Stress Tests on European Banks: Determinants of Banking Failure

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Abstract

Banks are very unique entities essential to the actual society, since generally every single individual needs one at least once in his life. Besides being a rare event, banking failures consequences are quite dramatic do society. A bank failure is different from a non-financial corporation failure, since the impact to society is bigger. With a bank failure, arises the possibility of a contagion effects and the possibility of destruction of clients' trust in the whole sector. Banks are also the main financing source of both families and companies.

Stress tests started to be executed by large financial institutions to trading books, in order to assess their potential losses under extremely adverse market conditions. The emergence of several crises, namely the recent sovereign debt crisis, changed stress tests from a small-scale exercise to a bigger-scale exercise and gave them an important role in policy.

This dissertation identifies the determinants of stress tests results in Europe. To achieve this goal, a Pooled Logit model was estimated with stress tests results as dependent variable and using as explanatory variables bank specific variables, like financial ratios, and macroeconomic variables of the bank's home country.

The results showed that both financial and macroeconomic variables influence the probability of stress tests failure. However, with the overcoming of the economic crises that haunted Europe in the last decade, and with the growth of banking regulation/supervision, the probability of a European bank failing stress tests and consequently having problems that could cause bankruptcy, has decreased.

Key Words: Bank Distress; Risk; Stress Tests; Supervision

JEL Codes: C23; G21

Resumo

Os bancos são entidades únicas e essenciais para a sociedade atual. Apesar de ser um evento raro, a falência de bancos tem um enorme impacto na sociedade. É este impacto que distingue a falência de um banco e a falência de uma empresa não financeira, uma vez que o impacto para a sociedade é maior no primeiro caso. Com a falência de um banco, surge a possibilidade de efeitos de contágio e de destruição da confiança dos clientes no setor, sendo os bancos a principal fonte de financiamento de particulares e empresas.

Os testes de *stress* começaram a ser desenvolvidos por grandes instituições financeiras, que os aplicavam a *trading books*. Com o surgir de várias crises, nomeadamente com a recente crise das dívidas soberanas, os testes de *stress* passaram de um exercício em pequena escala para um exercício de grande escala, começando ainda a ter um importante papel na política.

Para identificar os determinantes que explicam os resultados dos testes de *stress* à banca europeia, foi estimado um modelo *Pooled Logit* utilizando os resultados dos testes como variável binária dependente e como variáveis explicativas variáveis específicas dos bancos, como rácios financeiros, e variáveis macroeconómicas do país de cada banco.

Os resultados mostram que quer os rácios financeiros, quer as variáveis macroeconómicas, influenciam a probabilidade de falha nos testes de *stress*s. No entanto, com o ultrapassar das crises económicas e com o crescimento da supervisão bancária, a probabilidade de um banco falhar nos testes, e de poder vir a falir, diminuiu.

Palavras-Chave: Falência; Risco; Supervisão; Testes de *Stress*

Códigos JEL: C23; G2

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[1] The opinions and arguments contained in this report are the sole responsibility and not of ISCTE-IUL or of the author's employer

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“*Science is the great antidote to the poison of enthusiasm and superstition.*”

Adam Smith (1776:418)

1. Introduction

The theme of this thesis is stress tests, a theme barely developed in Portugal and an important theme regarding the financial sector of the economy. Alexander (2008:378) refers that "*If estimating VaR is like playing a pianola then stress testing is like performing on a concert grand.*", so it can be demonstrated that stress tests are a large scale and a spotlight event in which the performance of regulators will be analyzed.

Banks are crucial entities in the current society, and a banking failure[2] is a striking event. Banking failures are different from non-financial corporations' failures, since a unique bank failure can put at risk the clients trust and trigger the collapse of the entire banking system. This is the reason why banks are more supervised and controlled by authorities (Kick and Koetter, 2007).

Stress tests at a regulatory level started to be developed in the 1990's, when financial institutions encouraged risk managers to go beyond the standard risk metrics and to imagine circumstances that could create extreme losses (Alexander, 2008). They jumped into the spotlight with the 2007's tremendous financial crisis. The crisis peaked with the Lehman Brothers bankruptcy in the United States and continued in Europe with the sovereign debt crisis (Kouretas and Vlamis, 2010). Regulatory entities decided subsequently that is of extremely importance to supervise more clearly and efficiently the banking system, to prevent this type of events, because during crisis the potential losses that stress tests predicted were less than the losses that really occurred (Dent et al., 2016).

In the field of stress tests, the focus are the European banks, mainly the biggest and most important of the region. In Europe, stress tests are conducted by the European Bank Authority (EBA), but they were originally directed by the Committee of European Banking Supervisors (CEBS) in 2009, immediately after the beginning of the crisis in an attempt to prevent more losses and to control the financial system.

Since 2009, Europe suffered lots of transformations, namely in the economic conditions of the region. So, one point to analyze is the evolution of the methodology applied by EBA. We

[2] Situation where a financial institution becomes insolvent and unable to meet to its credit obligations

also want to compare this methodology with other alternatives applied in different countries or regions and by different authorities.

The main objective of this thesis is to discovery the determinants that influence the result of stress testing. Using an econometric model, we intend to answer the question why banks fail stress tests and then discuss the consequences of the failure to the financial sector.

The possible relevant variables are specific bank variables, like financial ratios, and macroeconomic variables and were mainly based in the CAMELS[3] Rating System.

However, stress tests are not a concept widely known by the population, even for people specialized in finance, so it is also important to explain the concept, focusing in their origin, purpose and importance.

Having all this in mind, the research questions are presented below:

- ***Why there is a specific methodology applied to stress tests in Europe? And why there is not a different one?***
- ***What determines the banks performance in stress testing and why? (key question)***
- ***What are the consequences for the banks that fail this kind of tests?***

At the end, attempting to show that reality can be explained by this dissertation and to check the robustness of our model, we will test its predictive accuracy by projecting 2018 stress tests results.

[3] A rating system implemented by the US banking institutions in 1979

2. Literature Review

The starting point of this essay is the concept of stress tests. In Finance, stress testing is a method used to access the risk associated to a portfolio. However to calculate the risk associated to a portfolio there are risk measures, like value-at-risk (VaR).

The key usefulness of stress tests comes from the usage that financial regulators give to them. Supervision authorities use stress tests to evaluate the fragilities of the financial system.

The main difference between stress test applied to portfolios and the ones applied by the regulators to the entire financial system are the objectives. In stress tests regulators want to identify the main vulnerabilities of the financial system and the overall risks, while stress tests applied to portfolios want to examine if there is an efficient allocation of capital according to risks (Blaschke et al, 2001).

For Oura and Schumacher (2012) stress testing is defined as a technique that measures vulnerability of a portfolio based on hypothetical scenarios relatively to institutions or to an entire financial system. According to Jorion (2006), the same concept is used to identify and manage extreme unusual situations that can cause huge losses. Also based on Jorion (2006) statements, the main differences between the two referred risk measures (value-at-risk and stress testing) are the conditions under which the losses occur. Value-at-risk calculates the potential losses under normal market conditions, while stress testing quantifies it for extreme market conditions, like a crisis.

Focusing more in the regulatory framework, Dent et al. (2016) state that stress testing is mainly used to assess the resilience of a bank, when it faces rare, but plausible, shocks that can cause huge losses. Stress tests can also be used to access if the bank management is performing a good job, testing the future of the bank under the natural evolution of the economy.

2.1 A brief stress tests history

Stress tests started to be used in the 1980's, as a tool of primordial risk management used to specific large risks (Kapinos et al., 2015). In the early 1990's, financial institutions, like banks, started to apply stress tests focused in the trading books (Blaschke et al., 2001; McGee and Khaykin, 2014), being this measure formalized in 1996 with an amendment to the international regulatory capital regime for market risk.

After the emergence of stress tests conducted by banks, policymakers started to use them to evaluate the resilience of the financial sector of the economy. This kind of tests became a crucial component of the Financial Sector Assessment Program (FSAP) created in 1999 due to the Asian Financial Crisis (Independent Evaluation Office of International Monetary Fund,

2004) and were performed by all countries that belong to the program. With this program, banks have taken more initiative, starting to develop and produce their own stress tests (Dent et al., 2016). Until the financial crisis of 2007, stress tests in Europe were only limited to banks following the Internal Rating-Based Approach for Capital Requirements for Credit Risk (Basel Committee on Banking Supervision - Bank for International Settlements, 2001). In 2007, the collapse of Lehman Brothers triggered the so-called US subprime crisis. According to Kouretas and Vlamis (2010), this crisis led indirectly to the origin of the sovereign debt crisis in the Eurozone.

With the recession, it was proved that deficiencies in risk measurement exist, since stress tests showed a better scenario than it actually occurred, being the real losses bigger than the estimated ones (Basel Committee on Banking Supervision - Bank for International Settlements, 2009). The financial crisis implied the largest financial reform since the 30's Great Depression, and changed the way stress tests were performed with regulation purpose, transforming stress tests from an isolated exercise with small-scale to a more general and large-scaled exercise (Dent et al., 2016).

The first example of this new regulation stress tests was the US Supervisory Capital Assessment Program (SCAP), conducted by the Federal Reserve in early 2009. In Europe, the first tests of this kind were conducted in late 2009 under the direction of the Committee of European Banking Supervisors (CEBS). After this and since the beginning of 2011, the European Banking Authority (EBA) started to conduct these tests.

To conclude, we can say that before the crisis stress tests had none or little direct impact in policy, but this situation changed after the 2007's crisis (Dent et al., 2016).

2.2 Classification

In 2001, Blaschke et al.[4] define several criteria to classify stress tests at the portfolio level, namely the type of the risk model, analyses, shock or scenario.

Regarding the type of risk model, stress tests can be applied in order to check the vulnerabilities of the institutions against credit risk, operational risk or market risk. Credit risk is defined as the risk that a counter-party will default its obligations (Blaschke et al., 2001). Operational risk is the risk resulting from losses related with failed internal processes, people and from external events (Basel Committee on Banking Supervision - Bank for International

[4] See Appendix A

Settlements, 2001). Market risk is the risk associated with losses coming from changes in the market prices (Blaschke et al., 2001).

Focusing on the type of analyses, three classifications arise. The first one is the sensitivity analyses (single-factor) stress tests, which consist in a sensitivity test that only varies a single factor without considering the relations of this factor with other factors (International Actuarial Association, 2013). It is commonly used to assess potential hedging strategies. The second stress test analysis is the multi-dimensional/scenario that, according to Jorion (2006) is process that based on a plausible event varies several risk factors. This analysis reflects several individual risk factors and the interaction between them, and it is generally used to assess particular situations. The third and final type of analysis is the extreme value or loss, used to quantify the losses of an extreme event (Embrechts et al., 1999).

Stress tests can also be classified depending on the type of shock, and so, in relation to this subject they can be allocated in three categories: underlying volatilities, underlying correlations or individual market variables. The first two categories, make stress tests scenarios designed to include changes in relationships between market variables, while the last one only makes stress tests scenarios designed to only take into consideration individual market variables, like prices.

Finally, stress tests can weight different type of scenarios, namely historical, hypothetical and Monte Carlo simulation scenarios. According to Alexander (2008) historical scenarios are based on events that occurred in the past and whose data is applicable to the present, in order to obtain the potential losses if that event occurs again. For hypothetical scenarios, the same author states that this type of tests does not need historical precedent, since they are scenarios created with the only purpose of stress testing. The last type of scenario is Monte Carlo simulation, which according to Allen (2013) consists in identifying plausibility with some type of probability measure and applying it to the different possible events, making regulators to consider only the losses caused by a few events that have at least a certain probability of happening.

2.3 Methodologies

According to Dent et al. (2016) stress tests carried out by regulators that affected simultaneously several financial institutions are called concurrent stress tests. This kind of tests can be performed through several approaches, being balance sheet, market price-based models and macro financial models the main ones (Jobst et al., 2013). Jobst et al. (2013) also explain in more detail the three main approaches.

The balance sheet approach is the oldest, the simplest, the most widely used and it has the advantage of producing direct results in terms of regulatory variables.

The market price-based models approach was developed based on risk management techniques and defines “systematic risk measures” based on dependencies between different risk factors. Unlike the balance sheet approach, market price-based models take into consideration the possibility of institutions fail simultaneously (joint default risk) and the sensitivity of stress test results to the historical volatility of risk factors when they defined the capital adequacy under stressful conditions. The main disadvantages of this approach are the fact that it does not produce direct results in terms of regulatory variables, needing additional steps and the fact that this approach is likely to include valuation methods and so tends to be less tractable.

Lastly, macro financial models are used to examine systemic risks that arise from the relations between the macroeconomic and financial environments. This approach can be implemented simultaneously with one of the two previous models.

The topic of this essay is related with concurrent stress tests of European banks, which as it was previously referred are conducted by EBA. The approach used by EBA is a balance sheet, more specific a static one, meaning that the bank balance sheets do not change through the forecast horizon. EBA run a joined-up adverse macro scenario with a three-year horizon, which is developed by the European Central Bank and European Systemic Risk Board (ESRB) with the purpose of capturing the systemic risks that represent the biggest threats to the stability of the European financial sector (Dent et al., 2016).

2.4 Limitations

Stress testing is an important and revolutionary technique, however as other techniques it is not perfect, and so it has limitations. According to the Committee on the Global Financial System - Bank for International Settlement (2000) the main limitation of stress tests is the fact that they depend a lot from the regulator choices in for example, what risk factors to stress or how to combine factors stressed.

Regulators choice have also an important role in analyzing the results of stress testing and identifying the implications that those results have in the bank, making the strategy of the bank to manage risk dependent of their interpretation.

For the Committee on the Global Financial System (2000), another important limitation is the fact that the main stress tests processes can determine the possible loss but cannot associate a probability to this loss.

Based on Dent et al. (2016) the limitations of stress tests are derived from the fact that stress tests are only a tool and consequently cannot be a substitute for the entire robust capital framework, they can only complement it. Another limitation that these authors refer is related with the robustness of stress testing, since stress tests are more or less robust depending on the robustness of the data and methodologies used.

2.5 European Banking Authority Stress Tests

EBA is one of the three entities that are part of European System of Financial Supervision (ESFS), being the other two entities the European Securities and Markets Authorities (ESMA) and the European Insurance and Occupational Pensions Authority (EIOPA). The date of foundation of EBA is 1st of January of 2011.

The two main functions of EBA are the promotion of equal supervisory practices, to achieve a harmonized prudential system and to evaluate the main risks and vulnerabilities of the European banking sector. It is in the framework of this last function that stress tests were performed by EBA, in close cooperation with the European Systemic Risk Board (ESRB).

Stress tests are considered one of the most important tools to assess the resistance of European financial institutions to adverse shocks, contributing also to assess the systematic risk of European financial system.

Since 2011, year of its foundation, EBA concluded three series of stress tests. The first one was performed in 2011, the second in 2014 and the last one in 2016. This type of tests is performed in a bank-by-bank basis and the sampled banks should have at least have a minimum of 30 thousand million euros in assets or the total sample of banks from a specific country should cover at least 50% of the country banking sector.

The type of adverse shocks that European financial institutions hypothetically face are adverse macro-economic scenarios, like crisis. The impact of such shock is measured in terms of the Common Equity Tier l Ratio[5] (CET1). A bank passes or fails stress tests depending on the value of Tier 1 capital. The choice of CET1 comes mainly from the decision of EBA to select a simple measure and a measure that can be issued directly by the bank.

EBA defines capital hurdle rates for both baseline (obtained from economic forecasts regarding the main macroeconomic variables) and adverse scenarios. If the Transitional Common Equity Tier 1 Ratio[6] of the bank is below the defined threshold under the baseline or adverse scenario, the bank fail stress tests. Otherwise, if the bank has a Transitional Common Equity Tier 1 Ratio over the defined threshold, he passes the stress tests with success, being resilient against the adverse scenario shock and meaning that management is performing a good job under normal conditions (baseline).

EBA stress tests assume a static balance sheet, a zero-growth assumption. This assumption should be applied to both assets and liabilities. The Profit and Losses, the revenues and the costs, should also admit the zero-growth assumption. Another assumption is that banks maintain the same business mix and model throughout the time horizon.

The main risks that EBA stress tests intend to assess are:

- Credit risk
- Market risk
- Sovereign risk
- Securitization
- Cost of funding

Credit risk is the risk that a borrower may not pay a loan, with banks losing the principal of the loan or the interest associated.

Market risk is the risk associated to the possibility that a bank, as investor, suffers losses due to factors that affected negatively the performance of the financial markets. This type of risk is also called systematic.

[5] Ratio of the bank's common equity tier 1 (primarily consists of ordinary shares, retained earnings and certain reserves) to its total risk-weighted assets.
[6] CET1 ratio with the application of transitional arrangements, such as phase-in of deductions and grandfathering arrangements

Sovereign risk is related with possibility that a foreign central bank changes its regulations, leading to a reduction or completely nullifying the value of its foreign exchange contracts. In this type of risk is also included the default in debt repayments by a foreign nation.

