diagnosing and forecasting the future financial situation of the candidate countries in order to avoid any destabilization effect. In addition, the identification of the regional disparities within

European countries can lead to focus on the countries and regions in the most need of receiving European financial help.

From a microeconomic point of view, our research is also useful for banks and other institutional investors since the international risk map can be a relevant input to assess the risk exposure of each institution. This tool would be complementary to the stress tests and other analyses of sovereign risk carried out by national and international financial supervisors in recent months.

4. Predicting public corruption with neural networks: An analysis of Spanish provinces

4.1. Introduction

Although political corruption has been around for a long time, it has attracted considerable attention in recent years, and the literature suggests it is on the increase (Salinas-Jiménez and Salinas-Jiménez, 2007; Transparency International, 2016). For example, Kaufmann and Bellver (2005) estimate that corruption represented some $1.1 trillion globally. According to a recent estimate from the International Monetary Fund (2016), the annual cost of bribery comes to about $1.5 to $2 trillion (roughly two percent of global GDP). Corruption can have a dramatically negative impact on a country's economic development, which may then in turn lead to more corruption. Spain is a good example of this vicious circle. Between 2007 and 2012, the financial wealth of Spanish households fell by €167 billion, the unemployment rate shot up from 8.8% to 26.2%, and the 2% public surplus turned into a 10.6% public deficit. Furthermore, the risk premium on Spanish treasury bonds reached a worrying 610 point peak in the summer of 2012. At the same time that tough measures to reduce government expenditure and public deficit were enforced, a number of political corruption cases were unearthed, causing alarm all over the country.[13] Moreover, the European Union Anti-Corruption Report issued by the European Commission (2014) highlighted serious concerns about the growth of corruption in certain countries including Spain. Moreover, 95% of Spanish citizens agreed that corruption is rife throughout the country.[14] Spain thus provides a unique framework to study the issue.

The aim of this paper is to provide a neural network prediction model of corruption based on economic factors. We contend that corruption must be detected as soon as possible in order to take corrective and preventive measures. Because public resources for combating corruption are limited, efforts should focus on areas most likely to be

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[13] A December 2014 survey by the Spanish Center for Sociological Research showed that 63.9% of Spanish citizens cited corruption as the country's major problem.

[14] http://ec.europa.eu/dgs/home-affairs/e-library/documents/policies/organized-crime-and-human-trafficking/corruption/docs/acr_2014_en.pdf

involved in corruption cases. We use a unique database that brings together the main cases of political corruption in Spain. We then propose an early warning corruption model to predict whether corruption cases are likely to emerge in Spanish regions given certain macroeconomic and political determinants. We use self-organizing maps (SOMs), a neural network approach, to predict corruption cases in different time horizons. Our model provides different profiles of corruption risk depending on the economic conditions of a region conditional on the timing of the prediction.

This paper contributes to the literature by developing a novel approach with three differential characteristics. First, unlike previous research, which is mainly based on the perception of corruption, we use data on actual cases of corruption. Second, we use the neural network approach, a particularly suitable method since it does not make assumptions about data distribution. Neural networks are quite powerful and flexible modeling devices that do not make restrictive assumptions on the data-generating process or the statistical laws concerning the relevant variables. Third, we report the probability of corruption cases on different time scenarios, so that anti-corruption measures can be tailored depending on the immediacy of such corrupt practices. Consistent with Huysmans, Martens, Baesens, Vanthienen and Van Gestel (2006), who also use SOMs and support vector machines to forecast changes in the perceived level of corruption, our model allows patterns of corruption to be identified on different time horizons.

Our results show that economic factors prove to be relevant predictors of corruption. We find that the taxation of real estate, economic growth, increased house prices, and the growing number of deposit institutions and non-financial firms may induce public corruption. We also find that the same ruling party remaining in power too long is positively related to public corruption. Depending on the characteristics of each region, the probability of corrupt cases emerging over a period of up three years can be estimated. We then detect different patterns of corruption antecedents. Whereas in some cases, corruption cases can be predicted well before they occur and thus allow preventive measures to be implemented, in other cases the prediction period is much shorter and urgent corrective political measures are required.

The remainder of this paper is organized as follows. Sections 4.2 and 4.3 review the literature on corruption and the foundations of SOMs, respectively. Section 4.4 explains the empirical characteristics of our early warning system. Section 4.5 presents the results of our model. Section 4.6 discusses the implications of our results. Finally, section 4.7 concludes.

4.2. Theoretical background

4.2.1. The literature on corruption

Prior literature reports a widespread consensus that corruption has detrimental effects on the economy (Ortega, Casquero and Sanjuán, 2016). Mauro (1998) reports the negative effect of the perception of corruption on investment and GDP growth for a sample of 106 countries. Salinas-Jiménez and Salinas-Jiménez (2007) find a negative relation between corruption, productivity, and economic growth for 22 OECD countries. Transparency International (2009) suggests that the most developed countries have lower levels of corruption. Using a set of micro-data from 67 countries, Pieroni and d'Agostino (2013) show that economic freedom helps to reduce corruption. In the same line, Rajkumar and Swaroop (2008) find that some public expenditure policies perform most poorly in places with high corruption. Cavoli and Wilson (2015) show that corruption imposes an inflationary bias on the optimal monetary policy, and Kunieda, Okada and Shibata (2014) provide evidence that the negative effect of government corruption on economic growth is channeled through higher tax rates and is amplified by capital account constraints. Alternatively, Saha and Gounder (2013) propose a quadratic relation between corruption and economic development. D'Agostino, Dunne and Pieroni (2016) report that the interaction between corruption and public spending has a strong negative impact on economic growth. Corruption, in general, threatens government legitimacy and economic freedom, leads to regressive taxes, and increases poverty (Nwabuzor, 2005).

When developing a model to predict corruption, the causes are as relevant as its consequences (Dong and Torgler, 2013; Kong and Volkema, 2016). Among the various explanations (i.e., political, historical, social, cultural), economic theory shows that corruption is fuelled when the monetary benefits outweigh the associated penalties. Based on a comprehensive review of the economic determinants of corruption, Aidt (2009) argues that corruption depends on three issues: deterrence measures, bureaucratic discretionary power, and the possibility of generating economic rents. The increased likelihood of being caught coupled with the severity of the penalties reduce the probability of corruption occurring. Similarly, by its enabling corruption to be controlled, freedom of the press is associated with increased real GDP per capita (Ambrey, Fleming, Manning and Smith, 2016). Education also acts as an important deterrent. Given the link between education and national income, corruption should be lower in richer countries (Treisman, 2000).

In addition, the economic rents to be gained from corruption can also act as an incentive. Van Rijckeghem and Weder (2001) show that corruption decreases when official wages increase. If wages are low, the opportunity cost of bureaucrats' accepting bribes decreases. Corruption also occurs more frequently in developing countries due to the lack of commensurate advancements in their legal, political, and social institutions (Kaymak and Bektas, 2015). A country's industrial organization also influences corruption levels; specifically, countries with less internal and external competition are more prone to corruption (Gerring and Thacker, 2005).

Empirical research is faced with the problem of how to measure corruption (Olken, 2009). Thus, prior research often uses surveys of corruption perceptions. For example, Clausen, Kraay and Nyiri (2011) analyze the relationship between corruption and confidence in public institutions using the Gallup World Poll database. They find that in countries where respondents report a high incidence of personal experiences with corruption, and in which corruption is perceived to be widespread, confidence in public institutions is also low. Pellegata and Memoli (2016) also confirm that corruption negatively affects citizens' confidence among European Union member states. Li, Gong and Xiao (2016) study the factors that explain the variation in people's perceptions of anti-corruption efficacy. Finally, Zheng, Liu, Huang and Tan (2017) found a negative effect of corruption perception on political participation. Other studies measure corruption in a variety of ways, including surveys of bribes that question possible bribe-payers and compare the estimated bribe with the reported costs of public goods, structural equations models, the analysis of noncompliance by public officials as compared to noncompliance within the general population, and the number of crimes against public administration officials (Del Monte and Papagni, 2007; Neiva de Figueiredo, 2013; Olken, 2007).

Nevertheless, as Treisman (2007) admits, perception-based data reflect impressions of corruption intensity rather than actual occurrences of corruption. These perceptions are subjective and can be influenced by respondents' beliefs as well as their social and economic conditions. Similarly, uncorrected measures of the perception of corruption might cause misleading conclusions to be drawn about the comparisons of corruption levels between countries (León, Araña and de León, 2013). Nevertheless, among the literature, few studies use real data on corruption. Objective data on corruption are difficult and complex to obtain, since crimes are committed in a hidden manner. If available, information is usually found in an unstructured way in the media, court records, etc. Some examples of this research are Dong and Torgler (2013) and Wu and Zhu (2011), who pinpoint the causes of corruption in China, and Stockemer and Calca (2013), who use municipal corruption cases in Portugal and find that highly corrupt areas have a higher turnout in elections than less corrupt areas.