Securitization is a complex process that uses financial engineering to transform an illiquid asset or group of illiquid assets into securities. The risks associated to this process increase when the complexity of the instruments increase, making harder the analysis of the future security performance. With instruments complexity increases the lack of transparency, making even worst the forecast of the security performance (Sabarwal, 2009).

Cost of funds is the interest rate paid by banks to obtain money to finance their activities. The spread between the cost of funds and the interest rate charged is one of the most important sources of profit of the financial institutions. The risk in this type of process comes when the cost of funding increases. If the cost of funding increases, the bank has three options. First, charge a bigger rate on loans, finding new costumers and making profit in these new loans. Second, keep the same rate, finding new costumers and losing money in this new loans. Third, charge a bigger rate on loans, but did not find new costumers, losing also money (Beau et al., 2014).

Figure 1 Banks Funding - Source: Beau, 2014

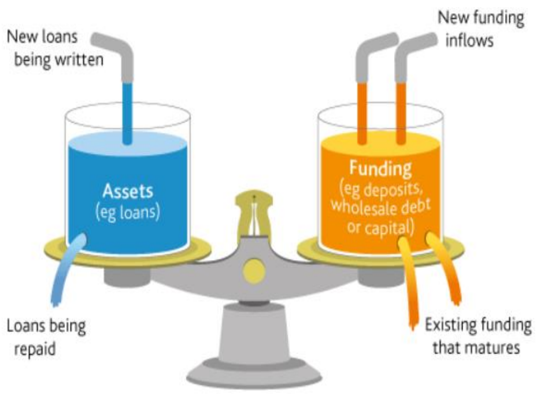


Figure 1, show us that must exist a balance between the assets held by the banks and the cost of the funds. If this balance is not achieved problems may rise and consequently banks can fall in distress.

For the 2016 stress tests results, EBA changed its approach and do not classify stress tests results as failures or successes, deciding only to communicate the banks risks to the country supervisors and doing efforts in the sense of keeping the capital in the banking system and repairing the unbalanced balance sheets. For the 2018 stress tests series, currently in course, EBA uses a similar approach.

2.6 Models

2.6.1 CAMELS Rating System

The CAMELS Rating System, officially Uniform Financial Institutions Rating System (UFIRS), was implemented in 1979 in the US banking institutions. This rating system analyses the banking sector through the balance sheets and profit and loss statements of the banks.

Until 1997, the system abbreviation was CAMEL, reflecting the five assessment areas: capital, asset quality, management, earnings and liquidity ratios. In 1997, a sixth area was added (sensitivity to market risk), and the system abbreviation stated to be CAMELS.

For each assessment area there is a rating, leading to an overall rating of the bank's financial condition. The ratings are from 1 to 5; the bigger the rating, the higher the supervisory concern.

The ratios used to evaluate the financial situation of the banks are the following:

- Capital Adequacy Ratio

It is the ratio of Tier I (common and preferred stocks, convertible bonds and bank's minority rights in Subsidiary companies) and Tier II (bank supplementary capital) capital to risk-weighted assets, being the Tier I at least 50% of the risk-weighted assets value.

The higher the ratio, the better is the bank's capital adequacy, meaning that the bank can benefit from self-financing and be more profitable than other banks.

- Asset Quality Ratio

It is the ratio of non-performing loans over 90 days less provisions (capital held by the bank to compensate delays in loans payments) to total loans.

A lower ratio value, means that the quality of the assets is higher.

- Management Quality Ratio

It is the ratio of total operating expenses to sales.

A lower ratio, means that the bank as a good management.

- Earnings Ratio

The earnings and profitability of the bank can be assessed by two ratios: Return on Equity (ROE) and Return on Assets (ROA).

ROE is the ratio of net profits to own capital and ROA is the ratio of net profits to total assets.

The higher the value of each one of the ratio, the more efficient is the bank.

- Liquidity Ratio

To assess the liquidity of the bank there are two ratios: L1 and L2.

L1 is the ratio of total deposits to total loans, while L2 is the ratio of circulating assets (cash in hand, investment portfolios, etc.) to total assets.

The higher the ratios, the higher the bank's liquidity.

- Sensitivity to Market Risk Ratio

It is the ratio of total securities to total assets. This ratio relates a bank's total securities portfolio with its assets and gives us the percentage change of its portfolio based on changes on the issuers of the securities or on the interest rates, for example. A smaller ratio value indicates that the bank portfolios are less susceptible to market risk.

2.6.2 Kick and Koetter (2007)

In 2007, Kick and Koetter developed a model to estimate the probabilities of financial distress in German banks.

The data was collected from the records of Bundesbank about distress events in German universal banks for the period of 1997 to 2004. The non-distress bank observations were included in one group. Then the distress events were categorized in four categories, according to their severity. In the first category were inserted the events that cause a reduction of annual operational profits of more than 25% or events that cause losses amounting to 25% of liable capital or events that may put at risk the existence of the bank as a going concern. In the second category, were introduced events that capture actions taken by the Federal Financial Supervisory Authority (BaFin) representing official warnings or disagreement. The third category includes events that caused the bank to receive support in the form of capital from his head association or events that cause bank operations to be limited by the BaFin. Finally, in the last category were included the events that caused a forced closure of the bank by the BaFin or events that caused takeovers of the bank by other banks, denominated restructured mergers.

The model developed by Kick and Koetter was a logit model:

$$P(Y_i > 1) = g(\beta_j X_i) \frac{exp(\alpha_j + \beta_j X_i)}{1 + exp(\alpha_j + \beta_j X_i)}, for\ j = 1,2, M - 1 \qquad (1)$$

M $\rightarrow$ number of event classes

X_i $\rightarrow$ vector of explanatory variables

$a; \beta$ $\rightarrow$ parameters to estimate

The vector of explanatory variables includes financial variables, macroeconomic variables of the bank's country and a dummy variable that equals one if the bank had a distress in the past.

The main deductions were that loan quality, cost efficiency and capitalization[7] have big status to explain distress, but cost efficiency and capitalization are only explanations for events of small distress[8]. Another main conclusion is that banks with past situations of distress will have a higher probability of facing a new distress in the future. It was also concluded that it is difficult to prevent a bank failure, when a certain level of distress has been achieved.

2.6.3 Čihak and Poghosyan (2011)

In 2011, Čihak and Poghosyan, developed a model to find the determinants of bank distress in Europe. The data was compiled based on two different sources, the Bureau Van Dijk's BankScope database and the NewsPlus database.

BankScope provided financial data for 5 708 banks in the EU-25 countries for the period of 1996 to 2007, and The NewsPlus database provided information to discover failing banks. Due to this last search, it was discovered 79 distress events in 54 banks.

In order to assess the impact of financial indicators in the probability of a bank distress, several versions of a Logistic (Logit) probability model were used, following Shumway (2001).

7 An increase in the capitalization ratio reduces the effect of category I and II of banks distress events

[8] Small distress events include the first two categories of distress

The principal model can be represented in the form of a log odd's ratio:

$$log \frac{P_{ij}}{1-P_{ij}} = \beta_0 + \sum_{k=1}^{K} \beta_k X_{k,ijt-1} \tag{2}$$

P_{ij} $\rightarrow$ probability that bank i located in country j will experience distress in period t

X $\rightarrow$ vector of K explanatory variables

$log \frac{P_{ij}}{1-P_{ij}}$ $\rightarrow$ log odd's ratio, measuring the probability of bank distress relative to the probability of no distress

Two different approaches can be applied to this model. The simplest one assumes independence of errors across individual banks, countries, and time, and estimates a logit. The second approach, is also to estimate a logit model, but including random effects[9]. The explanatory variables used in the models are financial indicators, namely capitalization, asset quality, managerial skills, earnings, and liquidity, macroeconomic variables of the bank's country residence, a measure of market concentration and stock market indicators.

The main conclusions are that capitalization has an important role on bank distress, but asset quality and earnings have even a bigger impact. Also, contingency effects have an important role in banks distress, with results showing that banks that perform their activity in a more concentrated market have more probability to suffer a distress. Lastly, another variable that increases the probability of a bank distress is the higher share of wholesale funding.

2.6.4 Apergis and Payne (2013)

Apergis and Payne (2013) create a Probit model to identify the impact of credit risk and macroeconomic factors in the prediction of European bank failures. In order to control for heteroscedasticity problems, they decide to apply robust estimation, which consist in a robust "sandwich" estimator for the asymptotic covariance matrix of the quasi-maximum likelihood.

The model consists in the following:

$$y_i = x_i\beta + \alpha_i + \varepsilon_i \tag{3}$$

$\varepsilon_i = 1$

y $\rightarrow$ binary variable with 1.0 for failure to pass the stress test, and 0.0 otherwise

α $\rightarrow$ individual country-specific effect

[9] Random effects assumes that the variation across the banks is random and uncorrelated with the independent variables

β → vector of parameters, it is estimated by using the cluster corrected covariance matrix method of maximum likelihood and Newton's method

i → bank i

The study includes data from 90 banks across 21 countries, for the years of 2010 and 2011. The type of variables were both macroeconomic variables, related with the country of the bank, and banking variables.

The main conclusions were that both type of variables are significant when we are talking about bank failures. Contributing to a higher probability of bank failure are greater ratios of non-performing loans to total loans and non-current loans to loans, lower capital adequacy ratios based on the Tier I capital, a higher leverage ratio, lower management quality, and a lower net interest income ratio. The same pressure to the risk of failure derives from lower returns on assets, a higher loans to deposits ratio, a lower ratio for liquid assets to total assets, greater variance of a bank's equity price, lower GDP growth, higher CDS, spreads, bigger overall banking non-performing loans ratio in the country of the bank and a higher LIBOR.

Another conclusion is that supervisory authorities have access to signals that can indicate a possible bank failure. Also, bank risk managers can detect those signals when looking into the intrinsic variables.

2.6.5 Betz et al (2013)

Betz et al. (2013) developed a model to predict distress in European banks using macroeconomic variables and bank specific variables. Behind their selection of variables is the CAMEL rating system, created in 1979 by the US regulators (section 2.6.1). The sample used consisted of quarterly data for 546 banks with at least EUR 1bn in total assets, and, since 2000Q1 until 2013Q2, corresponding to a total of 28 832 observations.

Since bank distress is a rare event when we are talking about European banks, a proxy was necessary and so, Betz et al. (2013) define as distress events bankruptcies, liquidations, defaults, forced mergers and state intervention.

The model used was a pooled logit model with bank distress as a dependent and dummy variable and the following variables tested as explanatory:

Figure 2 Model Variables - Source: Betz et al. 2013

		Estimates	(1) Benchmark	(2) Benchmark +
Bank-specific indicators		Intercept	-3.46 ***	-3.26 ***
	C^a	Capital ratio	-0.76 ***	-1.37 ***
		Tier 1 ratio		-5.91
	A^a	Impaired assets		0.14 .
		Reserves to impaired assets	-0.19	-0.15
		ROA	0.12 *	0.56 ***
		Loan loss provisions	0.09 .	0.18 .
	M^a	Cost to income	0.09	0.22 *
	E^a	ROE	-0.06	-0.28
		Net interest margin		0.23
	L^a	Interest expenses to liabilities	0.14 ***	0.50 **
		Deposits to funding	0.01	-0.33 **
		Net-short term borrowing	0.18 **	0.48
	S^a	Share of trading income	-0.14	-0.27 .
Country-specific banking sector indicators		Total assets to GDP	0.71 ***	1.71 ***
		Non-core liabilities	0.32 ***	0.28 ***
		Debt to equity	0.30 ***	0.37 ***
		Loans to deposits	0.14	0.05
		Debt securities to liabilities	-0.22 *	-0.19 *
		Mortgages to loans	0.03	0.21 *
Country-specific macro-financial indicators		Real GDP	-0.10 .	-0.06
		Inflation	0.06	0.15 **
		Stock prices	0.02	-0.05
		House prices	-0.38 ***	-0.28 **
		Long-term government bond yield	0.04	0.12
		International investment position to GDP	-0.50 ***	-0.46 ***
		Government debt to GDP	0.50 ***	0.43 ***
		Private sector credit flow to GDP	0.36 ***	0.23 ***

The main results are that both bank specific variables and macroeconomic variables for economic imbalance and banking sector vulnerabilities are relevant for banking distress prediction. The inclusion of both type of variables improves the model performance.

2.6.6 Kapinos et al. (2015)

Kapinos et al. (2015) use a top-down approach to create a method to stress testing banks. The method assesses the impact of several macroeconomics shocks on banks capitalization, and is based on a variable selection that identifies the main macroeconomic drivers that influence specific bank variables.

The approach also allows to identify the financial statement variables that contribute to bank heterogeneity, due to the response to macroeconomic shocks. The sample is composed by 156 US banks with assets at least of $10 billion for at least one quarter during the period from 2000Q1 to 2013Q3. For these banks, the data used was public quarterly data.

The model was estimated using two different dependent variables, pre-provision net revenue (PPNR) and net charge-offs (NCO) on all loans and leases, being PPNR = (interest income + noninterest income) - (interest expense + noninterest expense).

In order to recognize the relevant macroeconomic drivers, they use a least absolute shrinkage and selection operator (LASSO) approach (Tibshirani, 1996). This approach was used first to find the significant macroeconomic drivers for each of the banking variables of interest, and then, in a second step, using the set of variables discovered by LASSO as significant, an index of macroeconomic conditions was generated (Appendix B).

The same method was applied concerning the income statement and balance sheet variables, to find the relevant variables (Appendix C).

For each of the dependent variables, several specifications of the following model were estimated:

$$Y_{it} = \alpha_i + \beta_j Y_{it-1} + \sum_{p=1}^{P} \gamma_{j,p} f_t^p + v_{it} \tag{4}$$

P = 1,3 → number of different situations tested

j → associated with the coefficients β and γ reflects three alternative empirical strategies

β and γ → coefficients

i → bank i

t → period

α → specific effects

The first empirical strategy, standard-fixed effects, is an approach where only the vertical intercepts differ from one bank to another, $\beta_{(j)} = \beta$ and $\gamma_{(j)} = \gamma$. The second is the time series, which is an approach where the all coefficients are estimated for individual banks, $\beta_{(j)} = \beta_i$ and $\gamma_{(j)} = \gamma_i$, for i = 1,…,n. The third is the estimation of fixed-effects models which permits coefficients to vary for groups of banks based on their income statement and balance sheet characteristics, $\beta_{(j)} = \beta_g$ and $\gamma_{(j)} = \gamma_g$, for g = 1,…, G.

The main results point to an improvement in banking capitalization[10] in the recent years, however this type of shocks still have a significant impact in the deterioration of banks capital positions. Other conclusion was that macroeconomic variables can be drivers of banking variables.

[10] Measured by three ratios: Tier 1 leverage ratio, Total risk-based capital ratio and Tier 1 risk-based capital ratio

3. Database

The main purpose of this dissertation is to find the key determinants of stress testing, namely which factors or variables can define if a bank fails or passes in the tests.

The model has a dummy depended variable that assumes the value 1 if the bank fails stress tests and 0 otherwise. In relation to the explanatory variables, we use bank specific variables, like financial ratios, macroeconomic variables and two variables to assess contagion effects.

According to Wooldridge (2012), data used to estimate models can be of three types, namely cross-section, time series and panel data. Cross-section data is collected at the same time for several different individuals or institutions. Time series data is collected for the same individual or institution, but at different points in time. Finally, panel data is the combination of both, consisting in a time series for each cross-sectional data presented in the sample. In stress tests, there are several banks analyzed in each series, which is the cross-sectional part of the data, but since in this dissertation we want to analyze more than one stress tests series (several years), we also have a time series component as part of the data, classifying our data as panel data.

Also based on Wooldridge (2012), panel data can be balanced or unbalanced. In this case our data is unbalanced, since one bank can be analyzed in the 2011 stress tests series, but there is no obligation that the same bank needs to be analyzed in another stress tests series. The banks selected to the stress tests are only defined by the regulators criterions, which can change the sampled banks for each stress tests series.

The focus is in the data of the banks submitted to the stress tests of 2011, 2014 and 2016 in Europe. To collect this type of information, we used Bloomberg, European Central Bank (ECB), WorldBank and Eurostat for the macroeconomic variables and EBA, Yahoo Finance and Orbis for the specific bank variables. Being Orbis, a Bureau Van Dijk database, the main source of data.

Since EBA assumes a static balance sheet for the banks, the information of the variables were collected for the year before the stress tests series. For example for the 2016 stress tests series the information collected for the variables relates to 2015.

To identify banks that failed the stress tests and obtain their information, we used the specialized financial media and the results published by EBA.