4.2.2. The political framework of corruption

Interestingly, prior research finds a link between corruption and political decentralization (Fisman and Gatti, 2002; Ivanyna and Shah, 2011). Nevertheless, these studies, which use subjective indexes of perceived corruption and mostly fiscal indicators of decentralization, report conflicting conclusions. When focusing on political decentralization, most agree that the federal structure is associated with higher perceived corruption (Fisman and Gatti, 2002). Diaby and Sylwester (2014) find that in the former communist countries, bribes are higher under a more decentralized bureaucratic structure. In the same vein, Treisman (2002) finds that a larger number of administrative or governmental tiers correlate with higher perceived corruption. Fan, Lin and Treisman (2009) come to a similar conclusion using information on reported bribery. Albornoz and Cabrales (2013) argue that the effect of decentralization on corruption is conditional on the level of political competition. Decentralization is associated with lower levels of corruption if the level of political competition is sufficiently high.

Overall, the results suggest the danger of uncoordinated rent-seeking as government structures become more complex. A greater number of relationships and interactions between public officials and private agents in federal or decentralized states seem to provide increased opportunities for corrupt behavior. In any case, most studies that consider the causes of corruption focus on cross-country comparisons, and only a few employ within-country data (Fisman and Gatti, 2002; Leeson and Sobel, 2008).

Corruption in Spain has attracted considerable attention, especially in the most recent years, when many cases have been uncovered. Spain is a diverse country made up of different regions with varying economic and social structures, as well as different languages and historical, political and cultural traditions. Although Spain is not a federal state, it is a highly decentralized unitary state which endows its regions or autonomous communities (*Comunidades Autónomas*) with high levels of political and economic competences. Autonomous communities is the nomenclature of Territorial Units for Statistics 2 (NUTS-2) regions according to the European Commission classification,[15] with high levels of political and economic competences. The worrying macroeconomic imbalances of the autonomous communities in terms of excessive public deficit, public debt, and sovereign debt problems led the Spanish government to enact a stability program for 2011–2014 to accelerate fiscal consolidation which focused on the

[15] The Nomenclature of Territorial Units for Statistics classification is a hierarchical system for dividing up the economic territory of the European Union.

autonomous communities. Thus, the political structure of Spain seems to be related to some of this recently growing corruption.

In turn, this analysis of corruption problems among Spanish regional governments is quite timely as is the design of a model of corruption prediction based on macro-economic factors. Our paper contributes to the literature on corruption by using real data and by adopting a different approach which it is hoped will prove useful vis-à-vis understanding the complex process of corruption. Moreover, whereas other studies mainly determine the causes or the specific sign of certain variables related to corruption or predict crimes against the administration, our approach provides an estimation of the probability of new cases of corruption emerging for different time horizons.

4.3. SOMs

4.3.1. Unsupervised self-organizing maps

The literature is scarce on corruption from the point of view of data mining techniques. Prior research uses data mining techniques and, specifically, neural networks to predict patterns in some related fields such as crime (Li and Juhola, 2014; Li and Juhola, 2015), credit risk evaluation (Guo, Zhou, Luo, Liu and Xiong, 2016; Swiderski, Kurek and Osowski, 2012), fraud detection (Olszewski, 2014), and wellbeing (Carboni and Russu, 2015; Lucchini and Assi, 2013; Rende and Donduran, 2013). We argue that neural networks can be also applied to predict corruption.

SOMs are a kind of artificial neural network that aim to mimic brain functions so as to provide machine learning and pattern recognition (Jagric, Bojnec and Jagric, 2015; Kohonen, 1982). SOMs have the ability to extract patterns from large data sets without an explicit understanding of the underlying relationships. They convert nonlinear relations among high dimensional data into simple geometric connections among their image points on a low-dimensional display. The most important topological and metrical relations are preserved, as data points with similar properties are placed close to each other within the output (Kohonen, 2001). These properties have made SOMs a useful tool to detect patterns and obtain visual representations of large amounts of data. Consequently, predicting corruption is a field in which SOMs can become a powerful tool.

Figure 1 shows the most common version of SOMs. The input layer of neurons represents the original data set and is connected to the output layer of neurons through synaptic weights. The information provided by each neuron of the input layer is transmitted to all the neurons of the output layer. Thus, each neuron in the output layer receives the same set of input layer information. The first and most commonly used version of SOMs is considered an unsupervised network because no objective output occurs. Neurons learn in an unsupervised way to detect and identify data patterns in specific zones in a two-dimensional grid. SOMs are trained by means of an iterative process.

Nour (1994) sums up an SOM learning algorithm in three stages. First, the vector of initial weights $W_i(t)$ in t=0 is set randomly. At this moment, the maximum number or possible iterations in the training phase of the network (T) is defined. Second, an input vector X is added to the network, and the distance (similarity) D is computed using the Euclidean metric to find the closest matching unit c to each input vector as follows:

$$d_{i,j,(t)} = \sqrt{\sum_{h=1}^{k}\left(W_{i,j,h} - X_k\right)^2}.$$

Finally, the weight vector is updated according to the following rule:

$$W_{jik}(t+1) = W_{jik}(t) + \alpha \,.\left[X_k(t) - W_{jik}(t)\right],$$

where α is the learning ratio, $X_k(t)$ is the input pattern in t and W_{jik} is the synaptic weight that connects the k input with the (*j,i*) neuron in *t*. Not only is the winning neuron updated, but also the neighbors following a neighborhood function. The neighborhood ratio decreases with the number of iterations of the model so as to achieve a better specialization of each neuron. The process continues an iterative way until t reaches the maximum number of iterations T, and then jumps back to step 2. Following

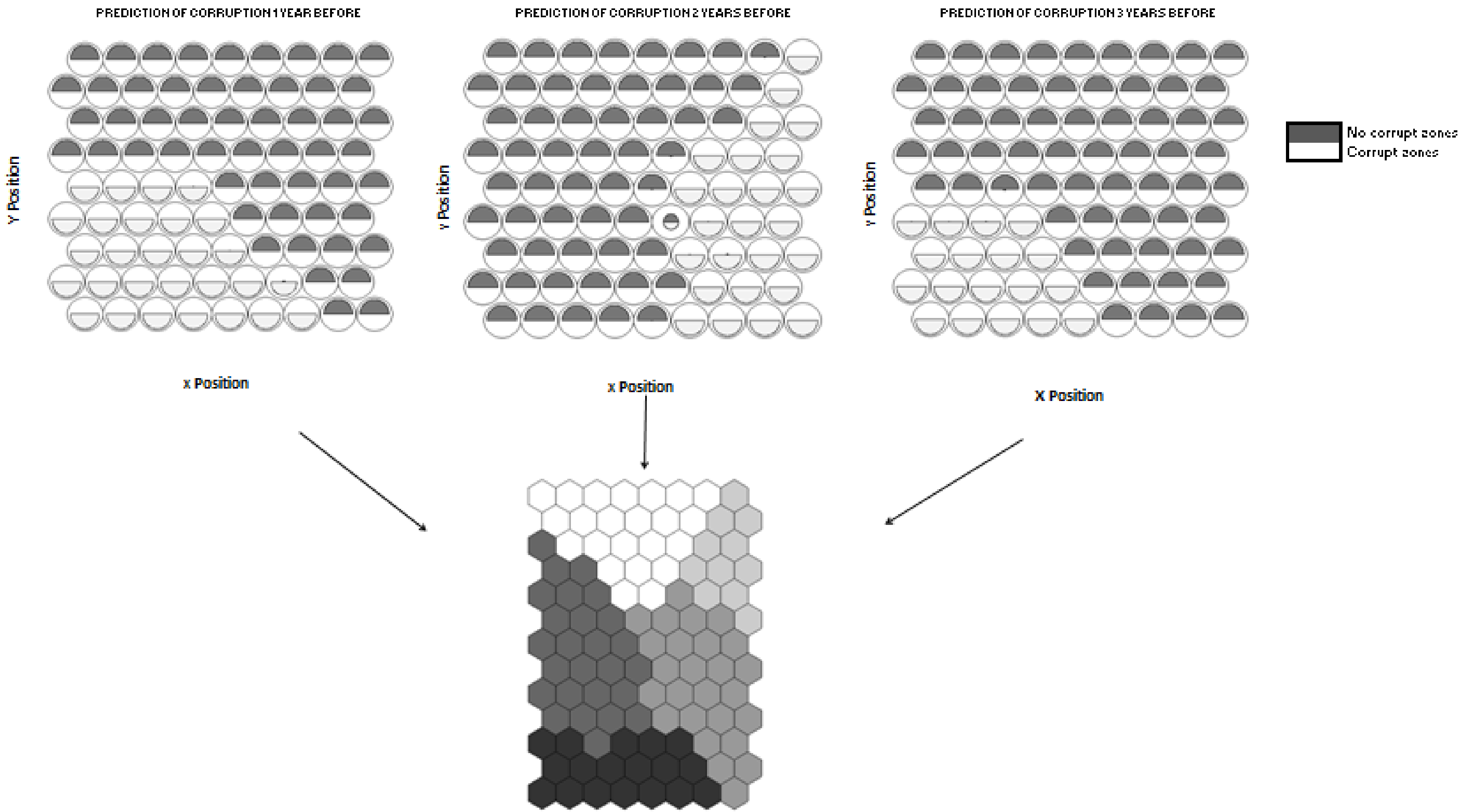
Gladyshev's theorem, SOM models almost always reach convergence (Lo and Bavarian, 1993).