Next, we describe briefly the stress tests of 2011, 2014 and 2016. In 2011, EBA conducted stress tests over 90 banks, and 8 of them failed the stress tests, since their CET1 were smaller than 5% under the baseline or under the adverse scenario. The 8 (9.00% of the total banks analyzed) banks that failed were: Oesterreichische Volksbank AG (Austria), EFG Eurobank and Agricultural Bank (Greece), and Caja de Ahorros del Mediterráneo, Catalunya Caixa, Banco Pastor, Unnim and Caja 3 (Spain). Due to the lack of data and to the high number of banks that no longer exist, this year was excluded from the database, except the information regarding the banks who failed, which will influence the dummy variable CE2[11].

In 2014, 123 banks were assessed by stress tests, from which 25 failed (20.00% of the total banks analyzed), since their CET1 under baseline scenario were smaller than 8.00% or their CET1 under adverse scenario were inferior to 5.50%. These 25 banks were: Oesterreichische Volksbank AG (Austria), Dexia and Axa (Belgium), Hellenic Bank and Bank of Cyprus (Cyprus), C.H.R. (France), Münchener Hypothekenbank eG (Germany), Eurobank, National bank of Greece and Piraeus Bank (Greece), Permanent tsb plc. (Ireland), Banca Carige S.P.A., Banca Piccolo Credito Valtellinese, Banca Popolare Dell'Emilia Romagna, Banca Popolare Di Milano, Banca Popolare di Sondrio, Banca Popolare di Vicenza, Veneto Banca S.C.P.A., Banca Monte dei Paschi di Siena S.p.A. and Banco Popolare (Italy), Coöperatieve Centrale Raiffeisen-Boerenleenbank B.A. (Netherlands), Banco Comercial Português Portugal), Nova Ljubljanska banka and Nova Kreditna Banka Maribor (Slovenia) and Liberbank (Spain). From the previous banks, 16 were below the defined thresholds for both

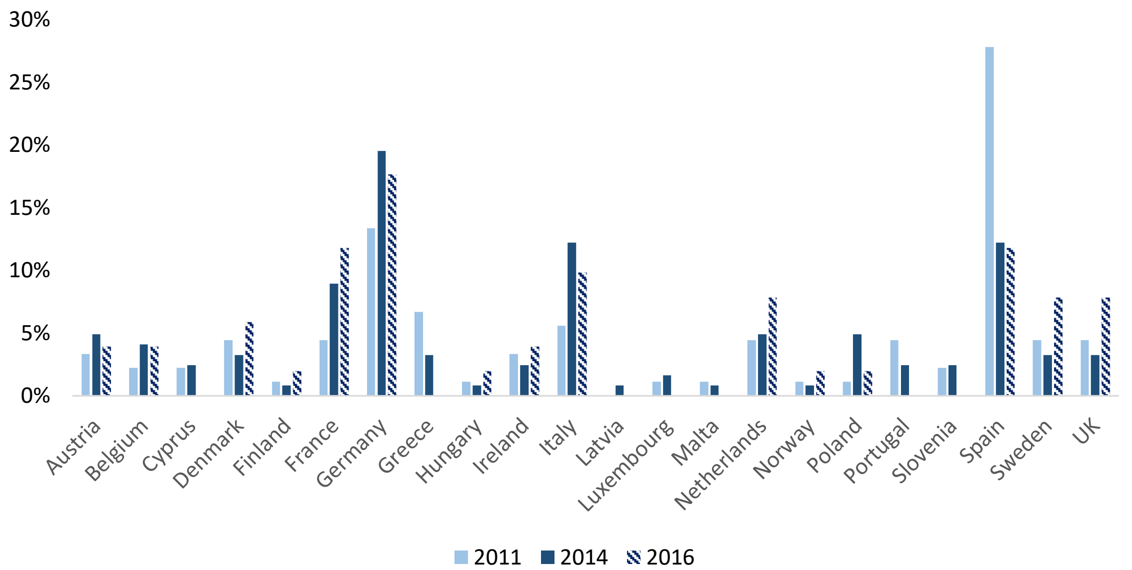
[11] Dummy variable used to access if a bank fail in a previous stress tests series affects the behavior/result in another stress test series.

baseline and adverse scenario, 8 were only below the threshold defined for the adverse scenario and only one was below the baseline scenario and above the adverse scenario.

In 2016, the stress tests were performed to about 51 banks. One limitation regarding the stress tests results in this year is that it wasn't defined a threshold to analyze if a bank fails or passes the stress tests. However, assuming the 2014 stress tests thresholds (transitional CET1 below 8.00% under the baseline scenario and 5.50% under the adverse scenario) the only bank that would fail the stress tests in 2016 is Banca Monte dei Paschi di Siena S.p.A., which presented a CET1 under adverse scenario of -2.23%.

Based on figure 3, we can conclude that Spain, Germany and Italy were the countries that had a higher percentage of banks analyzed in each stress tests series.

Figure 3 Percentage of banks countries to total banks analyzed each year - Source: EBA



4. Methodology

4.1 Model Type

The main objective of this dissertation is to find the main determinants of stress tests results for banking institutions.

To achieve this objective, the econometric model should present as dependent variable the stress tests results (pass or fail). Since this type of variable has clearly restricted values, this model is considered a limited dependent variable model (Wooldrigde, 2012).

$$P(y = 1|x) = G(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k) = G(\beta_0 + x\beta) \tag{5}$$

G $\rightarrow$ function taking on values strictly between zero and one

In the category of limited dependent variable model, logit and probit are the most commonly used. The main difference between both is related with the type of G function used.

In the probit model the function used is the standard normal cumulative distribution function:

$$G(z) = \Phi(z) = \int_{-\infty}^{z} \Phi(v) dv \tag{6}$$

In the logit model the function used is the logistic cumulative distribution function:

$$G(z) = \exp(z)/[1 + \exp(z)] = \Lambda(z) \tag{7}$$

The dataset that serves this dissertation is considered panel data. The panel data regressions, can have cross section effects, time effects or both.

For this type of data, three subtype of models can be estimated, namely Pooled Ordinary Least Squares, Random-Effects Model and Fixed-Effects Model.

Regarding the first one, a Pooled Ordinary Least Squares is simply an Ordinary Least Squares technique to estimate panel data, in which individual-specific and time effects are totally ignored.

$$y_{it} = x_{it}\beta + v_{it}, \tag{8}$$

i $\rightarrow$ bank i

t $\rightarrow$ period

where

$$v_{it} = c_i + u_{it}$$

This regression is only consistent if the error term is not correlated with the regressors.

$$cov(x_{it}, v_{it}) = 0$$

x → regressors

v → error

However, even if the covariance between the regressors and the error is zero, composite error are serially correlated.

So, to estimate sing this kind of model, it is necessary a robust variance matrix estimator and robust test statistics.

About Random Effects Model, the situation is different. In this kind of model, individual-specific effects are taken into account and are considered a random variable, which is not correlated with explanatory variables. The model also assumes that the cross-section part of the data was chosen as a random sample.

$$y_{it} = x_{it}\beta + c_{it} + u_{it} \tag{9}$$

where

$$E(u_{it}|\, x_{i1}, x_{i2}, \dots, x_{iT}, c_i) = 0$$

$$E(c_{it}|\, x_{i1}, x_{i2}, \dots, x_{iT}) = 0$$

$$var(u_{it}|\, x_i, c_i\,) = var(u_{it}) = \sigma_{u\prime}^2$$

$$var(c_i|\, x_i) == \sigma_{c\prime}^2$$

$$cov(u_{it}, u_{is}|\, x_i, c_i) = 0$$

Finally, the Fixed Effects Model. In this type of model, individual-specific effects is a random variable that is allowed to be correlated with the explanatory variables. The model also assumes that the cross-section part of the data was chosen as a random sample.

$$y_{it} = x_{it}\beta + c_{it} + u_{it} \tag{10}$$

where

$$E(u_{it}|\, x_{i1}, x_{i2}, \dots, x_{iT}, c_i) = 0$$

$$var(u_{it}|\, x_i, c_i\,) = var(u_{it}) = \sigma_u^2,$$

$$cov(u_{it}, u_{is}|\, x_i, c_i) = 0$$

The idea for estimate the coefficients is to transform the equations in order to eliminate the unobserved effect c_i.

The Fixed Effects transformation is obtained by first averaging the 10 equation:

$$\bar{y}_{it} = \bar{x}_{it}\beta + c_{it} + \bar{u}_{it} \tag{11}$$

$$y_{it} - \bar{y}_{it} = (x_{it} - \bar{x}_{it})\beta + c_{it} + u_{it} - \bar{u}_{it} \tag{12}$$

The independent variables or explanatory variables used are bank specific variables, like ratios, macroeconomic variables regarding the bank's country and two variables measuring the possible contagion effects. Most of these variables are based on the CAMEL rating system and in the presented in the literature review.

4.2 Model Variables

4.2.1 Stress Tests (StrTest)

The dependent variable of the model is the stress tests results, pass or fail. It is a dummy variable that equals 1 if bank i fails the stress test in period t and 0 if bank i does not fail the stress test in period t.

4.2.2 Non-Current Loans to Total Loans ratio (NCLL)

Non-Current Loans to Total Loans ratio is defined as the ratio of loans that will not mature in the next 12 months and the total loans.

According to Spong and Sullivan (1999), non-current loans to total loans ratio provides a clear measure to analyze the loan quality. A high ratio indicates a worse credit risk management, and so a bigger probability of a bank distress. So, it is expected that $\hat{\beta}_2$ presents a positive sign, since non-current loans to total loans ratio is positively correlated with the dependent variable.

4.2.3 Non-Performing Loans to Total Loans ratio (NPLL)

Non-performing loans to total loans ratio is the ratio of the non-performing loans to total loans, being non-performing loans defined as a loan in default or quasi in default. According to Čihak and Poghosyan (2011), the data on non-performing loans is not available for a use amount of banks, so can be used a proxy by the ratio of loan loss provisions to total loans, being loan loss provision the amount of money that banks have to cover losses from bad banks.

Bigger non-performing loans to total loans ratio leads to bigger vulnerability and increases the probability of bank failure, a conclusion stated by Apergis and Payne (2013). It is also one variable used in the CAMELS Rating System (section 2.6.1). So, it is expected that $\hat{\beta}_3$ presents a positive sign, since non-performing loans to total loans ratio is positively correlated with the dependent variable.

4.2.4 Tier 1 Capital ratio (T1)

Tier 1 capital is the ratio of banks core capital to its total risk-weighted assets, is the mandatory capital that banks are required to hold in addition to other minimum capital requirements. According to Apergis and Payne (2013), increases in Tier 1 capital reduce the probability of bank failure in the stress tests, because a higher Tier 1 means that the is more capital to absorb possible losses. So, it is expected that $\hat{\beta}_4$ presents a negative sign, since Tier 1 capital ratio is negatively correlated with the dependent variable.

When we are trying to collect data for T1 ratio, some of the banks (around 13% of the observations) do not have available this variable. However Common Equity Tier 1 (CET1), a component of this ratio is available for the entire set of observations.

CET1 plus Additional Tier 1 (AT1) are equal to Tier 1, being CET1 compose mostly by common stocks. Besides losing the AT1 effect (mostly composed by preferable shares and other high convertible instruments, like securities) a bigger CET1 also indicates that the bank has more capital to absorb possible losses, so it is expected that $\hat{\beta}_4$ still presents a negative sign.

4.2.5 Leverage ratio (LEV)

T1 Leverage ratio is the ratio of Tier 1 Capital (CET1) to total assets, it is also the inverse of the capitalization ratio. According to Čihak and Poghosyan (2011), leverage is one of the most discussed topics as an indicator of bank security. Čihak and Poghosyan also state that a higher leverage ratio makes the bank more sensitive to shocks. So, it is expected that $\hat{\beta}_5$ presents a positive sign, since leverage ratio is positively correlated with the dependent variable.

4.2.6 Management Quality ratio (MQ)

Management Quality ratio, is the aptitude of the bank managers to minimize expenses, it is the ratio of operating expenses to total revenues. According to Čihak and Poghosyan (2011) and Apergis and Payne (2013), a higher management quality ratio denotes a greater aptitude of managers to reduce expenses, decreasing the probability of bank failure. It is also one variable used in the CAMELS Rating System (section 2.6.1). So, it is expected that $\hat{\beta}_6$ presents a negative sign, since management quality ratio is negatively correlated with the dependent variable.

4.2.7 Net Interest Income (NII)

Net Interest Income is the difference between revenues generated by interest-bearing assets and the cost of servicing (interest-burdened) liabilities, it is the lending margin charged.

Since a loan is priced in accordance to its risk, a more risky loan will have a bigger price. A bigger lending margin charge is due to riskier loans, which present a high probability of default, consequently increase the probability of a bank failure (Apergis and Payne, 2013). However, according to Schmieder et al. (2011), net interest income is the most important source of income for banks. So, assuming that the income effect is greater than the risk effect associated to a higher net interest income, it is expected that $\hat{\beta}_7$ presents a negative sign, since net interest income is negatively correlated with the dependent variable.

4.2.8 Return on Assets (ROA)

Return on assets is measured as the ratio of net profit to average total assets and it measures the profitability of a bank. According to Apergis and Payne (2013), a higher return on assets denotes a higher prospection of banks growth, reducing the probability of a bank failure. It is also one variable used in the CAMELS Rating System (section 2.6.1). So, it is expected that $\hat{\beta}_8$ presents a negative sign, since return on assets is negatively correlated with the dependent variable.

4.2.9 Loans to Deposits ratio (LD)

Loans to deposits ratio is the ratio between the total loans and the total deposits of the bank. Deposits, as debt issuance and shareholders' equity are main sources of funds of a bank, being deposits the most stable source of funding. Bigger loans to deposits ratio, means that banks prioritize as source of funds other sources than deposits, increasing the credit risk

(Apergis and Payne, 2013). It is also one variable used in the CAMELS Rating System (section 2.6.1). So, it is expected that $\hat{\beta}_9$ presents a positive sign, since loans to deposits ratio is positively correlated with the dependent variable.

4.2.10 Liquid Assets to Total Assets ratio (LATA)

Liquid Assets to Total Assets ratio is the ratio between the total of liquid assets held by a bank and the total of its assets. Liquid assets are assets that can be changed for money quickly. The faster and more easily they can be converted into cash, the more liquid they are. They can be measured as the difference between equity and deposits plus loans, according to a classical microeconomic theory (Alger and Alger, 1999).

According to Alger and Alger (1999), the interbank market is one important source of funding, however it is very expose to credit risk, which can collapse the market. When a bank seeks for more liquidity in the interbank market, it will find difficulties if the respective probability of insolvency is high. Banks invest in liquid assets to prevent a collapse in the interbank market, and in order to cover large deposits withdrawals as a consequence of that collapse.

According to Apergis and Payne (2013), a bigger liquidity ratio makes the bank more resilient to liquidity crises, reducing the probability of a bank failure. So, it is expected that $\hat{\beta}_{10}$ presents a negative sign, since liquidity assets to total assets ratio is negatively correlated with the dependent variable.

4.2.11 Variance of Bank's Equity price (VEP)[12]

For measuring the market risk, it is used the variance of bank's equity price during a certain year. According to Ötker-Robe and Podpiera (2010), equity volatility measures the uncertainty of risk associated to an investment in the bank's equity. Apergis and Payne (2013) based in this analysis, conclude that a bigger equity volatility is associated to a bigger market risk, which increases the perspective of a bank failure.

Not all the banks presented listed shares, moreover most of them have unlisted shares. For the banks without unlisted shares, there is no way of estimate the variance of equity price based in the shares quotes, so VEP will not have value for these banks. In practice, this variable also works as a dummy, which is 1 for the listed banks and 0 for the unlisted banks. So, it is

[12] Measured based on daily prices

expected that $\hat{\beta}_{11}$ presents a positive sign, since variance of bank's equity price is positively correlated with the dependent variable.