4.3.2. Supervised SOMs

Although SOMs are often unsupervised, supervised SOMs can be created by incorporating the desired output in the training phase. The aim is to produce input vectors by linking the (numeric) target vectors with the data label and then training the network in the usual way. Prior research shows that supervised versions of SOMs outperform unsupervised SOMs in predicting problems (Hagenbuchner, Tsoi and Sperduti, 2001). In a supervised SOM, two maps can be trained at the same time—one containing the original data (X) without the class information and the other including only the class or target information (Y). A common winning unit for both maps can be determined by calculating a weighted combination of the similarities between the X object and all the units in the X map and the similarities between the corresponding output Y object and all the units in the Y map. A specific weight of X and Y spaces in this combination must be chosen. The training is done in the usual manner and is updated with the information from the winning unit and its neighborhood. As in unsupervised SOMs, the learning rate and size of the neighborhood decrease in each iteration.

This study trains three supervised versions of SOMs. The three models use macroeconomic variables and the region's corruption status (corrupt or not corrupt) one, two and three years ahead of the reference point, respectively. Each Spanish region is then classified for each time horizon using the three trained models (i.e., each region is classified three times), which predict the likelihood that a region will have an incident of corruption up to three years later. The position of each region in the trained maps is now transformed into a probability of corruption. This probability is then introduced as the last input that renders the early warning corruption system map. This last map is trained using an unsupervised SOM (because no information exists about the possible output). This final map, which classifies Spanish regions according to their corruption risk profile, provides a visual representation of corruption. Figure 14 illustrates the three supervised versions of SOM and the final unsupervised map.

Figure 14. Visual representation of our model



4.4. Early warning corruption systems

The information we use comes from the corruption database gathered by *El Mundo*,[16] one of the most influential newspapers in Spain. The database contains information about the criminal cases involving a politician or a public official reported in Spain since 2000. The accused can be either already sentenced or awaiting the verdict. Our unit of analysis is the Spanish provinces, which are considered NUTS-2 regions according to the European Commission classification. Spain consists of 52 provinces. A province is considered susceptible to corruption if at least one corruption case occurs in a given year. The dependent variable for each year and province is defined as a dummy variable that equals 1 if at least one corruption case has gone to trial in this province in a given year, and zero otherwise.

The number of corruption cases can be correlated with the population or the economic activity of a given region. Larger regions could be more prone to present more corruption cases because the number of politicians is also higher. Thus, we measure public corruption as the number of registered cases of corruption per 100,000 people each year. This metric was also used by Dong and Torgler (2013) when studying causes of corruption in China.

Although the date on which a corruption case is uncovered can easily be defined, the year in which a bribe occurs proves more difficult to detect. A public official may have been receiving bribes long before he or she was finally charged. Therefore, we use three supervised versions of SOMs to predict corruption one, two, and three years before cases were uncovered. The output of each model is a two-dimensional map with two regions: corruption and non-corruption zones. These partial maps allow us to reduce the input data into a position on each map. The SOM maintains the structure of the original data in a two-dimensional map, and therefore similar regions are placed

[16] http://www.elmundo.es/grafico/espana/2014/11/03/5453d2e6268e3e8d7f8b456c.html

close to one another in each map. Based on these maps, we classify each Spanish province, and, depending on the zone in which they are placed, we define them as corrupt or not corrupt at a given moment. Thus, SOM maps provide an easy way to visualize and compare the level of corruption in each province at the same time.

Finally, the output or probability of corruption of the three previous models is combined into a single final map to create a hybrid model. Results from hybrid models have been used as a way to obtain more accurate models than either of the techniques used separately. The result provides a map on which provinces can be placed according to their profile in terms of the probability of corruption occurring. We use the output of the different provinces in each map as input to train the final map. In this combined map, we provide no output or information about the presence or absence of corruption within a region in the training phase. This map is therefore trained in an unsupervised way.

Once the final map is trained, the *k*-means algorithm is used to display different groups of provinces conditional on their propensity for corruption. The likelihood of a province being considered corrupt in different time horizons is then computed and the main economic factors that cause corruption to occur in a region are identified.

Previous literature suggests that regions (countries) with similar socio-economic characteristics have a similar predisposition towards corruption. Consistent with analogous analyses (Aidt, 2003; Aidt, 2009), the macroeconomic conditions of the Spanish provinces are chosen to develop the maps. Table 1 provides a list and description of nine variables classified into five categories (budget balance, debt levels, economic growth, labor force and political factors). These variables enhance the comparability of our results in the international literature. The variables are discussed below:

- **Real estate taxation** is one of the main sources of revenue for municipalities and provinces. It is levied on the ownership of real estate, whether rural or urban. Local governments can exercise substantial discretion when applying this tax. Spanish law sets a minimum and a maximum tax rate, which is then applied at the discretion of each municipality. We compute the average tax rate in a province and compare this average rate with the maximum and minimum possible tax rates by law. A higher ratio can potentially induce more corruption by incentivizing tax evasion given the relation between tax rates, corruption, and tax evasion as shown by Ivanyna, Mourmouras and Rangazas (2010).

- **Debt per capita** is the province's total outstanding public debt relative to its population. The underlying rationale for this variable is the close relation between corruption and public debt. Cooray and Schneider (2013) show that corruption, increased government expenditure, and the size of the shadow economy lead to increased public debt. Grechyna (2012) concludes that corruption causes higher public debt levels for a sample of high income OECD countries, and Nguyen (2006) reaches the same conclusion for a group of emerging economies.

- **Debt service** measures the region's ability to repay its debt by comparing total public debt with total public revenues of each year.

- **Deposit institution growth** is computed by comparing the number of deposit institutions between two consecutive years. The increase in the number of deposit institutions is usually related to economic growth, which implies more interactions between the private and public sector, which can increase the likelihood of corruption (Goel, Nelson and Naretta, 2012).

- **Population growth** is the rate at which the number of inhabitants in a province increases between two consecutive years. Prior studies find a positive relation between corruption and population (Alt and Lassen, 2003; Damania, Fredriksson and Mani, 2004) based on the more frequent interactions between the private and public sectors in regions with a growing population. Knack and Azfar (2003) also find evidence that corruption increases as the population grows.

- **Variation in the number of registered companies** measures the increase or decrease in the number of live registered companies. As with previous indicators, an increase can imply greater economic growth and more investment in the region. In turn, as the number of companies increases, the incentive to pay bribes in order to secure a better position or market share than competitors also increases.

- **House price increase** accounts for the fact that a high proportion of corruption cases in Spain are related to the construction industry (Benito, Guillamón and Bastida, 2015). Between 1997 and 2006, an increase in household savings and population, combined with a reduction in the unemployment rate and the interest rate, caused house prices to rise by nearly 7% annually. The most corrupt areas are the regions in which urban and environmental standards are the least respected.

- **Unemployment rate** is the percentage of the total labor force that is unemployed and actively seeking employment and willing to work. The unemployment rate is usually related to high informal sectors and corruption. Saha and Gounder (2013) identify the unemployment rate among other determinants that explain differences in corruption between countries. Conversely, Bouzid (2016) finds that corrupt practices tend to increase the unemployment rate, especially in the case of young and educated job seekers.

- **Unemployment rate growth** is the variation of the unemployment rate between two consecutive years. Unemployment has a major impact on corruption. Habib and Leon (2002) and Rehman and Naveed (2007) show that corruption reduces the levels of foreign investment, and results in an increase in the unemployment rate.

- **Number of years in government**: the number of years the ruling party has been in office. Given politicians' interest in being re-elected, the ruling government can use the power to set up a network of relationships that help them to get re-elected (Besley and Case, 1995; Ferejohn, 1986). Ferraz and Finan (2007) find that in municipalities where mayors are in their second and final term, there is significantly more corruption than in similar municipalities where mayors are serving their first term in office.

- **Governments ruling in majority**: the winning party enjoys a majority if it obtains at least half plus one of the seats in the last election. In other cases, there will either be a coalition or a minority government. Tavits (2007) reports a negative correlation between majority government and corruption on a cross-section of countries. The main argument is that when there is a majority government, the responsibilities are clearer for citizens. In turn, when political institutions provide high clarity of responsibility, politicians face incentives to pursue good policies and reduce corruption.

Table 36: Initial set of macroeconomic variables

Variable Category/Code	Variable Name	Variable Calculation	Literature research
		Budget balance	
RE_TAXATION	Real estate taxation	(Real estate tax rate–Legal minimum tax rate)/(Legal maximum tax rate–Legal minimum tax rate)*100	Ivanyna, Mourmouras and Rangazas (2010)
		Debt levels	
DEBT_CAPITA	Debt per capita	Government's total debt/Province population	Cooray and Schneider (2013); Grechyna (2012); Nguyen and van Dijk (2012)
DEBT_SERVICE	Debt service rate	Outstanding debt/Total revenues	
		Economy growth	
DEPOT_INST	Deposit institution growth	(Number of deposit institutions year *N*– Number of deposit institutions *N*–1)/Number of deposit institutions *N*–1	Goel, Nelson and Naretta (2012)
POP_GROWTH	Population growth	(Total population year *N*–Total population year *N*–1)/Total population year *N*–1	Alt and Lassen (2003); Damania, Fredriksson and Mani (2004); Knack and Azfar (2003)
COMPANIES_GROWTH	Variation in the number of registered companies	(Number of active firms year *N*–Number of active firms year *N*–1)/Number of active firms year *N*–1	
HOUSE_GROWTH	House price growth	(Average of house prices per m^2 year *N*–Average of house prices per m^2 year *N*–1)/Average of house prices per m^2 year *N*–1	Benito, Guillamón and Bastida (2015)
		Labor force	
UNEMPL	Unemployment rate	Number of unemployed people over the age of 16/Total labor force	Habib and Leon (2002); Rehman and Naveed (2007); Saha and Gounder (2013); Bouzid (2016)
UNEM_GROWTH	Unemployment rate growth	(Unemployment rate year *N*–Unemployment rate year *N*–1)/Unemployment rate year *N*–1	
		Political factors	
YEARS_GOVER	Number of years in government	Number of years since the political party came into office	Besley and Case (1995); Ferraz and Finan (2007); Ferejohn (1986)
MAJORITY	The ruling party has an overall majority		Tavits (2007)

Other variables such as the crime rate, the educational level or electoral absenteeism were initially considered but data were not available with sufficient coverage.

Table 37 reports the mean; standard deviation; minimum; maximum; 25th, 50th, and 75th quartile and p-value of the Shapiro-Wilk normality test. According to this test, not all the variables are normally distributed at the 5% significance level. When the mean values are compared between regions with and without corruption cases, the non-normality of variables makes the nonparametric test (Mann-Whitney U test) more reliable than the parametric test. Thus, Table 38 reports the Mann-Whitney test.

Table 37: Descriptive statistics

Variable code	# Obs.	Mean	Std.	Min	Max	Q25	Q50	Q75	SW sig.
RE_TAXATION	400	0.185	0.102	0.000	0.433	0.117	0.173	0.262	0.000
DEBT_CAPITA	250	0.480	0.221	0.116	1.449	0.337	0.446	0.546	0.925
DEBT_SERVICE	250	0.063	0.030	0.017	0.192	0.044	0.057	0.078	0.633
DEPOT_INST	400	0.002	0.041	–0.204	0.102	–0.026	0.009	0.030	0.000
POP_GROWTH	400	0.010	0.012	–0.012	0.061	0.002	0.006	0.014	0.000
COMPANIES_GROWTH	400	0.013	0.035	–0.140	0.206	–0.015	0.012	0.035	0.281
HOUSE_GROWTH	400	0.002	0.081	–0.206	0.206	–0.058	–0.012	0.066	0.769
UNEM_GROWTH	400	0.144	0.180	–0.102	1.016	0.023	0.109	0.200	0.002
UNEMPL	400	0.090	0.030	0.020	0.210	0.050	0.080	0.110	0.000
YEARS_GOVER	400	17	7.81	1	24	5	17	20	0.000
MAJORITY	400	0.571	0.495	0	1	0	1	1	-

Note: SW sig. is the *p*-value to reject the null hypothesis of normal distribution of the variable according to the Shapiro–Wilk test.

Table 38 compares the mean of the variables between regions with and without corruption cases: 107 out of the 400 province-year observations were corrupt. The table provides the mean for each group in each year. The same analysis is reported one, two, and three years before cases were disclosed. Provinces in the sample are weighted considering the recorded cases of corruption per 100,000 people so as to avoid biases by population or government size. The last group of columns reports the *p*-value of the Mann-Whitney test of means equality. The lower the p-value, the more likely the means are to be different. The means of these variables are significantly different between regions with and without corruption cases, which confirms the choice of explanatory variables. The time framework is also relevant for the comparison. Tax range, population growth, unemployment rates, and number of years in office are significantly different between both groups of provinces one, two, and three years before corruption is uncovered, so that they are likely to play an important role in predicting corruption. One year before the corrupt acts are uncovered, the increase in unemployment and in the number of deposit institutions are also different (i.e., both are higher in corrupt regions). In contrast, three years before corruption is uncovered, the Mann-Whitney test shows significant differences in all the variables except debt service and governing with an absolute majority. Thus, as a preliminary conclusion, the differences between corrupt and non-corrupt regions diminish when we examine the moment at which corruption is reported.

In other kinds of prediction models such as bankruptcy models, the accuracy of the model and the predicting power of the individual variables increase as the bankruptcy date approaches (Grechyna, 2012; Ivanyna, Mourmouras and Rangazas, 2010). In our case, the trend is the opposite, with more significant differences for longer prediction periods. This finding suggests that corruption could have been uncovered some time before had a reliable method of prediction been available. Conversely, in the very short term, the differences between corrupt and non-corrupt regions diminish.

Public debt is not very different between corrupt and non-corrupt provinces. Less data exists about public debt because this information is only available from 2008 (see Table 3). Thus, due to missing data and lower predictive power, we drop DEBT_SERVICE and DEBT_CAPITA and retain the remaining nine variables for the remainder of our analysis. We do not find significant differences if a government is ruling with a majority or not. Consequently, we remove this variable for subsequent analysis.

Table 38. Test of means comparison

	Mean in t–1		Mean in t–2		Mean in t–3		Mann–Whitney U test		
	N	Y	N	Y	N	Y	U (t–1)	U (t–2)	U (t–3)
RE_TAXATION	0.169	0.218	0.173	0.216	0.176	0.214	0.000	0.000	0.002
DEBT_SERVICE	0.062	0.066	0.064	0.063	0.064	0.063	0.633	0.499	0.630
DEBT_CAPITA	0.480	0.481	0.490	0.453	0.488	0.437	0.925	0.080	0.030
COMPANIES_GROWTH	0.010	0.011	0.006	0.021	0.002	0.033	0.945	0.000	0.000
HOUSE_GROWTH	–0.012	0.000	–0.017	0.014	–0.026	0.042	0.968	0.041	0.000
POP_GROWTH	0.008	0.013	0.007	0.015	0.007	0.016	0.000	0.000	0.000
DEPOT_INST	–0.004	0.015	–0.009	0.028	–0.009	0.033	0.000	0.000	0.000
UNEMPL	0.093	0.099	0.099	0.086	0.102	0.075	0.052	0.009	0.000
UNEM_GROWTH	0.125	0.183	0.122	0.195	0.159	0.105	0.002	0.013	0.003
YEARS_GOVER	13.14	17.83	13.50	16.51	13.58	15.27	0.000	0.003	0.045
MAJORITY	0.58	0.56	0.58	0.57	0.56	0.54	0.112	0.250	0.320

Notes: N indicates no reports of corruption, and Y represents provinces in which corruption cases have gone to trial.

4.5. Empirical results

4.5.1. Time horizon prediction models

Once we test the ability of our variables to predict corruption in Spanish provinces, we create three different models of supervised SOMs. To validate each SOM, we divide the sample into training and validation subsets. Selected randomly, the training data in each SOM accounts for 70% of the sample.