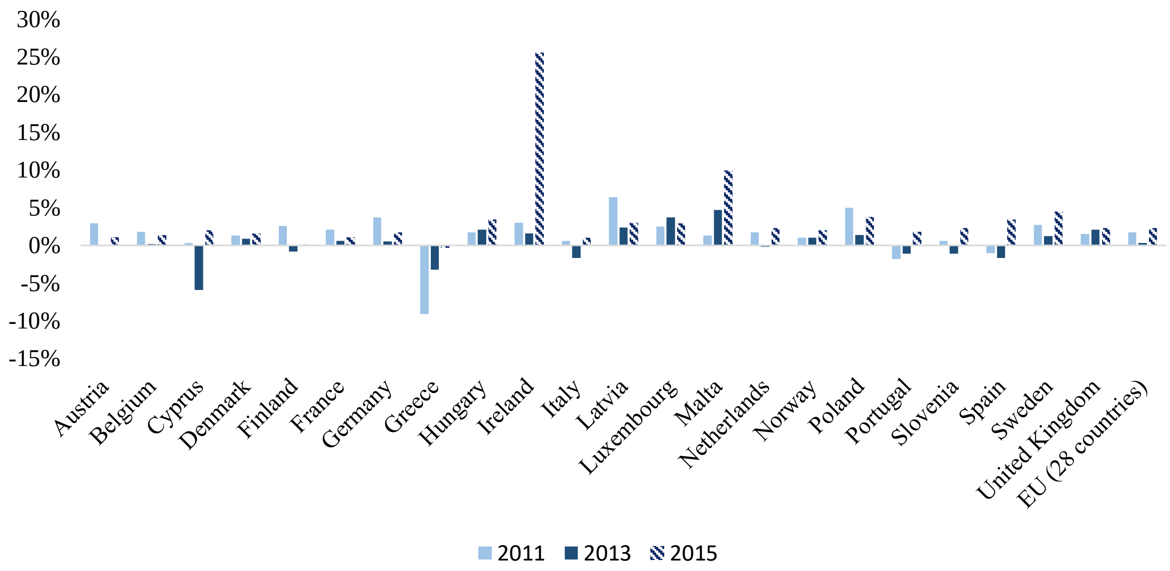
To cover events that do not change the market cap of the bank, but that affect the bank's stock price, like a stock split, the variance is calculated based on the adjusted closing price.

4.2.12 GDP Growth of the Bank's country (DY)

GDP growth is one of the key indicators of economic health. If the economy is growing, there is less risk of a bank failure (Apergis and Payne, 2013). In Europe the countries that presented the worse GDP growth were the peripheral countries, with the exception of Ireland (table 4).

In 2013, Mayes and Stremmel find that GDP growth has good predictive power and a negative effect when predicting banks distress. So, it is expected that $\hat{\beta}_{12}$ presents a negative sign, since GDP growth is negatively correlated with the dependent variable.

Figure 4 Real GDP growth rate in volume (%) - Source: Eurostat



4.2.13 Credit Default Swap Spread of the Bank's country (CDS)

Credit default swap is the most liquid of credit derivatives currently traded, being a derivative that transfers the credit risk from one investor (protection buyer), who is exposed to the risk, to another investor (protection seller), who is willing to accept that risk. The protection seller charges a fee (CDS spread) to the protection buyer, in exchange of his commitment to compensate the protection buyer if a default event occurs before maturity of the contract (Blanco et al., 2005).

When the risk of default increases, the CDS spread also increases, leading the protection seller to ask for a higher fee to assume the risk. According to Apergis and Payne (2013), a higher CDS spread implies a greater underlying risk, increasing the probability of a bank failure. So, it is expected that $\hat{\beta}_{13}$ presents a positive sign, since credit default swaps spreads are positively correlated with the dependent variable.

4.2.14 Non-Performing Loan ratio of the Bank's country (NPL)

The same variable as the one stated at point 4.2.3, but applied at the bank's country level. So it is expected that $\hat{\beta}_{14}$ presents a positive sign, since non-performing loans to total loans ratio is positively correlated with the dependent variable.

From the countries analyzed in this dissertation the one that stands out is Italy with NPL loans in the range of 14.40% to 20.92% (Figure 5).

Figure 5 2016 Non-performing loans across countries (%) - Source: WorldBank

4.2.15 Libor– OIS[13] Spread (LIBOR)

Libor-OIS spread is the difference between Libor interest rate and the overnight indexed swap rate. The Libor interest rate is the London interbank offer rate, which is the rate that bank

[13] Overnight Index Swap, which are an interest rate swap involving the overnight rate being exchanged for a fixed interest rate.

specify to lend to other banks. The OIS rate, designated overnight index swap, is the rate on a derivative contract on the overnight rate (Thornton, 2009).

The Libor-OIS spread started to have an important role in measuring the health of banks with the 2007 crisis, since until then the spread was close to zero. This spread reflects the risk to lend to other banks, so the higher the spread, the higher is the risk of lending, and consequently the bigger the probability of a bank failure (Apergis and Payne, 2013). So, it is expected that $\hat{\beta}_{15}$ presents a positive sign, since Libor-OIS spread is positively correlated with the dependent variable.

4.2.16 Unemployment rate of the Bank's country (UNEM) (appendix D)

The unemployment rate is the percentage of the total labor force that is unemployed but actively seeking employment and willing to work. According to Makri et al. (2013) the unemployment rate is one of the determinants of the non-performing loans, because households' unemployed present less income and the probability of defaulting their loan payments increases, and consequently increasing the probability of a bank failure.

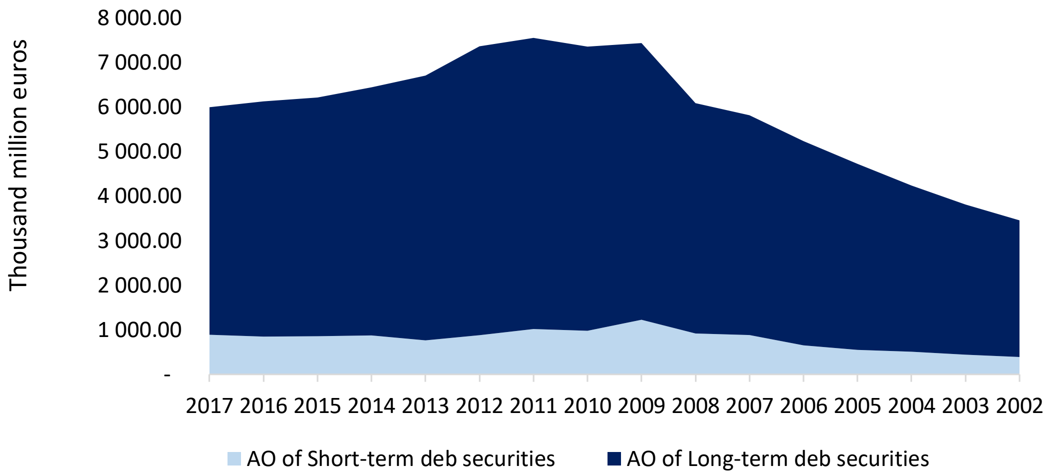
Also based on Klein (2013) from the International Monetary Fund, the level of non-performing loans tends to increase when the unemployment rate increases, at least in the Central and Eastern and Southeastern European countries.

The bigger the unemployment rate, the bigger the percentage of defaulting costumers, so it is expected that $\hat{\beta}_{16}$ presents a positive sign, since the unemployment rate is positively correlated with the dependent variable.

4.2.17 Debt Securities issued (DSI)

Banks can finance themselves through deposits, shareholders' equity or debt issuance. An issue of debt securities increases the total debt, making the responsibilities of the bank increase. A debt securities issuance is a source of founding that as to be repaid, and sometimes include regular payments, for example like bond coupons. If, the bank present already a fragile situation this source of financing will increase this fragility of the bank, making more probable a bank failure. So it is expected that $\hat{\beta}_{17}$ presents a positive sign, since debt securities issued are positively correlated with the dependent variable.

Figure 6 Amount outstanding of debt securities issued by banks in EU [28] - Source: ECB



Analyzing the amount outstanding of short-term and long-term debt securities issued by banks of European Union [28], we can conclude that the amount of long-term debt securities is much superior to the amount outstanding of short-term debt securities (Figure 6), in mean the amount outstanding of the short-term debt securities correspond to 13.26% of the amount outstanding of the long-term debt securities. It means that banks preferred to finance themselves with long-term securities. In this model the total debt securities issued corresponds to the sum of short-term and long-term debt securities issued.

4.2.18 Inflation rate of the Bank's country (INF) (appendix E)

The inflation rate measures how fast prices of goods and services rise over time and it is a major concept in macroeconomics. According to Demirguc-Kunt and Huizinga (2000) banks generally profit in environments of inflation, so the probability of a bank failure decreases. It is expected that $\hat{\beta}_{18}$ presents a negative sign, since the inflation rate is negatively correlated with the dependent variable.

4.2.19 Banks Size (SIZE)

One way of measuring a bank size is to analyze the value of its assets. The bigger the assets owned, the greater is the size (Laeven et al., 2014).

According to Laeven et al. (2014), usually large size banks present a higher systematic and individual risk than smaller banks. The risk of a large bank increases when it has insufficient capital or when it presents unsustainable funding. Also, large banks, being a complex corporation structure have more probabilities to fail. From the social welfare perspective banks are too large to operate.

There are banks considered too big to fail, which assets growth at a higher rate than their country's economy, even in crisis. The number of these banks decreases, but the remaining ones became even bigger. However, recent results showed that these banks are not immune to failure. Deutsche Bank, one of the biggest 2000's banks, is facing huge problems, mainly due their poor management performance, demonstrating that even the too big to fail banks have risk of collapse. So, it is expected that $\hat{\beta}_{19}$ presents a positive sign, since banks size is positively correlated with the dependent variable.

4.2.20 Banks profitability (PROF)

Net interest margin can be calculated as the difference between the investment returns and the investment expenses, divided by the average earning assets. It is considered a better measure of profitability of banks than for example return on assets, since studies show that the net interest margin of banks start to decline before a crisis, while the return on assets stayed more stable in those situations (Saksonova, 2014).

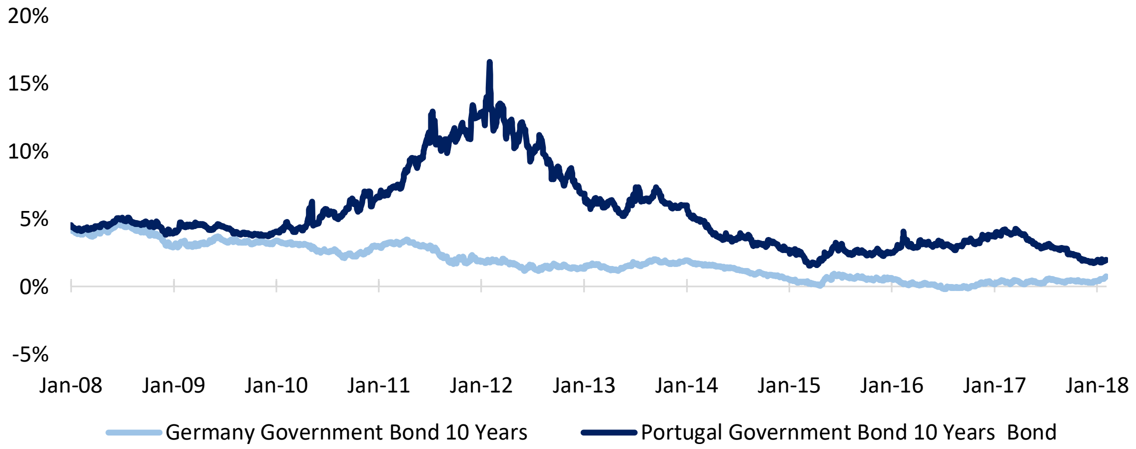
A bigger bank profitability measured by the net interest margin decreases the probability of a bank failure, and so, it is expected that $\hat{\beta}_{20}$ presents a negative sign.

4.2.21 Government Bond Yields (GBY)

Government bonds are bonds issued by a government. The government bond yield is the rate that governments pay to borrow money for different lengths of time. The higher the yield, the greater the possibility of government default, since investors demand a higher rate to compensate the higher risk.

A bigger probability of a government default denotes problems in the economy, namely a recession, increasing the probability of a bank failure. So it is expected that $\hat{\beta}_{21}$ presents a positive sign, since government bond yields are positively correlated with the dependent variable.

Figure 7 Portuguese and German 10 years yield curve - Source: Bloomberg



In Figure 7 we can see that the Portuguese yields achieve their maximum in the worse period of the crisis. On the opposite side, the German yields decrease since 2009, achieving a minimum of 0%, more or less in 2015.

4.2.22 The Yield Curve (YC)

The yield curve plots interest rates, at any point in time, of bonds that have the same credit default probability, but different maturities. According to Haubrich and Dombrosky (1996), the difference between the interest rates at 10 years and the interest rate at 3 months (spread) has substantial predictive power of GDP growth. However, several countries do not have data for the 3-month yield.

Based on the Collin-Dufresne et al. (2001), the slope of the yield curve will be defined as the difference between the 10-year government bond yield and the 2-year government bond yield. If an economy is growing, the 10-year interest rate should be higher than the 2-year interest rate, otherwise, and economy is facing a recession. So, it is expected that $\hat{\beta}_{22}$ presents a negative sign, since yield spreads are negatively correlated with the dependent variable.

4.2.23 Contagion Effect in Similar Banks (CE1)

According to Hardy (1998), a bank failure is a rare event, but it is usual that appear in clusters. To assess this contagion effect in similar banks, and similar meaning banks with similar size (similar value in total assets), a dummy variable will be used. This dummy variable equals 1 if there is a similar bank that faced a failure, and 0 if not.

To check for this effect, the banks were divided in 10 percentiles based on their total assets value (Tables 1 and 2). If a bank falls inside that percentile, then the other banks that belong to that percentile will also have a similar probability of failure, presenting the value 1 for the CE1 dummy variable. These analyses were done for both years (2014 and 2016).

Table 1 Bank percentiles for 2014

Percentile	**Total Assets – th euro**
P1	14 315 565.701
P2	32 292 558.800
P3	40 837 217.046
P4	50 792 062.945
P5	77 586 000.000
P6	113 455 003.200
P7	181 877 137.600
P8	275 831 242.120
P9	740 177 600.000
P10	1 939 091 037.974

Table 2 Bank percentiles for 2016

Percentile	**Total Assets – th euro**
P1	103 946 927.173
P2	120 199 540.200
P3	146 176 698.800
P4	180 190 824.800
P5	215 713 000.000
P6	270 462 689.076
P7	477 896 941.648
P8	1 001 757 980.218
P9	1 486 156 727.586
P10	2 217 502 801.592

4.2.24 Contagion Effect in Similar Banks (CE2)

According to Kick and Koetter (2007), banks that faced distress in the past, will have a higher probability of facing a new distress events in the future, like failures. So, to assess this contagion effect, a dummy variable will be used. This dummy variable presents the value 1 if the bank faced a failure in stress tests in the past, and 0 if not.

Starting with the analysis of banks stressed in 2014, we can conclude that both Österreichische and Eurobank failed stress tests in the past, and so the dummy variable equals to one for this two banks. For the 2016 stress tests series, Banca Monte dei Paschi di Siena S.p.A., Banco Popolare - Società Cooperativa and Coöperatieve Centrale Raiffeisen-Boerenleenbank B.A, failed at least in one stress tests past series, and so, the variable CE2 will be one for each one of them.

4.2.25 Dividends Paid by Banks (DIV)

Dividends is a distribution of a proportion of earnings to shareholders. According to Admati (2012) and Admati (2011), when banks pay dividends to shareholders, the amount of capital to cover losses decreases, making the bank more exposed to shocks, and increasing the probability of a bank failure. Banks should pay their investors at one point in time, but not until they are strong enough. So, it is expected that $\hat{\beta}_{25}$ presents a positive sign, since dividends paid are positively correlated with the dependent variable.

4.3 Initial Model

Based on the variables described in the previous subchapter, the initial model is:

$$StrTest_{it} = \beta_1 + \beta_2 NCLL_{it} + \beta_3 NPLL_{it} + \beta_4 T1_{it} + \beta_5 LEV_{it} + \beta_6 MQ_{it} + \beta_7 NII_{it} + \beta_8 ROA_{it} + \beta_9 LD_{it} + \beta_{10} LATA_{it} + \beta_{11} VEP_{it} + \beta_{12} DY_{it} + \beta_{13} CDS_{it} + \beta_{14} NPL_{it} + \beta_{15} LIBOR_{it} + \beta_{16} UNEM_{it} + \beta_{17} DSI_{it} + \beta_{18} INF_{it} + \beta_{19} SIZE_{it} + \beta_{20} PROF_{it} + \beta_{21} GBY_{it} + \beta_{22} YC_{it} + \beta_{23} CE1_{it} + \beta_{24} CE2_{it} + \beta_{25} DIV_{it} + u_{it} \quad (13)$$

i $\rightarrow$ bank i

t $\rightarrow$ period

5. Estimation Results

5.1 Data Description

The initial model presents an explained variable (StrTest) and 25 possible explanatory variables.

These 26 variables present distinct formats and behaviors that originate differences in the maximum, minimum and average values of each one of them. The number of observations also vary from variable to variable, since not all the banks/countries have information available for all the variables.

Table 3 Descriptive Statistics

Variable	Format	Number of Observations	Minimum	Maximum	Average
StrTest	Dummy	174	0	1	
NCLL	Percentage	119	-0.952	98.924	63.458
NPLL	Percentage	155	0.090	46.273	9.109
T1	Percentage	174	-3.710	72.510	14.050
LEV	Percentage	137	0	12.987	5.070
MQ	Percentage	171	-168.519	402.677	64.447
NII	Number (th eur)	171	-90 000	32 812 000	3 890 794.235
ROA	Percentage	173	-16.790	4.429	0.003
LD	Percentage	173	3.574	2 371.613	158.023
LATA	Percentage	173	0.837	71.290	18.516
VEP	Number (th eur)	39	0.010	15 910 535.979	408 145.340
DY	Percentage	174	-5.900	25.600	0.753
CDS	Number (usd)	171	12.872	824.440	98.579
NPL	Percentage	174	0.000	38.557	7.538
LIBOR	Percentage	174	0.246	0.613	0.354
UNEM	Percentage	174	3.500	27.500	10.792
DSI	Number (th eur)	157	6 000	229 030 000	49 255 275.865
INF	Percentage	174	-0.900	2.600	0.953
SIZE	Number (th eur)	174	33 16 077	2 217 502 801.592	314 183 182.330
PROF	Percentage	171	-0.041	7.116	1.486
GBY	Percentage	165	0.629	8.216	1.874
YC	Percentage	145	0.960	3.159	1.811
CE1	Dummy	174	0	1	
CE2	Dummy	174	0	1	
DIV	Number (th eur)	120	0.000	461 000	54 512.234

Most of the variables presented in the database are financial ratios and macroeconomic variables, which are presented in the percentage format. However, there are also three dummy variables, and five variables that assume integer numbers.

From the above table, we can see that that the variable with less observations is VEP, since most of the banks presented unlisted shares, as stated in chapter 4.

From the variables in number format, SIZE is the variable with the biggest value in all the dataset, however the variable with biggest average is VEP. In the variables with percentage format, NCLL is the one with highest value, being MQ the one with the highest average.

Only NCLL, T1, MQ, NII, ROA, DY, INF and PROF have negative values.

5.2 Final Model Development

The initial model has 25 explanatory variables, however, as the number of observations is small, and in order to preserve the degrees of freedom, we excluded several explanatory variables considered initially. The ones excluded are those with less economic and financial explanatory power of failure.

After the re-estimation of the models without the variables with less economic and financial explanatory power of failure, there are several explanatory variables in the models whose estimated coefficients are not statistically significant, since the p-value associated to the individual significance tests are higher than the usual significance level, leading to the non-rejection of the null hypothesis.

T-test hypothesis:

$$\begin{cases} H0: \beta j = 0 \\ \text{H1: } \beta\text{j} \neq 0 \end{cases}, j = 1, \dots, n$$

Later, we estimate several models considering different combinations of explanatory variables, considered statistically significant. The resulting model is presented next (table 4):

$$StrTest_{it} = \beta_1 + \beta_2 NPLL_{it} + \beta_3 LATA_{it} + \beta_4 DY_{it} + \beta_5 PROF_{it} + \beta_6 UNEM_{it} + \varepsilon_{it} \tag{11}$$

i → bank i

t → period

In chapter 4, it was referred that binary models can be estimated based on different assumptions about the relation between the individual effects and the explanatory variables: Pooled, Fixed-Effects or Random Effects regressions. For each one of these regressions we present the estimation results:

Table 4 Pooled Final Models

Pooled Logit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	2.079	1.274
NPLL	0.129	0.044***
LATA	-0.113	0.042***
DY	-1.200	0.376***
UNEM	-0.182	0.069***
PROF	-1.733	0.736**

Pooled Probit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	0.977	0.709
NPLL	0.065	0.0227***
LATA	-0.060	0.022***
DY	-0.564	0.180***
UNEM	-0.084	0.04511**
PROF	-0.947	0.399**

N	152
Pseudo R^2	0.483

N	152
Pseudo R^2	0.474

Signicance levels: * : 10% | ** : 5% | * : 1%**

Table 5 Random Effects Final Models

Random Effects Logit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	2.079	1.274
NPLL	0.129	0.044***
LATA	-0.113	0.042***
DY	-1.200	0.376***
UNEM	-0.182	0.069***
PROF	-1.733	0.736**

Random Effects Probit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	-0.361	2.362
NPLL	0.261	0.088***
LATA	-0.386	0.107***
DY	-2.719	0.779***
UNEM	-0.467	0.129***

N	152
Number of groups	108

N	154
Number of groups	110

Signicance levels: * : 10% | ** : 5% | * : 1%**

When we are trying to run in Stata the model presented in tables 4 and 5 but for Logistic Fixed Effects Regression, the following message appear: “note: multiple positive outcomes within groups encountered. note: 107 groups (150 observations) dropped because of all positive or all negative outcomes”. The Fixed Effects model is based on information from changes within an individual (is this case, banks), and so, what this message is trying to say to us is that we cannot estimate a fixed effects regression since the majority of the banks (107 of 127 banks included in our sample) do not change over time. There are three reasons for this absence of change over time. The first reason is the methodology of EBA, who just apply stress tests to a defined range of banks that fulfill certain criterions. As consequence of this methodology some banks can be only analyzed in a certain year, and there is just one observation for that bank and so it is considered that the bank do not change over time. The second reason is the unavailability of information for certain variables for some banks, which leads to the exclusion of the entire observation of the final sample. For example EBA can apply stress tests to the a bank for both years, but for instance if the bank do not present information for the variable NPLL in the second year, this observation is excluded from the final sample and there is just one observation for that bank, leading to the same conclusion as the first reason. The third reason is related with the fact that the biggest part of the banks analyzed by EBA do not change the results of stress tests from one year to the next. For the largest part of the sampled banks, they both pass the two stress tests series. For the Probabilistic Regression does not exist such thing as a Fixed-Effects model, so there is no need to test this hypothesis.

In table 4 there are two final models, a Logit and a Probit. To select between the two, a set of statistics is used.

Table 6 Comparative statistics between Pooled Logit and Pooled Probit Models

	Log Likelihood	**Akaike Information Criterion**	**Bayesian Information Criterion**	**Correctly Classified Observations**	**Pseudo R^2**
Pooled Logit	-30.505	75.009	96.176	90.132%	0.483
Pooled Probit	-31.097	74.194	92.337	86.842%	0.474

According to the literature, when we are estimating a model the objective is to maximize the Log Likelihood, so a higher value indicates a better-fitting model. Regarding the Information Criterions, it is exactly the opposite, a smaller value indicates a better-fitting model.

In binary regression is not common to compute the traditional R-squared because the value tends to be between 0.2 and 0.6 not achieving the common limits of that measure in the linear regression model. This is the reason why McFadden R^2/Pseudo R^2 squared are used. However, this pseudo R^2 is also a standard goodness of fit measure, with the same role of the R^2 but for binary models. It varies between 0 and 1, and the closer the value of the statistic is to 1, the better the model fits and it gives us an estimation of the explanatory power of our model (Wooldridge, 2012).

McFadden or Pseudo R^2:

$$R^2 McFadden = 1 - \frac{\log(LC)}{\log(L_{null})}$$

LC = likelihood of the estimated model = log likelihood

L_{null} = likelihood function for a model with no predictor = restr. log likelihood

When we compare the results of both Logit and Probit, the results are somewhat mixed: the Logit presents a higher Log Likelihood, but on the other hand presents higher values for the Information Criterions (Akaike and Bayesian). Probit is exactly the opposite, presents small Log Likelihood and smaller values for the Information Criterions.

The Pseudo R^2 is very similar for both, a difference of just 0.009 separates the models, with a slightly value for Logit. However Behavioural Travel Modelling (1979) states that values of 0.2 and 0.4 for Pseudo R^2 are considered a good fit, so since both values of the two models are slightly superior to this threshold the Pseudo R^2 will not have decision power regarding which model to choose.

In order to decide which model to choose, we look into the percentage of Correctly Classified Observations, assuming 0.5 as the limit to define if a bank failed or passed in the stress tests. If the bank presents a probability higher than 0.5 it fails the stress tests. For this statistic the values are slightly different, with the Logit model achieving a value of approximately 90%, while Probit only achieves approximately 87%. This 3% difference, corresponds to more five corrected guesses, since the observations are only 152, it is an important indicator.

So, based on the below arguments and taking into account that the main purpose of the model is to classify correctly the observations, we choose the Logit model as better-fitting model.

In table 7 we have the Random Effects models for both Logit and Probit regressions. In order to decide each one of them fits the data better, we compare the following statistics:

Table 7 Comparative statistics between Pooled Logit and Pooled Probit Models

	Log Likelihood	**Akaike Information Criterion**	**Bayesian Information Criterion**
Random-Effects Logit	-30.595	75.190	96.357
Random-Effects Probit	-34.766	81.532	99.754

According to table 7, the Random-Effects Logit is the one that fits data in a better way, since presents the largest Log Likelihood value and the smallest values for both Information Criterions.

So, we can conclude that the Pooled Logit model is preferable to the Pooled Probit model and the Random Effects Logit model is better than the Random Effects Probit model.

In order to decide between the Pooled Probit model and the Random Effects Logit model, we have to perform several statistic tests, described below.

Table 8 Random Effects Logit Model

Random Effects Logit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	2.079	1.274
NPLL	0.129	0.044***
LATA	-0.113	0.042***
DY	-1.200	0.376***
UNEM	-0.182	0.069***
PROF	-1.733	0.736**

N	152
Log Likelihood	-30.595
Wald chi2	19.730
Prob > chi2	0.001
Sigma_u	0.001
Likelihood Ratio Test of Rho	0.500

Signicance levels: * : 10% | ** : 5% | * : 1%**

Based on table 8, we can state that there is a Random Effects model, since the probability associated to the Wald Test in smaller than the critical p-value associated to the confidence level, rejecting the null hypothesis.

Wald Test:

$$\begin{cases} H0: \beta_2 = \beta_3 = \beta_k \\ \exists\, \beta_i \neq 0 \end{cases}, i = 1, k$$

As previously referred there is no Fixed Effects Model, and consequently there is no need to run the Hausman Test, because the inexistence of a Fixed Effects Model lead automatically to the choice of the Random-effects Model.

Hausman Test:

$$H = (\beta c - \beta e)'(Vc - Ve)^{-1}(\beta c - \beta e)$$

Null hyphotesis: Random-Effects Model is consistent and efficient

where

βc is the coefficient vector from the consistent estimator

βe is the coefficient vector from the efficient estimator

Vc is the covariance matrix of the consistent estimator

Ve is the covariance matrix of the efficient estimator

The inexistence of Fixed-Effects Model as other consequence, there is no need to run the F-Test, which faces the Fixes-Effects Model to the Pooled Logit model.

Breusch-Pagan Lagrange Multiplier test:

$$\begin{cases} \text{H0: } \sigma_u^2 = 0 \text{ (Pooled is consistent)} \\ \text{H1: } \sigma^2 \neq \text{ (Pooled is not consistent)} \end{cases}$$

The Breusch-Pagan Lagrange Multiplier test has under the null hypothesis the consistency of the Pooled regression. However in Stata it is not possible to run the Breusch-Pagan Lagrange Multiplier test after a Random-Effects Panel Binomial Logistic regression, so we you will look into the sigma_u and rho p-value (table 8).

The sigma_u[14] (σ_u) of the Random effects model is 0.001 which is not zero, but close to it, meaning that the variance between the observations is practically null. Looking into the p-value of the Likelihood Ratio Test of Rho, which considerer that Random Effects are equal to zero under the null hypothesis, we can conclude that the Pooled Regression is consistent and there is no Random Effects regression, since the p-value (0.500) is higher than the critical p-value associated to the confidence level. We can conclude that in our model there is absence of specific effects (Baum, 2006).

[14] Variance between observations

Table 9 Comparative statistics between Pooled and Random Effects Model

	Log Likelihood	**Akaike Information Criterion**	**Bayesian Information Criterion**
Pooled Logit	-30.505	75.009	96.176
Random Effects Logit	-30.595	75.190	96.357

When we compare the results of both Pooled Logit and Random Effects Logit, the results are clear: the Pooled Logit presents a higher Log Likelihood, and smaller values for the Information Criterions (Akaike and Bayesian), pointing in the same direction as the rho p-value test. Thus, our final model is a Pooled Logit.

Looking in to table 3, it is possible to conclude that the average value for DY and PROF is much smaller than the average of NPLL, LATA and UNEM, so it should be used the logarithmic form of the variables with higher average (Wooldridge, 2012). The three variables also follow the condition of being always positive. This transformation leads to the following final model:

Table 10 Final Model with logarithmic forms

Pooled Logit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	4.012	2.634
log(NPLL)	1.053	0.443**
log(LATA)	-1.029	0.425**
DY	-1.0.38	0.349***
log(UNEM)	-1.788	0.883**
PROF	-1.370	0.632**

N	152
Pseudo R^2	0.409

Signicance levels: * : 10% | ** : 5% | * : 1%**

According to Cameron and Trivedi (2009), if there is no type of control for the individual effects in the Pooled estimation applied to panel data, it is possible that Cov $[u_{it}, u_{is}] > 0$ with t≠s, meaning that our model can have autocorrelation problems. This autocorrelation problems, impacts the standard errors and the t-statistics, underestimating the first and overestimating the second.

In order to overcome this possible problem, we will use a cluster-robust standard error option in order to obtain panel-robust standard errors. These panel-robust standard errors consider the observations independent across groups (clusters), but not necessarily inside each group.

Table 11 Final Model with logarithmic forms and panel-robust standard errors

Pooled Logit Regression		
Variable	**Coefficient**	**Robust Std. Error**
Intercept	4.012	2.642
log(NPLL)	1.053	0.480**
log(LATA)	-1.029	0.339***
DY	-1.0.38	0.400**
log(UNEM)	-1.788	0.873**
PROF	-1.370	0.521***

N	152
Pseudo R^2	0.409

Signicance levels: * : 10% | ** : 5% | * : 1%**

Comparing the results presented in tables 10 and 11, we can state that the inclusion of panel-robust standard errors do not change the coefficient estimates. The only changes are related with the standard error and with t-test, which consequently changes the p-value of the variables. Although, these p-values changes do not make none of the variables non-significant.

$$StrTest_{it} = \beta_1 + \beta_2 \log(NPLL)_{it} + \beta_3 \log(LATA)_{it} + \beta_4\, DY_{it} + \beta_5\, PROF_{it} + \\ + \beta_6 \log(UNEM)_{it} + \varepsilon_{it} \quad (12)$$

5.3 Final Model Quality

Starting from analyzing the estimated coefficients significance. All the estimated coefficients are statistically significate at 10 % and 5 % levels, except the Intercept.

The statically insignificancy of the intercept or constant can be ignored, since the intercept just by itself does not have a high meaning. However, the intercept will not be excluded from the model, because we do not want to create a model where the response function is zero when all the predictors are zero.

The signals of the estimated coefficients are in line with literature reviews, except for the variable UNEM. For UNEM the literature reviews points in the direction of a positive sign, however when we estimate the model the signal is exactly the opposite, negative. This means that in practice, a higher unemployment rate in the bank's country leads to a small probability of the bank failing the stress test.

The next step is to test the model multicollinearity. As we can see in table 12, the individual and the mean VIF are clearly below 10, so there is no evidence of multicollinearity issues (Wooldridge, 2012).

Table 12 Variance Inflation Factors (VIF) of Final Model

Variable	VIF	SQRT VIF	R^2
log(NPLL)	1.510	1.229	0.338
log(LATA)	1.280	1.131	0.218
DY	1.080	1.039	0.073
log(UNEM)	1.590	1.261	0.330
PROF	1.240	1.114	0.195
MEAN VIF	1.320		

Another problem very common regarding econometric models is the heteroscedasticity problem. Heteroscedasticity describes a situation in which the error term is not the same across all range of values of the independent variables.

According to Wooldridge (2012), heteroscedasticity is a problem not applicable to the type of model (Logit) we are estimating, since maximum likelihood estimation has already taken into account the heteroscedasticity in Var(y|x).

Since the data used in the basis of this model is inserted in panel data category and this type of data presents a cross-sectional component and a time-series component, it is important to test the autocorrelation. However, in section 5.2 we introduced panel-robust standard errors, which already correct the possible autocorrelation.

Finally, other important issue that is usually explored for econometric regressions is the normality of the error term. For our type of model (Logit), the error term is symmetrically distributed about zero (Wooldridge, 2012), so there is no need to test this assumption.

To assess the model fit, we used three tests: Pearson's goodness-of-fit test, Hosmer-Lemeshow goodness-of-fit test and Area under the ROC curve test.

Regarding the first, Pearson's goodness-of-fit test. This test has under the null hypothesis that the chosen model fits the data in an accurate way. It follows a chi-square distribution of (M-k) degrees of freedom (Hosmer and Lemeshow, 2000).