SOMs are usually implemented in an unsupervised way, and the network does not receive any output information provided in the training phase. We improve the model by providing the network with the output (corrupt or not corrupt region) so as to train the map, converting the model into a supervised version. The distance of the input to a unit is defined as the sum of the separate distances for X (macroeconomic variables) and Y (region situation) spaces. The prediction is carried out using only the X space. Introducing class membership information into the learning process increases the performance relative to traditional SOMs (Hagenbuchner and Tsoi, 2005). As part of the preprocessing, all the variables are linearly scaled to have a zero mean and unit variance. Each model uses the same macroeconomic variables but a different independent variable, which is a binary variable depending on whether any corruption cases have been reported in the province in year t–1, t–2, and t–3. The size of each two-dimensional map is fixed following the recommendations of Kohonen (1993) and Kaski and Kohonen (1994) to maintain a balance between quantification and topological errors. The quantification error is calculated as the average distance between each data vector and its best matching unit or final position in the map. The topological error measures the topology preservation and is calculated as the proportion of all the data vectors for which the first and second best matching units are not adjacent. Different SOM sizes (5×5, 6×6, 7×7, 8×8, 9×9, 10×10, 11×11, and 12×12) and different learning parameters are tested to determine the parameters that render the lowest error rate in classification. Test results show that the best parameters are similar for each of the three supervised maps. Specifically, the optimal size is a 9×9 cell grid, and the weight assigned to the X data is 0.5. Learning rate and decay are initially set at 0.6 and 0.1, respectively. The chosen neighborhood function is Gaussian. Each map is also trained in two phases: a rough training phase with a large initial neighborhood width and a fine-tuning phase with a small initial neighborhood width.

In these prediction models, two types of error can occur: predicting as corrupt a province that is not involved in corruption cases and not predicting as corrupt a province that is. Thus, to assess the results of our model, we compare predicted cases with actual observed cases for both corrupt and non-corrupt provinces.

Table 39 provides the results. We report the classification results of the training and validation sample for the three models. As previously stated, the performance of the model improves as long as corruption is predicted on a longer term basis. The adjustment of the training sample is 86.74% one year before corruption comes to light and 88.49% when we use information three years in advance. Similarly, the proportion of accuracy for the test sample is 74.17% one year in advance and 84.30% three years in advance.

Table 39. Results of the classification

	Corruption in 3 years			Corruption in 2 years			Corruption in 1 year		
Observed\Predicted	0	1	Overall (%)	0	1	Overall (%)	0	1	Overall (%)
Training sample									
0	190	14	93.14	180	13	93.26	168	16	91.30
1	18	56	75.68	18	68	79.07	21	74	77.89
Total	208	70	88.49	81	279	88.89	189	90	86.74
Test sample									
0	78	10	88.64	62	21	74.70	60	19	75.95
1	9	24	72.73	9	28	75.68	12	29	70.73
Total	87	34	84.30	71	49	75.00	72	48	74.17

We compare the results of our supervised SOM models with two of the most widely used artificial neural network approaches within the field of task classification: multi-layer perceptron and the radial basis function network. Table 40 shows the correct classification rates of the three methods. There are no major differences among the three methods, although it is the SOM approach which provides the best results. Although the multi-layer perceptron approach predicts non-corrupt cases slightly better, the SOM predicts corrupt cases more accurately. These results confirm the ability of the supervised SOM to predict corruption at least as well as most supervised models. However, SOM also provides a visual representation of provinces at the same time, which provides a quick snapshot of the situation in provinces and the risk of corruption.

Table 40. Correct classification percentage calculated with data from the test sample

	Years before corruption		
	3	2	1
Non-corrupt cases			
SOM	88.64	74.70	75.95
MLP	**89.77**	**77.31**	**78.48**
RBF	86.36	72.29	74.68
Corrupt cases			
SOM	**72.73**	**75.68**	**70.73**
MLP	69.70	67.57	**70.73**
RBF	63.63	70.27	65.85
Total accuracy			
SOM	**84.30**	**75.00**	74.17
MLP	76.67	74.17	**75.83**
RBF	73.33	71.67	71.67

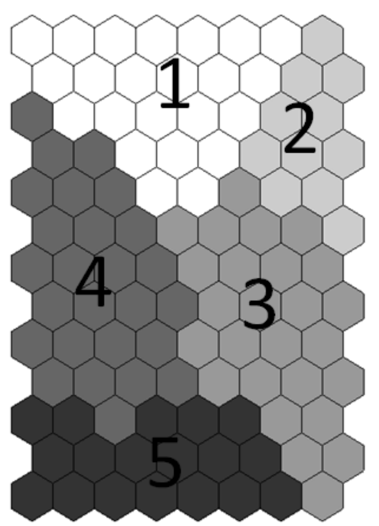
4.5.2. SOM early corruption warning system

In the final step of the analysis, the output of the three previous SOMs is combined to obtain a final map or early warning corruption system. The resulting probability of each region on each map is trained as a standard unsupervised SOM. Up to this point, the trained models produce three different maps and the probability of a given province having corruption cases. In this step, the different corruption profiles from the different time horizons are combined to create a visual tool. The input of this final map is the probability of a given province having corruption cases in the last three trained models, as previously explained. Following the same previously discussed method to determine the size of the map, a trained map of 13×8 cells is obtained. Once the model is trained, all the regions are classified inside this new unsupervised map. In the final step, the optimal separations or clusters in the map are identified.

A key decision concerns the number of groups to be formed. If the number is too low, the groups will be too heterogeneous. However, too many groups can result in characteristics common to the regions being insufficiently identified. The ideal number of groups is one that maximizes intra-group homogeneity and inter-group heterogeneity. Following previous literature, we apply the *K*-means non-hierarchical clustering function to find an initial partitioning (Kuo, Ho and Hu, 2002; Moreno, Marco and Olmeda, 2006). The clustering process has no predefined classes, so the number of groups must be set a priori. Prior studies propose several measures to check the validity and quality of the results: the Silhouette index, the homogeneity and separation index, the weighted inter-intra index, and the Davies-Bouldin index, among others.

The Davies–Bouldin index (Davies and Bouldin, 1979) is one of the most widely used algorithms (Kang, Liu, Zhou and Li, 2016). It is a function of the ratio within-cluster variation to between-cluster variations. The smaller the index, the better the partition. According to this index, the optimal number of groups in our sample is five. Figure 15 provides the final map.

Figure 15. Early corruption warning system final map



Groups are labeled according to the proportion of detected corruption cases, with group 1 (group 5) having the fewest (most) cases of corruption. In turn, different profiles of corruption are established using this approach. In the next section, the main characteristics of the corruption profiles are described and the implications and uses of this approach are discussed.

4.5.3. Discussion

Table 41 shows the different incidence of corruption across groups. Groups 5 and 4 reported corruption cases in 70.22% and 44.24% of included regions, respectively. Groups 2 and 3 are intermediate groups, with a corruption rate of 31.58% and 34.74%, respectively. Group 1 comprises provinces with the lowest corruption rate, with only 8.01% of the provinces involved in corruption cases.

Table 41. Percentage of corrupt provinces by group and time before detection

Group identification	Number of provinces by group	Corrupt provinces 3 years before (%)	Corrupt provinces 2 years before (%)	Corrupt provinces 1 year before (%)	Corrupt cases to total regions ratio (%)
1	179	6.70	5.59	11.73	8.01
2	19	63.16	15.79	15.79	31.58
3	71	19.72	19.72	64.79	34.74
4	56	56.36	63.64	12.73	44.24
5	75	50.67	81.33	78.67	70.22
Total	399[a]	26.82	30.83	34.09	100.00

[a]Although we analyze 400 region-year observations, the information for the Balearic Islands in 2005 was not available.

Table 42 provides the mean of the explanatory variables for each group. The last two columns report the cluster-wise comparison using analysis of variance (F-test and p-value). The result from the analysis of variance shows significant differences in the economic situation among groups. Taken together, Tables 41 and 42 provide some interesting insights into corruption in Spain. The variables indicating economic growth are highly correlated with corruption. In other words, although prior literature reports the negative effect of corruption on growth and investment, the most corrupt regions in our sample grew rapidly in the time before corrupt cases were identified. Table 42 highlights the two extreme situations on our map: group 1, which includes the least corrupt regions, and groups 4 and 5, which comprise the most corrupt regions.