Pearson's goodness-of-fit Test:

$X^2 = \sum_{j=1}^{M} \frac{(y_j - m_j p_j)^2}{m_j p_j (1-p_j)}, X^2 \sim X_{M-k}^2$

where

M = number of covariate patterns

m_j = number of observations having covariate pattern j

y_j = number of positive responses among observations with covariate pattern j

p_j = predicted probability of a positive outcome in covariate pattern j

Hosmer-Lemeshow goodness-of-fit test is a test similar to the previous referred Pearson's goodness-of-fit Test. Under the null hypothesis there is all the statement that the chosen model fits the data in an accurate way. It also follows a chi-square distribution, but of (g-2) degrees of freedom. This test is based in percentile-type of grouping (g), that usually equals to 10 (Hosmer and Lemeshow, 2000).

Hosmer-Lemeshow goodness-of-fit Test:

$\hat{C} = \sum_{j=1}^{M} \frac{(0_k - n_k{}' \bar{\pi}_k)^2}{n_k{}' \bar{\pi}_k (1-\bar{\pi}_k)}$ (31)

where

$n_k{}'$ = total number of sujects in the kth group

c_k = number of covariate patterns in the kth decile

0_k = number of responses among the $c_k$covariate patterns

$\bar{\pi}_k$ = average estimated probability

Table 13 Person chi-square goodness-of-fit Test

Number of observations	152
Number of covariate patterns	151
Pearson X^2	85.840
Prob > X^2	1.000

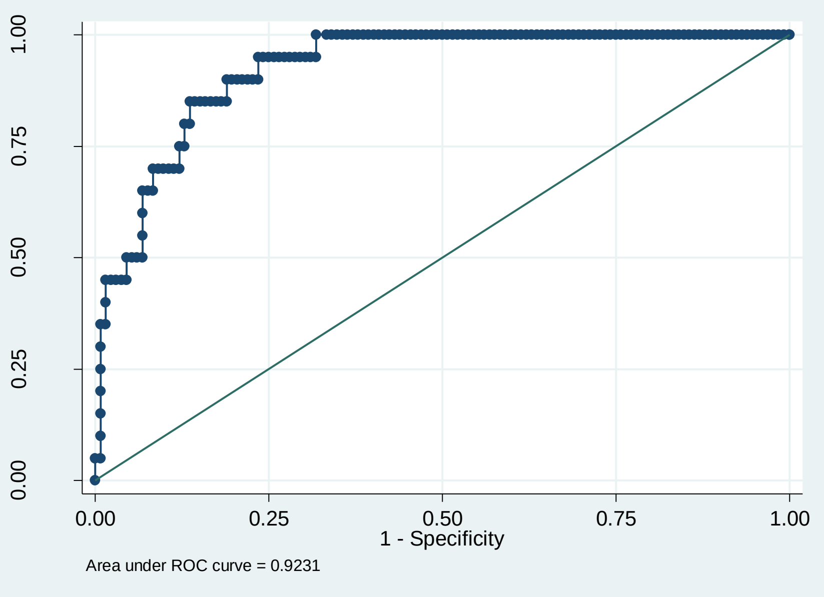
Table 14 Hosmer-Lemeshow goodness-of-fit Test

Number of observations	152	152	152	152
Number of groups	20	10	5	3
Pearson X^2	6.870	2.220	1.030	0.500
Prob > X^2	0.991	0.974	0.793	0.479

The probabilities associated to both tests, are clearly higher than the 5% significance level, so we do not reject the null hypothesis and both test point to a model that fits the data in an accurate way.

For last, the Area under the ROC curve test. The Area under the ROC curve ranges from zero to one and measures the model's ability to discriminate between the banks who failed the stress tests and those who do not. (Hosmer and Lemeshow, 2000).

Figure 8 Area under the ROC curve



The probability associated to the Area under the ROC curve is 0.923, which according to Hosmer and Lemeshow (2000) is considered an outstanding discrimination. So, the Area under the ROC curve test is one more argument contributing to the conclusion that our model fits the data in an accurate way.

5.4 Coefficients Analysis

Estimated Model

$$StrTest_{it} = \widehat{\beta_1} + \widehat{\beta_2}\log(NPLL)_{it} + \widehat{\beta_3}\log(LATA)_{it} + \widehat{\beta_4}\,DY_{it} + \widehat{\beta_5}\,PROF_{it} + \widehat{\beta_6}\log(UNEM)_{it} \quad (13)$$

i = 1,…,152 t = 2014;2016

Logit equation:

$$p(StrTest) = \frac{\exp(\beta_1 + \beta_2 \times \log(NPLL) + \beta_3 \times \log(LATA) + \beta_4 \times DY + \beta_5 \times PROF + \beta_6 \times \log(UNEM))}{1 + \exp(\beta_1 + \beta_2 \times \log(NPLL) + \beta_3 \times \log(LATA) + \beta_4 \times DY + \beta_5 \times PROF + \beta_6 \times \log(UNEM))} \leftrightarrow$$

$$\leftrightarrow \text{logit}\big(p\,(StrTest)\big) = \beta_1 + \beta_2 \times \log(NPLL) + \beta_3 \times \log(LATA) + \beta_4 \times DY + \beta_5 \times PROF + \beta_6 \times \log(UNEM) \quad (14)$$

The interpretation of the coefficients will be based on an approach called odds ratio that consists in the ratio: probability of the event divided by the probability of the nonevent.

$$\widehat{\beta_1} = 4.012$$

Since we are talking about banks, it does not make sense to analyze a situation in which variables like LATA are zero, in this model the intercept does not have a meaning.

$$\hat{\beta}_2 = 1.053$$

The log(NPLL) odds ratio is 2.866. Since this value is higher than 1, the probability of a success (StrTest=1) is greater than the probability of a failure (StrTest=0). So, an increase in NPLL increases the probability of a banking failure in stress tests.

$$\widehat{\beta_3} = -1.029$$

The log(LATA) odds ratio is 0.357. Since this value is smaller than 1, the probability of a success (StrTest=1) is smaller than the probability of a failure (StrTest=0). So, an increase in LATA decreases the probability of a banking failure in stress tests.

$$\hat{\beta}_4 = -1.038$$

The DY odds ratio is 0.354. Since this value is smaller than 1, the rezoning is the same as for the variable log(LATA). So, when DY increases, the probability of a banking failure in stress tests decreases.

$$\widehat{\beta_5} = -1.788$$

The PROF odds ratio is 0.167. Once again the value of odds ratio is smaller than 1, so an increase in PROF also decreases the probability of stress test failure by banks.

$$\widehat{\beta_6} = -1.370$$

The log(UNEM) odds ratio is 0.254. The value of the odds ratio is also smaller than 1, so when UNEM increases the probability of failure in stress tests by banks decreases.

5.5 Marginal Effects Analysis

Marginal effect of a logit model:

$$m_j^{logit} = \beta_j p(1-p) \tag{15}$$

The marginal effect is zero at p=0 and at p=1, and it reaches its maximum value of 0.25 at p=0.5. So the marginal effect reaches its maximum when the probability is near 0.5, and minimum when p is near 0 or 1.

Table 15 Marginal Effects

Variables	**Average Marginal Effect**
log(NPLL)	0.019
log(LATA)	-0.018
DY	-0.019
log(UNEM)	-0.032
PROF	-0.024

Regarding the marginal effects we can see in table 15 that only NPLL presents a positive average marginal effect. This means that on average a 1% increase in NPLL leads to an increase of 0.00019 percentage points in the probability of a failure in the stress tests. In contrast, all the other independent variables present a negative marginal effect, meaning that on average a 1% increase in LATA decreases the probability of a stress test failure by 0.00018 percentage points, on average a 1% increase in DY decreases the probability of a stress test failure by 0.019

percentage points, on average a 1% increase in UNEM decreases the probability of a stress tests failure by 0.00032 percentage points and on average a 1% increase in PROF decreases the probability of a stress test failure by 0.024 percentage points.

6. Projection

In 2018, EBA started to conduct the fourth series of stress tests with a similar methodology of the 2014 series. In this series will be analyzed 49 banks from 15 countries.

The distribution of the banks is the following:

Table 16 Banks stressed in 2018

Bank	Country	Probability of Failure
Erste Group Bank AG	Austria	1.798%
Raiffeisen Bank International AG	Austria	0.954%
Belfius Banque SA	Belgium	*
KBC Group NV	Belgium	10.603%
Bayerische Landesbank	Germany	13.033%
Commerzbank AG	Germany	*
Deutsche Bank AG	Germany	*
DZ BANK AG Deutsche Zentral-Genossenschaftsbank	Germany	21.645%
Landesbank Baden-Württemberg	Germany	12.110%
Landesbank Hessen-Thüringen Girozentrale AdöR	Germany	14.208%
Norddeutsche Landesbank - Girozentrale -	Germany	29.102%
NRW.BANK	Germany	15.008%
Danske Bank	Denmark	11.328%
Jyske Bank	Denmark	10.506%
Nykredit Realkredit	Denmark	15.251%
Banco Bilbao Vizcaya Argentaria S.A.	Spain	0.230%
Banco de Sabadell S.A.	Spain	0.774%
Banco Santander S.A.	Spain	0.207%
BFA Tenedora De Acciones S.A.U.	Spain	*
CaixaBank, S.A.	Spain	2.486%
OP Financial Group	Finland	4.347%
BNP Paribas	France	9.851%
Group Crédit Mutuel	France	*
Groupe BPCE	France	14.099%
Groupe Crédit Agricole	France	11.084%
La Banque Postale	France	5.131%
Société Générale S.A.	France	13.835%
OTP Bank Nyrt.	Hungary	0.028%
Allied Irish Banks plc	Ireland	*
Bank of Ireland Group plc	Ireland	*
Banco BPM S.p.A.	Italy	23.496%
Intesa Sanpaolo S.p.A.	Italy	*
UniCredit S.p.a.	Italy	*
Unione di Banche Italiane Società Per Azioni	Italy	25.938%
ABN AMRO Group N.V.	Netherlands	2.472%
Coöperatieve Rabobank U.A.	Netherlands	3.023%
ING Groep N.V.	Netherlands	2.029%
N.V. Bank Nederlandse Gemeenten	Netherlands	*

DNB Bank Group	Norway	9.811%
Polska Kasa Opieki SA	Poland	0.386%
Powszechna Kasa Oszczednosci Bank Polski SA	Poland	0.124%
Nordea Bank – group	Sweden	8.420%
Skandinaviska Enskilda Banken – group	Sweden	4.141%
Svenska Handelsbanken – group	Sweden	3.201%
Swedbank – group	Sweden	3.438%
Barclays Plc	United Kingdom	17.974%
HSBC Holdings Plc	United Kingdom	10.868%
Lloyds Banking Group Plc	United Kingdom	12.252%
The Royal Bank of Scotland Group Plc	United Kingdom	8.501%

* For the banks that do not have all the variables available the probability was not calculated.

Since the results will only be published on the 2nd of November of 2018, a backtesting forecasting is not possible. So, in order to overcome this problem a projection of results will be made.

The probability of failure is estimated based on the balance sheet of 2017 and with the value of macroeconomic variables for the same year.

The equation used to calculate the probability of failure is the following:

$$p(strtest = 1) = \frac{\exp(4.012216 + 1.052903 * \mathrm{LOG(NPLL)} - 1.029297 * \mathrm{LOG(LATA)} - 1.037888 * \mathrm{DY} - 1.370106 * \mathrm{PROF} - 1.787971 * \mathrm{LOG(UNEM)})}{\exp\left(4.012216 + 11.052903 * \mathrm{LOG(NPLL)} - 1.029297 * \mathrm{LOG(LATA)} - 1.037888 * \mathrm{DY} - 1.370106 * \mathrm{PROF} - 1.787971 * \mathrm{LOG(UNEM)}\right) + 1}$$

Assuming that a bank will fail the stress tests if the probability of failure is at least 50%, none of the banks that we considerer to projection will fail the 2018 stress tests.

Italian and German banks are among the most likely to fail stress tests, with probabilities between 20% and 30%. If the Italian case is expected due to the bad loans situation that came from the worst economy crisis since 1861, the second case is more suspect. German banks do not have a bad loans problem, but a structural one, with too many banks fighting in the same space and not all with the same need to satisfy shareholders.

7. Conclusion

This thesis provides an analysis of the determinants that define a stress tests result, passage or failure, for a European bank. The stress test outcome is used to assess which banks are in trouble and consequently, which banks may need a capital enforce, a forced merger or a state intervention. In the data sample there were several examples of banks, like Banca Monte dei Paschi di Siena, who failed the stress test and a year later it was subject to a recapitalization.

The database was based in the banks analyzed by EBA in the 2014 and 2016 stress tests series. Since the banks analyzed were not the same, because of the selection criterion that is based on the total value of assets of the bank and it depends from year to year the database is considered an unbalanced panel data. The stress tests results vary from year to year, but it is in 2014 that the most percentage of banks analyzed failed the tests, achieving a value of 20% failures.

The results of the model, a Pooled Logit, indicate that there are no specific effects in the model. The model considered both bank specific variables, like financial ratios, and macroeconomic variables significant for the stress tests failure explanation. Contributing to a bigger probability of failure there is higher non-performing loans to total loans ratio, as predicted by the literature. In contrast, bigger gross domestic product growth, bigger liquid assets to total assets ratio and higher profitability of the bank lead to a small probability of bank failure, not surprisingly the results stated by literature. Other variable that has significant contribute when increases to decrease the probability of a bank failure in the stress tests is the unemployment rate, totally contradicting the literature. Some authors like Munteanua (2012), found this effect in previous papers. The possible explanations for this surprising effect are three. First, there is an old theory in which employers benefit from unemployment rate, since they reduce their costs with workers. However, when the unemployment rate increases, the demand for the company products also decrease. According to Engels (1844), companies should always have a reserve army of unemployed workers, to produce in large scale in the liveliest months and making more profit. Assuming that the saving with workers effect is higher than the decrease in demand, companies will have a higher profit will consequently pay their debt, including loans and make new investments. So, consequently banks will also have small non-performing loans ratio and will grant new loans in order to fulfill companies' investment needs. Second, when we face a financial crisis there are higher unemployment rates. Under this conditions central banks try to alleviate the impact of the crisis providing an ample liquidity to banks in a way to restart the interbank market. This injection of liquidity leads to a reduction of probability of banking failure. Third, according to Jiménez and Saurina (2006) loans conceded during boom periods have more probability of default than loans conceded during a crisis, because in boom periods the collateral requirements are less rigid and mistakes in the lending policy are more likely. In times of crisis, denoted by a higher unemployment rate, banks present a better lending policy decreasing the probability of a default, and using reserves to cover the losses originated during the boom periods.

With this model it was established a connection between financial and macroeconomic variables and banking health, providing supporting material to supervision authorities in order to see early warnings of problems in the banks health. This kind of information can also be used by the bank itself in order to check if they are following a correct policy and if that is the best direction.

In order to test the accuracy of the model, the stress tests results for 2018 were projected. These projected results showed that banks that have a higher probability of fail stress tests belong to Italy and Germany, however, this probability is not very high, being smaller than 50%. This can be explained by the highest bank regulation and by the recovery of economies and financial sector of the countries that recently suffered a crisis.

A stress test failure, indicates a possible bank failure, which has severe consequences to the economy. According to Gilbert, R. and Kochin, L. (1989) a baking failure as three effects: wealth, direct employment and credit constraints. The wealth effects is explained by the losses suffered by the bank shareholders and by the unsecured depositors. Also, if a bank fails people lose jobs, so is the second effect. Finally, if a bank suffered a failure, borrowers can have more difficulties to finance themselves.

The accuracy of the model is affected by data, software and methodology limitations. The first limitation of the model is related with the database, since from the three series of stress tests performed by EBA, the 2011 series was excluded. This exclusion is based in the lack of data to fulfill the requirements of the model, namely due to bank mergers and due to absence of available financial reports. The second is the inaccessibility of some variables regarding some of the banks analyzed in 2014 and 2016 stress tests. The third one is methodological, since in the 2016 stress tests series it wasn't defined a threshold to analyze if a bank fails or passes the stress tests. The fourth is a software limitation, coming from the way that Stata works on observations that have not available data, since when it occurs he completely eliminate the observation from the sample, decreasing even more the sample size. One way to overcome this limitation is applying the method of dummy variables introduced by Cohen and Cohen (1975), but it completely bias the results. The fifth and last limitation is also based on data, and consists in the unavailability of some model variables for approximately 20% of the banks stressed in the 2018 stress tests.

All these limitations contribute to a less accurate model, however, based on the results and in the literature review we have a model in line with the academic results.