Table 42. Means distribution by group

	Gr. 1 (%)	Gr. 2 (%)	Gr. 3 (%)	Gr. 4 (%)	Gr. 5 (%)	Mean (%)	F. Stat.	Sig.
RE_TAXATION	15.55	17.35	22.73	17.99	22.70	18.60	11.041	0.000
COMPANIES_GROWTH	0.28	3.00	–0.08	2.42	2.30	1.02	12.457	0.000
HOUSE_GROWTH	–2.92	5.72	–1.14	1.66	1.29	–0.77	3.559	0.007
POP_GROWTH	0.54	1.45	0.86	1.50	1.56	0.96	15.936	0.000
DEPOT_INST	–1.74	2.26	–0.33	2.40	3.37	0.23	35.894	0.000
UNEMPL	9.84	6.48	11.32	8.03	8.75	9.49	10.668	0.000
UNEM_GROWTH	11.27	10.67	15.21	14.27	22.39	14.45	5.501	0.000
YEARS_GOVER	8.23	9.76	15.82	22.14	19.11	16.35	8.349	0.000

Our model suggests a link between corrupt regions and the real estate bubble that occurred in Spain during our sample period (2005–2012). As a consequence of the high liquidity in the financial market and low interest rates, increased demand for houses fueled the construction industry and led to an increase in real estate prices, which were financed by new bank branches and deposit institutions. The spillover effects of the construction industry laid the foundation for Spain's rapid economic growth in the late 1990s and early years of the twenty-first century.

However, this accelerated growth came at a cost. In the most corrupt regions (i.e., group 5 and, to some extent, group 4), the number of deposit institutions grew much faster than the population. The number of non-financial firms also increased in these regions, which resulted in strong competition and may have led to bribery as a way to obtain a better position in such competitive markets. Thus, our model shows that regions with real estate prices growing faster than the average and both the number of deposit institutions and non-financial firms growing faster than the population are among the most prone to generate corruption cases. The mass media and the courts, which have proved that some companies paid bribes to officials to strengthen their position in the market and obtain public licenses, especially in the construction sector, support this model. These bribes could have been received by officials who had been in office for a long time. Actually, in groups 4 and 5 the ruling party has been in power longer than in less corrupt regions. Thus, these officials are likely to have had enough time to create a network of corrupt practices. Conversely, the characteristics of the least corrupt group, group 1, are quite dissimilar from most corrupt groups 4 and 5. Group 1 provinces have the lowest tax pressure and the lowest population growth. Public authorities still have the power to increase some taxes should there be a future economic recession or macroeconomic difficulties. In addition, the growth in the number of firms is below the mean. This group of provinces has the lowest increase both in real estate prices and in the number of deposit institutions. Finally, it also has the highest turnover in power, such that the ruling party has not been in power for too long.

In addition to the economic and political factors related to corruption, the time horizon of the corruption is quite relevant, especially when resources to fight corruption are limited and scarce. Thus, if different temporal patterns were detected, resources could be allocated in the different regions more efficiently. For example, in regions where a high likelihood of corruption exists in the short term, more resources and efforts should be assigned. It also allows the establishment of actions plans to avoid corruption in the medium or long term in the less risky regions.

Two main patterns have been identified in terms of time dimension. These patterns are attributable to the different economic and political models in each region. As explained, Spanish regions have followed quite a diverse historical and social evolution, which has resulted in distinct economic and political situations. The first model concerns groups 3 and 5, and shows a clear increasing trend before corruption is detected. For instance, in group 3 the proportion of provinces identified as corrupt three years before the corruption was discovered is 19.72%, whereas this proportion soars to 64.79% one year before (see Table 6). Group 5 shows similar results. This trend may imply that, in these regions, efforts to discover and fight corruption must be short term because it is difficult to identify and prevent corruption several years before it happens. Second, the opposite trend holds in groups 2 and 4: the closer to the moment of detection, the lower the corruption rate. In group 2, for instance, the proportion of corrupt provinces three years before detection is 63.16%, whereas this percentage is only 15.79% the year before. Consequently, efforts to fight corruption should be long term, and public authorities should be aware that corrupt behaviors arise in these regions in the long run.

For regions placed in the groups more prone to corruption in the short term (Groups 3 and 5), resources to investigate the potential public crimes should be increased as soon as possible. However, the early detection of the corruption patterns is not useful enough if not supported by law measures. These measures should assure a quick reply to avoid that the corrupted behavior persist. For example, as usual, when there are some traces of corruption, an investigation process is opened. The effectiveness of the investigation highly depends on the existence of more judicial resources against corruption and independent courts. The work of these courts should be carried out by the public intervention personnel or by inspectors with inquestionable independence and objectivity, elected by majority support and not only for the ruling Government. Furthermore, in the case a politician is formally charged, he/she should be expelled, even in a preventive way, given the social concern of such behavior.

The situation can be different for regions in which the corruption cases could arise in the medium or long term (groups 2 and 4). The investigation should be initiated as well, but the priority is different. In these cases the measures should promote a strategic plan against corruption with more complex or deeper laws. The best way to reduce or avoid corruption in the future is through prevention. Some examples of these deeper proposed measures could be17: A reform of the Law on Political Party Financing and the Law on Conflicts of Interest; a modification of the Criminal Procedure Act to increase the penalties for tax fraud and public corruption; to ensure the independency of the Judicial Authority and the Prosecutor General's Office; the digitization of public information and transparency; the creation of a specialized public agency or tax office to recover the money defrauded by corruption; or the review of incompatibility of political positions in the public sector. Citizens have also the responsibility to demand a battery of actions to persecute and punish corruption. This applies specially to public officers. Any civil servant who has witnessed or has proofs of public crimes should be encouraged to report the crimes in due course.

To conclude, we address the question concerning the reliability of our results by comparing our predictions with previous literature. Given the innovative nature of our research, the main question is the way in which we measure corruption and the importance we attach to economic factors as causes of corruption. Habib and Leon (2002) use the number of crimes against public administration as a proxy for political corruption and show that this metric performs as well as other corruption indexes. Therefore, we analyze whether the crimes against public administration rate differs across the groups as we have defined them. Table 43 provides results which corroborate our model.

[17] Some of these measures are under study or in the process of implementation.

Table 43. Average annual crimes against public administration per 100,000 inhabitants

Group	Mean number of crimes
1	0.926
2	1.269
3	1.498
4	1.355
5	1.562

Data come from judicial statistics from the Spanish National Statistics Institute. The number of crimes against public administration is scaled by the population of each region to calculate the mean value for each group. Groups 1 and 5 have the lowest and highest rate of crimes against public administration, respectively. Furthermore, the trend toward more crimes against public administration is almost uniform as corruption increases (with the exception of group 3, which has more crimes than group 4). The conclusion is that the model, as outlined in this study, provides an accurate forecast of the likelihood of corruption cases, and reliability is validated by comparing the results with those of similar studies.

4.6. Concluding remarks

We develop a model of neural networks to predict public corruption based on economic and political factors. We apply this model to the Spanish provinces in which corrupt cases have been uncovered by the media or have gone to trial. Unlike previous research, which is based on the perception of corruption, we use data on actual cases of corruption. The output of our model is a set of SOMs, which allow us to predict corruption in different time scenarios before corruption cases are detected.

Our model provides two main insights. First, we identify some underlying economic and political factors that can result in public corruption. Taxation of real estate, economic growth, and an increase in real estate prices, in the number of deposit institutions, and the same party remaining in office for a long time seem to induce public corruption. Second, our model provides different time frameworks to predict corruption. In some regions, we are able to detect latent corruption long before it emerges (up to three years), and in other regions our model provides short-term alerts, and suggests the need to take urgent preventive or corrective measures.

Given the connection we find between economic and political factors and public corruption, some caveats must be applied to our results. Our model does not mean that economic growth or a given party remaining in power causes public corruption but that the fastest growing regions or the ones ruled by the same party for a long time are the most likely to be involved in corruption cases. Economic growth per se is not a sign of corruption, but rather it increases the interactions between economic agents and public officers. Similarly, being in office too long might prove to be an incentive for creating a network of unfair relations between politicians and economic agents. In addition, more competitive markets may induce some agents to pay bribes in order to obtain public concessions or a better competitive position. These results are consistent with some research exploring the relation between economic growth and corruption (Chen, Jaradat, Banerjee, Tanaka, Ko and Zhang, 2002; Kaufman and Rousseeuw, 2009; Kuo, Ho and Hu, 2002).

Since corruption remains a widespread global concern, an important issue on our research is the generalizability of our model and the proposed actions. We have used quite common macroeconomic and political variables that are widely available from public sources in many countries. In turn, our model can be applied to other regions and countries as well. Of course, the model could be improved if country or region-specific factors were taken into account.

Our approach is interesting both for academia and public authorities. For academia, we provide an innovative way to predict public corruption using neural networks. These methods have often been used to predict corporate financial distress and other economic events, but, as far as we are aware, no studies have yet attempted to use neural networks to predict public corruption. Consequently, we extend the domain of neural network application. For public authorities, we provide a model that improves the efficiency of the measures aimed at fighting corruption. Because the resources available to combat corruption are limited, authorities can use the early corruption warning system, which categorizes each province according to its corruption profile, in order to narrow their focus and better implement preventive and corrective policies. In addition, our model predicts corruption cases long before they are discovered, which enhances anticipatory measures. Our model can be especially relevant in countries suffering the severest corruption problems. In fact, European Union authorities are highly concerned about widespread corruption in certain countries.

The study of new methodologies based on neural networks is a fertile field to be applied to a number of legal and economic issues. One possible direction for future research is to extend our model to the international framework and to take into account country-specific factors. Another application may be the detection of patterns of corruption and money laundering across different countries in the European Union.

5. Conclusions

The number of studies trying to explain the causes and consequences of the economic and financial crises usually rises considerably after a banking crisis occurs. The dramatic effects of the most recent financial crisis on the real economy around the world call for a better comprehension of previous crises as a way to anticipate future crisis episodes. It is precisely this objective, preventing future crises, the main motivation of this PhD dissertation.

We identify two important mechanisms that have failed during the latest years and that are closely related to the onset of the financial crisis: The assessment of the solvency of banks along with the systemic risk over the time, and the detection of the macroeconomic imbalances in some countries, especially in Europe, which made the financial crisis evolve through a sovereign crisis. Our dissertation is made up of three different essays, trying to go a step ahead in the knowledge of these mechanisms.

In the first essay, we develop a model of neural networks to study the bankruptcy of U.S. banks, considering the specific features of the current financial crisis. We first reach a more in-depth understanding of the causes of the crisis and how the financial statements of banks deteriorated over the time and resulted in the burst of the financial crisis. We combine multilayer perceptrons and self-organizing maps, two different techniques of neural networks, to provide a tool that displays the probability of distress up to three years before bankruptcy occurs.

Coherently with the motivation of this dissertation, we posit that the failure of the detection of the macroeconomic imbalances in some countries is another factor related to the onset of the financial crisis. Accordingly, in our second essay we use self-organizing maps and a set of the usual macroeconomic variables to compare the financial situation of the European countries in 2009. Our results show the existence of several groups of countries, each one of them with specific characteristics. We also find that Government expenditure and the saving rate are the most influential variables on the macroeconomic financial imbalances. We also study the influence of the macroeconomic situation of each Spanish AA.CC. and German state on the national situation. We find that the macroeconomic situation of the regional entities is a key determinant of the country financial (im)balance.

The two first essays are closely related to the financial crisis and the possible impact on the real economy. Nevertheless, we also are concerned about other factor that could affect the recovery of the economy after the crisis. Corruption is clearly one of these factors. Thus, in the third paper we develop a neural networks model to predict public corruption based on economic and political factors. We apply this model to the Spanish provinces in which corrupt cases have been uncovered by the media or have gone to trial. The output of our model is a set of SOMs, which allows us to predict corruption in different time scenarios before corruption cases are detected. Our model provides two main insights. First, we identify some underlying economic and political factors that can result in public corruption. Taxation of real estate, economic growth, and an increase in real estate prices, in the number of deposit institutions, and the same party remaining in office for a long time seem to induce public corruption. Second, our model provides different time frameworks to predict corruption. In some regions, we are able to detect latent corruption long before it emerges (up to three years), and in other regions our model provides short-term alerts, and suggests the need to take urgent preventive or corrective measures.

Our model can be helpful to improve the efficiency of the measures aimed at fighting corruption. Resources available to combat corruption are limited, and authorities can use the early corruption warning system, which categorizes each province according to its corruption profile, in order to narrow their focus and better implement preventive and corrective policies.

Taken together, our research can provide interesting insights to a wide number of potentially interested agents. First, our procedure can be a useful tool for bank supervisors and other stakeholders to delineate the risk profile of each bank. As far as the supervisory authority is concerned, the preventive measures to correct imbalances can be different in the short, medium, or long term depending on the probability of banking failure—that is, on the group to which the bank belongs. Investors, depositors, and other participants in capital markets can assess the risk profile of their investment and, consequently, define their optimal risk-return combination. Our model outperforms most of the previous ones in terms of predicting ability, which was compared against a wider set of alternative methods than previous papers do. Moreover, our model is simpler and, at the same time, provides a clearer visualization of the complex temporal behaviors.

Our research also provides interesting insights for policymakers. We provide a complementary method to analyze the international macroeconomic financial situation. Yet, the identification of groups of similar countries can allow discovering possible channels of financial contagion and financial turbulences propagation across countries. Thus, our model could serve as an early warning system for some countries when the counterpart countries get into financial troubles. In the same vein, the enlargement of the EU can be eased through diagnosing and forecasting the future financial situation of the candidate countries to avoid any destabilization effect. In addition, the identification of the regional disparities within European countries can lead to focus on the countries and regions in the most need of receiving European financial help.

From a microeconomic point of view, our research is also useful for banks and other institutional investors since the international risk map can be a relevant input to assess the risk exposure of each institution. This tool would be complementary to the stress tests and other analyses of sovereign risk carried out by national and international financial supervisors in recent months.

The study of new methodologies based on neural networks is a fertile field to be applied to a number of legal and economic issues. In this dissertation, we use these methodologies to explain the origins of the financial crisis and to avoid or limit the effects of future crisis.

This dissertation is aimed to be the starting point of future research in this field and to keep on contributing to the literature. As most of the research, this dissertation is not exempt of some weaknesses or limitations. Neural networks have usually been seen like black boxes, being difficult to explain how the predictions are issued. Moreover, the results can suffer from difficulties to be generalized because of model overfitting, which results in needing a lot of time to train the models and to obtain the most adequate configuration. However strongly the explanation ability of the models is tested, the comparability of the models remains as a critical issue and the extension to other samples or environments can be troublesome. Overfitting risk always remains in every study.

There are other more specific limitations in this dissertation. When trying to predict the bankruptcy of banks, we do not control for all the macroeconomic factors potentially affecting the banks propensity to fail. Furthermore, since our study focuses on commercial banks, some concerns may arise about whether our results can be applied to large investment banks. In addition, when trying to understand and predict the public corruption, we base on local or country specific variables, in this case Spanish macroeconomic variables Although the variables we used are commonly available for each country, especially in Europe, we have not applied the model to other countries, so the validations of the model in other institutional frameworks remains a concern.

Far from discouraging us, the above mentioned limitations motivate us to go on with our research. In this sense, the next step will be to replicate the results of the European banks stress test using only the financial statements of banks. The underlying intuition is that most of the European stress test results can be predicted, which could cast some doubts on this supervisory tool. Our aim is to suggest different ways to improve the existing early warning systems in line with the content of this dissertation.

Another avenue for future research is the role of the external rating agencies in the financial crisis. These agencies play an outstanding role and have been under severe criticisms. During some crisis episodes such as the Asian or Russian financial crises in the late 1990s and in the recent global crisis, the rating agencies have failed to predict the financial turbulences. Concerns on the quality of ratings have called for new research, mainly based on qualitative rather than quantitative information. In turn, we plan to show the importance of the qualitative information by replicating the credit ratings using the country reports issued by the European Commission for the European Member States. It will be another tool to improve the international financial stability.

6. Appendix A: List of acronyms

AACC: Autonomous Communities

ANOVA: Analysis of Variance

CAMEL: supervisory rating system (Capital adequacy, Assets, Management, Earnings and Liquidity)

CDO: Collateralized Debt Obligation

CIA: Central Intelligence Agency

DA: Discriminant analysis

EBA: European Banking Authority

ECB: European Central Bank

EMU: Economic and Monetary Union

EU: European Union

EWS: Early Warning system

FDIC: Federal Deposit Insurance Corporation

GDP: Gross Domestic Product

IMF: International Monetary Fund

IQR: Interquartile range

LR: Logistic regression

MBS: Mortgage-Backed Security

MIP: Macroeconomic Imbalance Procedure

MLP: Multilayer perceptron

NN: Neural networks

NUTS: Nomenclature des Unités Territoriales Statistiques

OECD: Organization for Economic Cooperation and Development

RF: Random forest

ROC: Receiver operating characteristic

SGP: Stability and Growth Pact

SOM: Self-organizing map

SVM: Support vector machine

UK: United Kingdom

US: United States

7. Appendix B: Bibliometrics

The PhD regulation of the University of Valladolid states that "*the thesis will consist of a minimum of three scientific articles prepared by the PhD student and accepted or published in an impact medium, according to the criteria of the ANECA for the area of knowledge in which the thesis is presented, and always within the period in which the student has been enrolled in the doctoral program*". This appendix is aimed to prove that the essays of this PhD dissertation meet the above-mentioned requirements.