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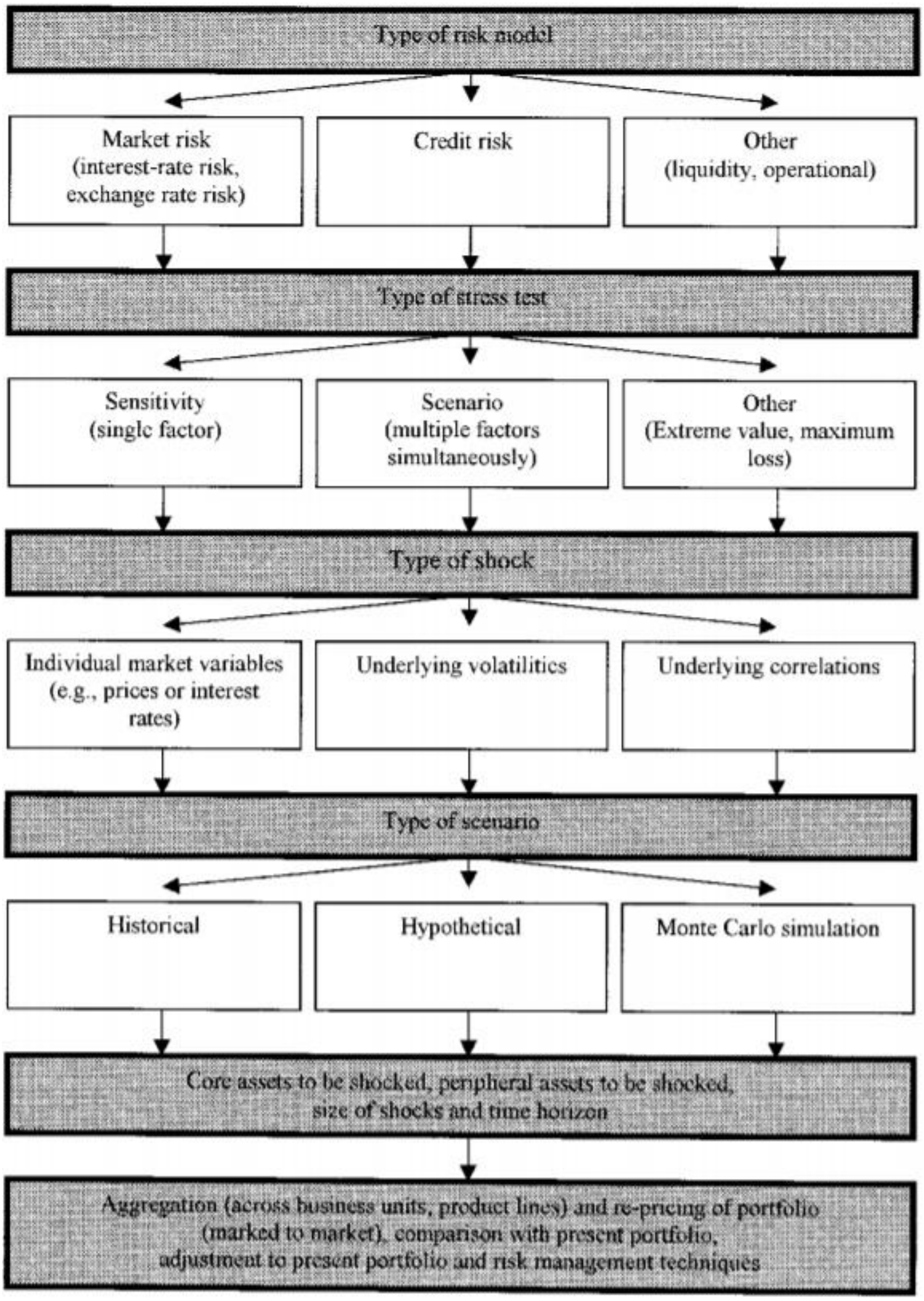
9. APPENDIX

A. Stress tests classification

Figure 9 Stress Testing of Financial Systems: Overview of Issues, Methodologies, and FSAP Experiences - Source: Blaschke et al.



B. Significant macroeconomic drivers

Table 17 Significant macroeconomic drivers - Source: Kapinos et al.

Variable	PPNR				NCO			
	MPCF Linear		MPCF Polynomial		MPCF Linear		MPCF Polynomial	
	2013	2014	2013	2014	2013	2014	2013	2014
VIX Level	X	X	X	X				X
BBB Spread	X	X	X	X	X	X	X	X
CREPI Growth					X	X		X
DJIA Growth	X	X		X			X	X
HPI Growth	X	X	X	X	X	X	X	X
Mortg Rate Change	X	X		X				
10yr-TB Spread								
5yr-TB Spread*				X				
Prime-TB Spread*								
RDI Growth	X		X	X		X		X
RGDP Growth		X				X		
Unemp Rate Change		X		X	X	X	X	X
CPI Inflation	X	X	X	X	X			X

Note: * 2014 CCAR only

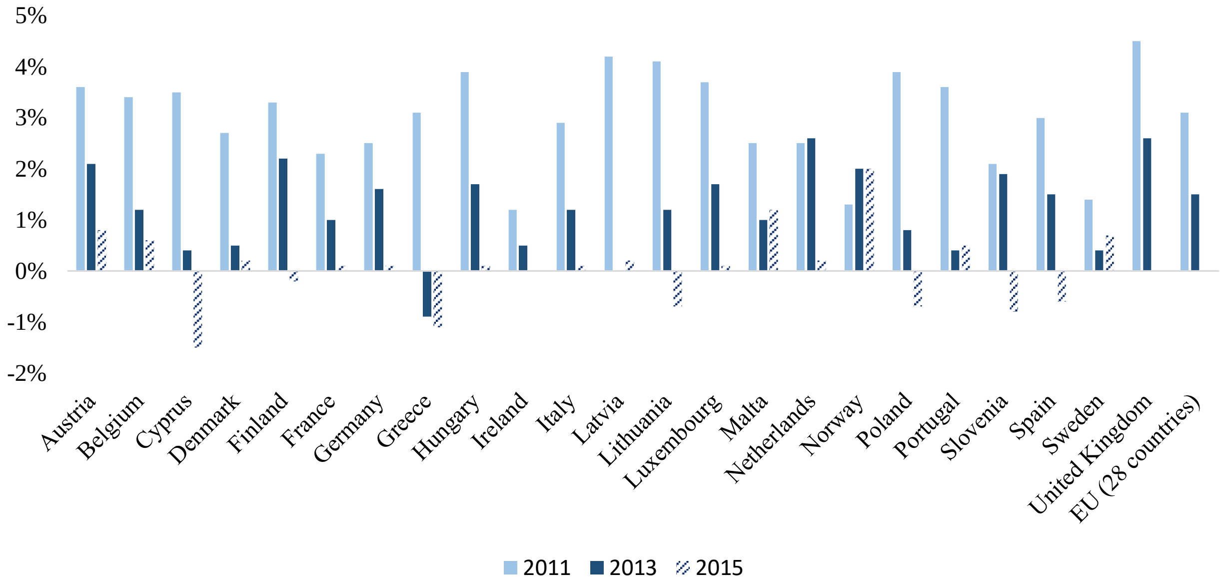
C. Significant banking drivers

Table 18 Significant banking drivers - Source: Kapinos et al.

Variable	2013 vintage		2014 vintage	
	PPNR	NCO	PPNR	NCO
Concurrent variables				
Asset growth (4-quarter average)				
Loan growth (4-quarter average)				
One-bank holding company flag				
Multiple-bank holding company flag				
Bank specialization: C&I				
Bank specialization: Consumer & credit card				
Bank specialization group: Commercial real estate				
Bank specialization group: Mortgage				
Lagged variables (lags 1-4)				
Total equity / assets				
Tier 1 capital / assets	X		X	
Deposits / assets	X		X	
Brokered deposits / deposits	X		X	
Dividends / assets	X		X	
Compensation expenses / assets			X	
C&I loans / assets	X		X	
Consumer loans / assets				
Real estate loans / assets				
Other real estate owned / assets	X		X	
Total loans & leases / assets	X		X	
C&I loans / total loans				
Consumer (credit card) loans / total loans				
Consumer (non-credit card) loans / total loans		X		X
Real estate construction loans / total loans				
Real estate multifamily & commercial loans / total loans			X	
HELOC & Jr liens loans / total loans				
1-4 family residential loans / total loans				
Other loans / total loans				
30-89 days past-due loans / total loans	X	X	X	X
90+ days past-due loans / total loans				
Loans in non-accrual / total loans	X	X	X	X
Nonperforming assets / assets	X		X	
Share of assets with with 0% risk-weight				
Share of assets with with 20% risk-weight				
Share of assets with with 50% risk-weight				
Share of assets with with 100% risk-weight				
Trading account assets / assets				
Total available-for-sale securities / assets (fair market value)				
Total held-to-maturity securities / assets (amortized cost)		X		X
Auto loans securitization activity / assets	X		X	
C&I loans securitization activity / assets	X		X	
Credit Card loans securitization activity / assets	X		X	
Other consumer loans securitization activity / assets	X		X	
HELOC securitization activity / assets				
1-4 family residential loans securitization activity / assets	X		X	
Other loans & leases securitization activity /assets				
Total loan securitization activity / assets				
Securitization activity / assets				

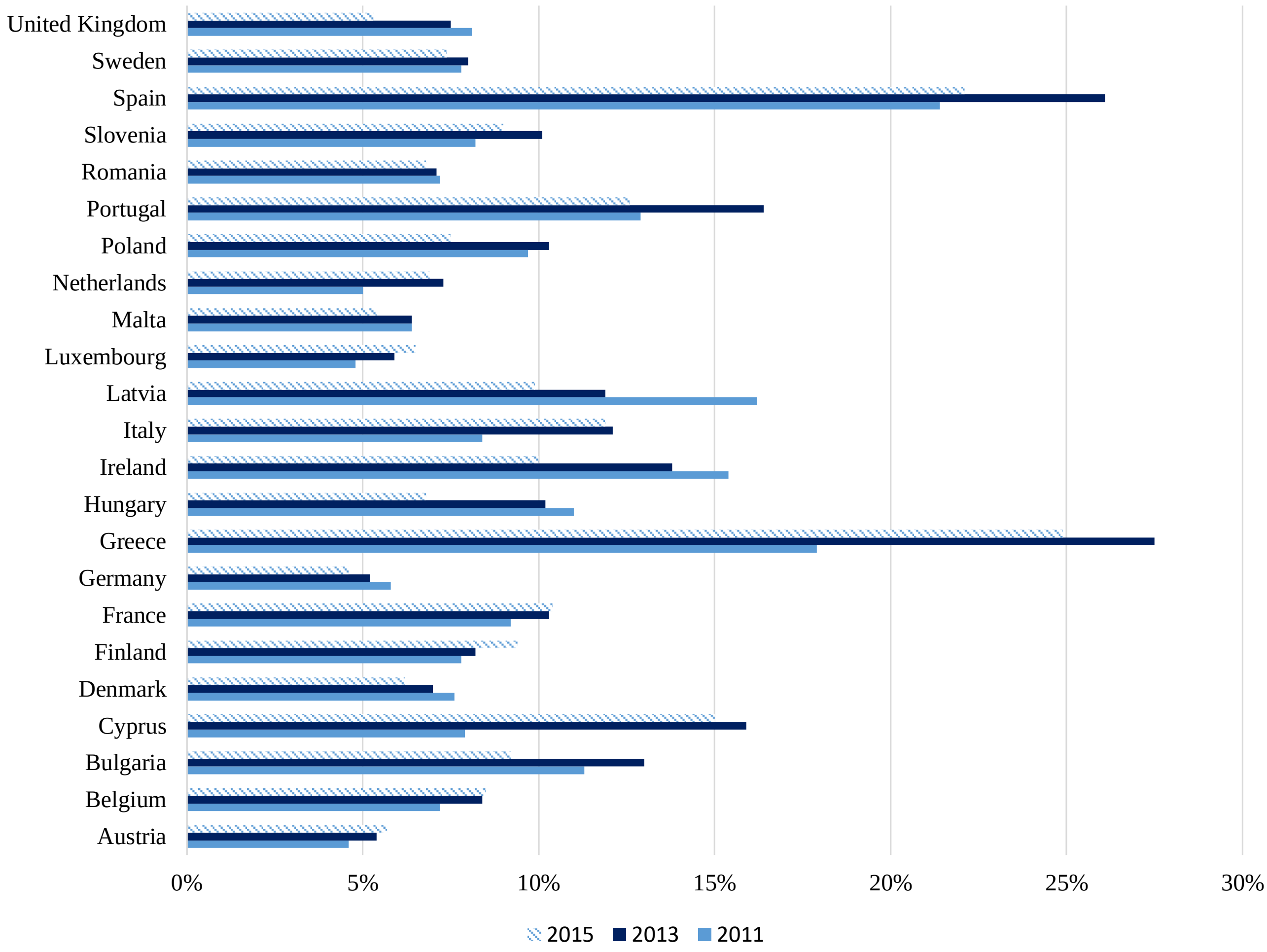
D. Inflation rate of the bank's country

Figure 10 Inflation rate - Source: Eurostat



E. Unemployment rate of the bank's country

Figure 11 Unemployment rate by country - Source: Eurostat



F. Banks stressed

2011:

- ERSTE BANK GROUP (EBG)
- RAIFFEISEN BANK INTERNATIONAL (RBI)
- OESTERREICHISCHE VOLKSBANK AG
- DEXIA
- KBC BANK
- MARFIN POPULAR BANK PUBLIC CO LTD
- BANK OF CYPRUS PUBLIC CO LTD
- DANSKE BANK
- JYSKE BANK
- SYDBANK
- NYKREDIT
- OP-POHJOLA GROUP
- BNP PARIBAS
- CREDIT AGRICOLE
- BPCE
- SOCIETE GENERALE
- DEUTSCHE BANK AG
- COMMERZBANK AG
- LANDESBANK BADEN-WURTTEMBERG
- DZ BANK AG DT. ZENTRAL-GENOSSENSCHAFTSBANK
- BAYERISCHE LANDESBANK
- NORDDEUTSCHE LANDESBANK -GZ-
- HYPO REAL ESTATE HOLDING AG, MUNCHEN
- WESTLB AG, DUSSELDORF
- HSH NORDBANK AG, HAMBURG
- LANDESBANK BERLIN AG
- DEKABANK DEUTSCHE GIROZENTRALE, FRANKFURT
- WGZ BANK AG WESTDT. GENO. ZENTRALBK, DDF
- EFG EUROBANK ERGASIAS S.A.
- NATIONAL BANK OF GREECE

- ALPHA BANK
- PIRAEUS BANK GROUP
- AGRICULTURAL BANK OF GREECE S.A. (ATEbank)
- TT HELLENIC POSTBANK S.A.
- OTP BANK NYRT.
- ALLIED IRISH BANKS PLC
- BANK OF IRELAND
- IRISH LIFE AND PERMANENT
- INTESA SANPAOLO S.p.A
- UNICREDIT S.p.A
- BANCA MONTE DEI PASCHI DI SIENA S.p.A
- BANCO POPOLARE - S.C.
- UNIONE DI BANCHE ITALIANE SCPA (UBI BANCA)
- BANQUE ET CAISSE D'EPARGNE DE L'ETAT
- BANK OF VALLETTA (BOV)
- ING BANK NV
- RABOBANK NEDERLAND
- ABN AMRO BANK NV
- SNS BANK NV
- DNB NOR BANK ASA
- POWSZECHNA KASA OSZCZEDNOSCI BANK POLSKI S.A. (PKO BANK POLSKI)
- CAIXA GERAL DE DEPOSITOS, SA
- BANCO COMERCIAL PORTUGUES, SA (BCP OR MILLENNIUM BCP)
- ESPIRITO SANTO FINANCIAL GROUP, SA (ESFG)
- BANCO BPI, SA
- NOVA LJUBLJANSKA BANKA D.D. (NLB d.d.)
- NOVA KREDITNA BANKA MARIBOR D.D. (NKBM d.d.)
- BANCO SANTANDER S.A.
- BANCO BILBAO VIZCAYA ARGENTARIA S.A. (BBVA)
- BFA-BANKIA
- CAJA DE AHORROS Y PENSIONES DE BARCELONA

- EFFIBANK
- BANCO POPULAR ESPANOL, S.A.
- BANCO DE SABADELL, S.A.
- CAIXA D'ESTALVIS DE CATALUNYA, TARRAGONA I MANRESA
- CAIXA DE AFORROS DE GALICIA, VIGO, OURENSE E PONTEVEDRA
- GRUPO BMN
- BANKINTER, S.A.
- CAJA ESPANA DE INVERSIONES, SALAMANCA Y SORIA, CAJA DE AHORROS Y MONTE DE PIEDAD
- GRUPO BANCA CIVICA
- CAJA DE AHORROS Y M.P. DE ZARAGOZA, ARAGON Y RIOJA
- MONTE DE PIEDAD Y CAJA DE AHORROS DE RONDA, CADIZ, ALMERIA, MALAGA, ANTEQUERA Y JAEN
- BANCO PASTOR, S.A.
- GRUPO BBK
- CAIXA D'ESTALVIS UNIO DE CAIXES DE MANLLEU, SABADELL I TERRASSA
- CAJA DE AHORROS Y M.P. DE GIPUZKOA Y SAN SEBASTIAN
- GRUPO CAJA3
- BANCA MARCH, S.A.
- CAJA DE AHORROS DE VITORIA Y ALAVA
- CAJA DE AHORROS Y M.P. DE ONTINYENT
- COLONYA - CAIXA D'ESTALVIS DE POLLENSA
- CAJA DE AHORROS DEL MEDITERRANEO
- NORDEA BANK AB (PUBL)
- SKANDINAVISKA ENSKILDA BANKEN AB (PUBL) (SEB)
- SVENSKA HANDELSBANKEN AB (PUBL)
- SWEDBANK AB (PUBL)
- ROYAL BANK OF SCOTLAND GROUP plc
- HSBC HOLDINGS plc
- BARCLAYS plc
- LLOYDS BANKING GROUP plc