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Article

Self-organizing maps as a tool to compare financial macroeconomic imbalances: The European, Spanish and German case*

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ABSTRACT

The economic recession in the European countries during the current financial crisis and the widespread worsening of the financial situation have resulted in wide macroeconomic differences across countries. In this paper we use the method of self-organizing maps (SOM) to compare the macroeconomic financial imbalances among European countries. We detect different profiles of countries and identify the public expenditure and the saving rate as the most critical variables that impacts on the national financial situation. In addition, since several countries of the European Union have regions with some degree of economic and financial competences, we study the influence of the regions on the whole country. Thus, we classify and compare the Spanish and German regions and we prove the impact of the regional situation on the whole country situation.

1. Introduction

The current financial crisis, although initially a bank-level crisis, has resulted in a situation of generalized illiquidity in financial markets and financial instability. Whereas in the first months the crisis had a microeconomic impact over the firms and the financial intermediaries, it later reached macroeconomic dimensions and the solvency of some countries became under discussion.

The switch from microeconomic financial distress to macroeconomic distress can be verified from 2010 in after. At the beginning of 2010, the European Union (EU), the International Monetary Fund (IMF) and the European Central Bank (ECB) granted 110 billion of euros credit to Greece given the inability of this country to serve its public debt. Some days later, a permanent fund for ransom of 750 billion was created due to the threat of international contagion and in order to reinforce the international reliability of the European currency. Some months later, in November 2010, Ireland received 87 billion of euros as financial help to refinance the public debt. In April 2011, Portugal asked and received from the EU and the IMF financial help amounting to 78 billion of euros. In addition, the implausibility of Greece to serve the interest of the public debt after the first bailout casted new doubts about the stability of the euro area after May 2011. From April 2012, the main European concern has focused on Spain, which has received 100 billion of euros credit line from the EU.[1] More recently, in March 2013, a 10 billion of euros bailout was announced for Cyprus.

In a financial environment so globalized as the current one, the national financial distresses can be transmitted to other countries, be a threat for the global economic recovery and lead to a generalized collapse of the credit flow to the real economy. In spite of the fact that in July 2011 the European Banking Authority (EBA) published the results of the stress tests of the financial institutions[2] with an acceptable result in general terms, financial markets did not rely completely on the States and Governments. In fact, the credit rating of the United States and of many European countries worsened in the summer of 2011.

An implication of these facts is that Europe should have some tools to assure the effective comparability among countries as a means to assure the efficiency of the correctional policies. In addition, early warning systems in the European financial system

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[1] A more in detail presentation of the main yardsticks throughout the financial crisis can be found in the ECB website http://www.ecb.int/ecb/html/crisis.es.html.

[2] http://www.eba.europa.eu/EU-wide-stress-testing/2011/2011-EU-wide-stress-test-results.aspx.

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Self-organizing maps as a tool to compare financial macroeconomic imbalances: The European, Spanish and German case (Article)

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University of Valladolid, Spain

Abstract

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The economic recession in the European countries during the current financial crisis and the widespread worsening of the financial situation have resulted in wide macroeconomic differences across countries. In this paper we use the method of self-organizing maps (SOM) to compare the macroeconomic financial imbalances among European countries. We detect different profiles of countries and identify the public expenditure and the saving rate as the most critical variables that impacts on the national financial situation. In addition, since several countries of the European Union have regions with some degree of economic and financial competences, we study the influence of the regions on the whole country. Thus, we classify and compare the Spanish and German regions and we prove the impact of the regional situation on the whole country situation. © 2012 Asociación Española de Finanzas.

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Bankruptcy visualization and prediction using neural networks: A study of U.S. commercial banks

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ABSTRACT

We develop a model of neural networks to study the bankruptcy of U.S. banks, taking into account the specific features of the recent financial crisis. We combine multilayer perceptrons and self-organizing maps to provide a tool that displays the probability of distress up to three years before bankruptcy occurs. Based on data from the Federal Deposit Insurance Corporation between 2002 and 2012, our results show that failed banks are more concentrated in real estate loans and have more provisions. Their situation is partially due to risky expansion, which results in less equity and interest income. After drawing the profile of distressed banks, we develop a model to detect failures and a tool to assess bank risk in the short, medium and long term using bankruptcies that occurred from May 2012 to December 2013 in U.S. banks. The model can detect 96.15% of the failures in this period and outperforms traditional models of bankruptcy prediction.

1. Introduction

The recent financial crisis, the generalization and propagation of systemic risk in a more and more global financial environment, and the high social costs of bank failures have drawn attention to the mechanisms of control of banks solvency (Wang, Ma, & Yang, 2014). The 2009 Basel Committee on Banking Supervision papers, widely known as the Basel III Accord,[1] advise banking regulators to develop capital and liquidity rules sufficiently rigorous to allow financial firms to withstand future downturns in the global financial system.

The Basel III Accord follows the capital agreement found in the 1988 accord, commonly known as Basel I. Basel I is enforced by law in the G10 and adopted by over 100 other countries. The goal of this 1988 roundtable was to minimize credit risk. However, innovation and financial changes in the world led to the need in 2004 for a more comprehensive set of guidelines known as Basel II. The purpose of this new framework was to promote greater stability in the financial system and reduce the social costs of financial instability. To fulfill this aim, the accord requires banks to classify their loan portfolio and identify the risks that they may face through their lending and investment practices to ensure that they hold enough capital reserves. Basel II put in place a broader view of financial risk that incorporated the differences among credit, operational, and market risk. In addition, the accord gave both supervisors and markets a wider range of action.

The collapse of a number of financial institutions in the United States at the beginning of the crisis in 2007 due to the emergence of new financial products and risks, the fall of real estate prices, and biased pricing methods of real estate premises exposed Basel II's shortcomings. The industry clearly required new standards for supervision of financial intermediaries and new metrics of financial risk. Our paper joins the stream of analysis that examines the failures of U.S. banks in recent years. In so doing, we follow the recommendations of the G20 Finance Ministers and Central Bank Governors who met June 3–5, 2010, in Busan, Korea, and "[welcomed] the progress on the quantitative and macroeconomic impact studies which will inform the calibration of... new rules.".

We develop a hybrid neural network model to study the bankruptcy of U.S. banks by combining a multilayer perceptron (MLP) network and self-organizing maps (SOMs). With this contribution, we complement previous evidence and update the methods of risk assessment (Oreski & Oreski, 2014). Our aim is twofold: descriptive and predictive. First, we describe the main characteristics of U.S. distressed banks and how bank failures have evolved from the onset of the financial crisis in 2007. The implementation of our

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[1] In December 2009, the Basel Committee on Banking Supervision published two consultative documents entitled "Strengthening the Resilience of the Banking Sector" and "International Framework for Liquidity Risk Measurement, Standards and Monitoring".

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Bankruptcy visualization and prediction using neural networks: A study of U.S. commercial banks (Article)

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Abstract

We develop a model of neural networks to study the bankruptcy of U.S. banks, taking into account the specific features of the recent financial crisis. We combine multilayer perceptrons and self-organizing maps to provide a tool that displays the probability of distress up to three years before bankruptcy occurs. Based on data from the Federal Deposit Insurance Corporation between 2002 and 2012, our results show that failed banks are more concentrated in real estate loans and have more provisions. Their situation is partially due to risky expansion, which results in less equity and interest income. After drawing the profile of distressed banks, we develop a model to detect failures and a tool to assess bank risk in the short, medium and long term using bankruptcies that occurred from May 2012 to December 2013 in U.S. banks. The model can detect 96.15% of the failures in this period and outperforms traditional models of bankruptcy prediction.

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2014	29/123	Q1	76.829	12/81	Q1	85.802

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Predicting Public Corruption with Neural Networks: An Analysis of Spanish Provinces

Félix J. López-Iturriaga[1,2] · Iván Pastor Sanz[1]

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Abstract We contend that corruption must be detected as soon as possible so that corrective and preventive measures may be taken. Thus, we develop an early warning system based on a neural network approach, specifically self-organizing maps, to predict public corruption based on economic and political factors. Unlike previous research, which is based on the perception of corruption, we use data on actual cases of corruption. We apply the model to Spanish provinces in which actual cases of corruption were reported by the media or went to court between 2000 and 2012. We find that the taxation of real estate, economic growth, the increase in real estate prices, the growing number of deposit institutions and non-financial firms, and the same political party remaining in power for long periods seem to induce public corruption. Our model provides different profiles of corruption risk depending on the economic conditions of a region conditional on the timing of the prediction. Our model also provides different time frameworks to predict corruption up to 3 years before cases are detected.

Keywords Corruption · Prediction · Early warning system · Neural networks · Self-organizing maps

JEL Classification C45 · D73

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