2014:

- BAWAG P.S.K. Bank für Arbeit und Wirtschaft und Österreichische Postsparkasse AG
- Raiffeisenlandesbank Niederösterreich-Wien AG
- Raiffeisenlandesbank Oberösterreich AG
- Erste Group Bank AG
- Raiffeisen Zentralbank Österreich AG
- Österreichische Volksbanken-AG with credit institutions affiliated according to Article 10 of the CR
- Dexia NV
- Belfius Banque SA
- KBC Group NV
- AXA Bank Europe SA
- Investar (Holding of Argenta Bank- en Verzekeringsgroep)
- Hellenic Bank Public Company Ltd
- Co-operative Central Bank Ltd
- Bank of Cyprus Public Company Ltd
- Danske Bank
- Jyske Bank
- Sydbank
- Nykredit
- OP-POHJOLA GROUP
- Banque PSA Finance
- BPI France (Banque Publique d'Investissement)
- C.R.H. - Caisse de Refinancement de l'Habitat
- Groupe Crédit Mutuel
- La Banque Postale
- RCI Banque
- Société de Financement Local
- BNP Paribas
- Groupe Crédit Agricole
- Groupe BPCE

- Société Générale
- Aareal Bank AG
- Deutsche Apotheker- und Ärztebank eG
- HASPA Finanzholding
- IKB Deutsche Industriebank AG
- KfW IPEX-Bank GmbH
- Landeskreditbank Baden-Württemberg-Förderbank
- Landwirtschaftliche Rentenbank
- Münchener Hypothekenbank eG
- NRW.Bank
- Volkswagen Financial Services AG
- Wüstenrot Bausparkasse AG
- Wüstenrot Bank AG Pfandbriefbank
- Deutsche Bank AG
- Commerzbank AG
- Landesbank Baden-Württemberg
- DZ Bank AG Deutsche Zentral-Genossenschaftsbank
- Bayerische Landesbank
- Norddeutsche Landesbank-Girozentrale
- Hypo Real Estate Holding AG
- HSH Nordbank AG
- Landesbank Hessen-Thüringen Girozentrale
- Landesbank Berlin Holding AG
- DekaBank Deutsche Girozentrale
- WGZ Bank AG Westdeutsche Genossenschafts-Zentralbank
- Eurobank Ergasias
- National Bank of Greece
- Alpha Bank
- Piraeus Bank
- OTP Bank Ltd
- Allied Irish Banks plc
- The Governor and Company of the Bank of Ireland

- Permanent tsb plc.
- Banca Carige S.P.A. - Cassa di Risparmio di Genova e Imperia
- Banca Piccolo Credito Valtellinese
- Banca Popolare Dell'Emilia Romagna - Società Cooperativa
- Banca Popolare Di Milano - Società Cooperativa A Responsabilità Limitata
- Banca Popolare di Sondrio
- Banca Popolare di Vicenza - Società Cooperativa per Azioni
- Credito Emiliano S.p.A.
- Iccrea Holding S.p.A
- Mediobanca - Banca di Credito Finanziario S.p.A.
- Veneto Banca S.C.P.A.
- Intesa Sanpaolo S.p.A.
- UniCredit S.p.A.
- Banca Monte dei Paschi di Siena S.p.A.
- Banco Popolare - Società Cooperativa
- Unione Di Banche Italiane Società Cooperativa Per Azioni
- ABLV Bank
- Banque et Caisse d'Epargne de l'Etat
- Precision Capital S.A. (Holding of Banque Internationale à Luxembourg and KBL European Private Banke)
- Bank of Valletta plc
- Bank Nederlandse Gemeenten N.V.
- Nederlandse Waterschapsbank N.V.
- ING Bank N.V.
- Coöperatieve Centrale Raiffeisen-Boerenleenbank B.A.
- ABN AMRO Bank N.V.
- SNS Bank N.V.
- DNB Bank Group
- ALIOR BANK SA
- BANK BPH SA
- BANK HANDLOWY W WARSZAWIE SA
- BANK OCHRONY SRODOWISKA SA

- GETIN NOBLE BANK SA
- POWSZECHNA KASA OSZCZEDNOSCI BANK POLSKI S.A. (PKO BANK POLSKI)
- Caixa Geral de Depósitos
- Banco Comercial Português
- Banco BPI
- SID - Slovenska izvozna in razvojna banka
- Nova Ljubljanska banka d. d.
- Nova Kreditna Banka Maribor d.d.
- Banco Financiero y de Ahorros
- Cajas Rurales Unidas
- Catalunya Banc
- Caja de Ahorros y M.P. de Zaragoza
- Kutxabank
- Liberbank
- NCG Banco
- MPCA Ronda
- Banco Santander
- Banco Bilbao Vizcaya Argentaria
- Caja de Ahorros y Pensiones de Barcelona
- Banco Popular Español
- Banco de Sabadell
- Banco Mare Nostrum
- Bankinter
- Nordea Bank AB (publ)
- Skandinaviska Enskilda Banken AB (publ) (SEB)
- Svenska Handelsbanken AB (publ)
- Swedbank AB (publ)
- Royal Bank of Scotland Group plc
- HSBC Holdings plc
- Barclays plc
- Lloyds Banking Group plc

2016:

- Erste Group Bank AG
- Raiffeisen-Landesbanken-Holding GmbH
- Belfius Banque SA
- KBC Group NV
- Danske Bank
- Jyske Bank
- Nykredit Realkredit
- OP Osuuskunta
- Groupe Crédit Mutuel
- La Banque Postale
- BNP Paribas
- Groupe Crédit Agricole
- Groupe BPCE
- Société Générale S.A.
- Deutsche Bank AG
- Commerzbank AG
- Landesbank Baden-Württemberg
- Bayerische Landesbank
- Norddeutsche Landesbank Girozentrale
- Landesbank Hessen-Thüringen Girozentrale
- NRW.BANK
- Volkswagen Financial Services AG
- DekaBank Deutsche Girozentrale
- OTP Bank Nyrt.
- Allied Irish Banks plc
- The Governor and Company of the Bank of Ireland
- Intesa Sanpaolo S.p.A.
- UniCredit S.p.A.
- Banca Monte dei Paschi di Siena S.p.A.
- Banco Popolare - Società Cooperativa

- Unione Di Banche Italiane Società Per Azioni
- ING Groep N.V.
- Coöperatieve Centrale Raiffeisen-Boerenleenbank B.A.
- ABN AMRO Group N.V.
- N.V. Bank Nederlandse Gemeenten
- DNB Bank Group
- Powszechna Kasa Oszczędności Bank Polski SA
- Banco Santander S.A.
- Banco Bilbao Vizcaya Argentaria S.A.
- Criteria Caixa, S.A.U.
- BFA Tenedora de Acciones S.A.U.
- Banco Popular Español S.A.
- Banco de Sabadell S.A.
- Nordea Bank - group
- Svenska Handelsbanken - group
- Skandinaviska Enskilda Banken - group
- Swedbank – group
- HSBC Holdings
- Barclays Plc
- The Royal Bank of Scotland Group Public Limited Company
- Lloyds Banking Group Plc

G. Intermediate Pooled Models

Table 19 Re-estimated initial models - Pooled

Pooled Logit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	65.945	38.192*
NPLL	0.654	0.381*
T1	-1.134	0.779
MQ	-0.178	0.105*
NII	9.240e-06	5.320e-06*
ROA	-5.529	3.122*
LD	0.011	0.009
LATA	-0.585	0.418
DY	-6.879	3.661*
CDS	0.007	0.028
NPL	-0.411	0.372
UNEM	-1.002	0.587*
DSI	-5.870e-09	1.270e-07
INF	-10.286	7.091
SIZE	-2.000e-07	1.180e-07*
PROF	-11.259	6.233*
GBY	-1.180	2.157

N	127
Pseudo R^2	0.858

Pooled Probit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	37.148	20.500*
NPLL	0.373	0.213*
T1	-0.625	0.398
MQ	0.102	0.058*
NII	5.230e-06	2.900e-06*
ROA	-3.155	1.668*
LD	0.006	0.005
LATA	-0.329	0.232
DY	-3.912	1.996**
CDS	-0.012	0.015
NPL	-0.232	0.202
UNEM	-0.576	0.332*
DSI	-1.010e-08	7.230e-08
INF	-5.780	3.782
SIZE	-1.120e-07	6.410e-08*
PROF	-6.384	3.210**
GBY	-1.594	1.157

N	127
Pseudo R^2	0858

Signicance levels: * : 10% | ** : 5% | *** : 1%

Table 19 models present several explanatory variables whose estimated coefficients are not statistically significant.

So, we estimate the models again excluding the variables with the higher p-value DSI (0.963 in Probit and 0.889 in Logit), GBY (0.584 in Logit and 0.562 in Probit) and CDS (0.432 in Probit and 0.412 in Logit).

Table 20 Table 19 re-estimated models without DSI, GBY and CDS

Pooled Logit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	4.653	3.084
NPLL	0.129	0.072*
T1	-0.167	0.123
MQ	-0.001	0.007
NII	-8.030e-07	1.170e-06
ROA	0.088	0.178
LD	2.900e-04	0.002
LATA	-0.101	0.048**
DY	-0.813	0.496
NPL	0.016	0.111
UNEM	-0.170	0.091*
INF	-0.163	0.871
SIZE	8.610e-10	1.270e-08
PROF	-1.491	1.016

Pooled Probit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	1.725	1.560
NPLL	0.066	0.039*
T1	-0.048	0.056
MQ	4.012e-04	0.004
NII	-3.790e-07	6.620e-07
ROA	0.093	0.095
LD	5.616e-04	0.001
LATA	-0.058	0.026**
DY	-0.398	0.277
NPL	0.029	0.062
UNEM	-0.084	0.050*
INF	0.080	0.463
SIZE	-2.060e-10	6.960e-09
PROF	-0.940	0.114

N	151
Pseudo R^2	0.534

N	151
Pseudo R^2	0.520

Signicance levels: * : 10% | ** : 5% | * : 1%**

The models presented in table 20 still have non-significant variables, so we exclude the variables SIZE (0.946 in Probit and 0.976 in Logit), INF (0.852 in Probit and 0.863 in Logit), MQ (0.846 in Probit and 0.913 in Logit) and NPL (0.963 in Probit and 0.0.886 in Logit) which presented the higher p-value, and then we re-estimate the models.

Table 21 Table 20 re-estimated models without DSI, GBY and CDS

Pooled Logit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	4.355	1.982
NPLL	0.142	0.054***
T1	-0.163	0.114
NII	7.18e-07	5.87e-07
ROA	0.129	0.146
LD	-2.437e-0.4	0.002
LATA	-0.102	0.045**
DY	-0.869	0.410**
UNEM	-0.170	0.084**
PROF	4.355	1.982**

Pooled Probit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	2.006	1.030*
NPLL	0.079	0.030***
T1	-0.053	0.054
NII	-3.910e-07	3.340e-07
ROA	0.106	0.081
LD	4.703e-04	0.001
LATA	-0.060	0.025**
DY	-0.465	0.228**
UNEM	-0.090	0.048**
PROF	-0.883	1.030**

N	151
Pseudo R^2	0.532

N	151
Pseudo R^2	0.518

Signicance levels: * : 10% | ** : 5% | *** : 1%

T1, NII, ROA and LD are the only non-significant variables, so they are excluded from both models and we re-estimate them.

After this new estimation all the variables presented in both models are significant (Table 4).

H. Intermediate Random Effects Models

Table 22 Re-estimated initial models – Random Effects

Pooled Logit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	327.634	105.267***
NPLL	3.307	1.025***
T1	-5.644	2.134***
MQ	-0.875	0.286***
NII	4.580e-05	1.440e-05***
ROA	-27.056	8.501***
LD	0.055	0.023**
LATA	-2.832	1.128**
DY	-33.569	10.04***
CDS	-0.103	0.069
NPL	-2.108	0.922**
UNEM	-5.034	1.66***
DSI	2.100e-09	3.400e-07
INF	-51.826	19.193***
SIZE	-9.900e-07	3.200e-07***
PROF	-55.064	16.594***
GBY	5.14	5.41

N	127
Number of groups	92

Pooled Probit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	41.086	60.734
NPLL	-0.692	1.047
T1	-0.113	0.167
MQ	5.790e-06	8.560e-06
NII	-3.489	5.124
ROA	0.007	0.011
LD	-0.364	0.56
LATA	-4.326	6.322
DY	-0.013	0.025
CDS	-0.256	0.415
NPL	-0.637	0.945
UNEM	-1.100e-08	8.130e-08
DSI	-6.395	9.735
INF	-1.200e-07	1.840e-07
SIZE	-7.061	10.316
PROF	0.741	1.63
GBY	0.412	0.612

N	127
Number of groups	92

Signicance levels: * : 10% | ** : 5% | *** : 1%

In Table 22 models present several explanatory variables whose estimated coefficients are not statistically significant. The variables DSI, GBY and CDS (0.995, 0.342 and 0.138 p-value, respectively) are excluded from the Random Effects Logit since are the statistically non-significant variables.

Regarding the Random Effects Probit, the excluded variables are CDS, DSI e GBY, which present the highest p-value (0.891, 0.650 and 0.587, respectively).

So, we estimate the models again without the referred variables.

Table 23 Table 21 re-estimated Models

Pooled Logit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	4.653	3.084
NPLL	0.129	0.072*
T1	-0.167	0.123
MQ	-0.001	0.007
NII	-8.030e-07	1.170e-06
ROA	0.088	0.178
LD	2.900e-04	0.002
LATA	-0.101	0.048**
DY	-0.813	0.496
NPL	0.016	0.111
UNEM	-0.170	0.091*
INF	-0.163	0.871
SIZE	8.610e-10	1.270e-08

Pooled Probit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	5.035	6.818
NPLL	0.166	0.184
T1	-0.128	0.189
MQ	0.001	0.01
NII	-1.000e-06	2.120e-06
ROA	0.225	0.337
LD	-0.002	0.005
LATA	-0.154	0.153
DY	-1.159	1.32
NPL	0.064	0.191
UNEM	-0.226	0.243
INF	0.043	1.326
SIZE	-2.000e-09	1.990e-08

PROF	-1.491	1.016

PROF	-2.48	2.772

N	151
Number of groups	107

N	151
Number of groups	0.520

Signicance levels: * : 10% | ** : 5% | * : 1%**

Both models from table 22 still present several non-significant variables, so we exclude the variables with the highest p-value. From the Random Effects Logit we exclude the variables SIZE (p-value 0.946), LD (p-value 0.902), NPL (p-value 0.886) and INF (p-value 0.852).

In the Random Effects Probit we eliminate from the model the variables INF (p-value 0.974) , MQ (p-value 0.932), SIZE (p-value 0.919), LD (p-value 0.766), NPL (p-value 0.736) and NII (p-value 0.626).

Table 24 Table 22 re-estimated Models

Pooled Logit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	4.355	1.982
NPLL	0.142	0.054***
T1	-0.163	0.114
NII	7.18e-07	5.87e-07
ROA	0.129	0.146
LD	-2.437e-0.4	0.002
LATA	-0.102	0.045**
DY	-0.869	0.410**

Pooled Probit Regression		
Variable	**Coefficient**	**Std. Error**
Intercept	5.541	4.214
NPLL	0.214	0.132
T1	-0.142	0.164
ROA	0.220	0.243
LATA	-0.182	0.119
DY	-1.632	1.063
UNEM	-0.306	0.197
PROF	-2.953	1.995

UNEM	-0.170	0.084**
PROF	4.355	1.982**

N	151
Number of groups	107

N	151
Number of groups	0.518

Signicance levels: * : 10% | ** : 5% | * : 1%**

The variables T1, NII, ROA and LD are the only non-significant variables in the Random Effects Logit, so we eliminate them from the model and we estimate again. This new estimation finally leads to a model without non-significant variables (Table 5).

In the Random Effects Probit all the variables are non-significant, however we exclude the ones with high p-value, namely T1 (p-value 0.386), ROA (p-value 0.366) and PROF (p-value 0.139). With this exclusion we change from a model without significant variables to a model in which all the variables are significant (Table 5).