Bank Distress in the European Union 2008-2015: A General Assessment

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Abstract

This paper focuses on EU banks that experienced distress during 2008-2015 and provides evidence regarding bank-specific variables, such as the CAMEL indicators, size and revenue diversification and macroeconomic and banking sector variables and the probability of distress. The sample employed is unique in terms of the definition of distress and in considering only bank parent companies. Results indicate that a combination of the above variables explains the probability of distress well and emphasizes the importance of the simple equity ratio, size, and revenue diversification. The paper also focuses on banks in EU countries that faced economic problems during the above period (GIIPS plus Cyprus) and documents that the probability of bank distress in these countries has been influenced by different factors, in comparison to the rest of the EU.

Keywords: Bank distress; CAMEL; Capital ratio; European Union; Financial crisis; Logit model; Probability of distress; Revenue diversification; Size; State support.

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1. Introduction

Bank distress or even the possibility of it seriously affects the stability of the economy of a nation or economic union. As we have witnessed during the latest financial crisis, in the EU and elsewhere, such events may cause “bank runs”, which in turn may result in the malfunctioning of credit and capital markets. Naturally, such a development has serious implications on the real economy, such as bankruptcies of companies and steep increases in unemployment.

To avoid such negative developments, governments and central banks usually intervene to stabilize the banking system and preserve economic stability. For example, in the EU between 2008 and 2014, there have been government interventions both on the asset and liability side of the balance sheet of banks. More specifically, on the asset side more than 641,8 billion Euros were spent in the recapitalization of banks (4,6% of 2014 GDP of the EU-28) whereas, on the liability side, over 1,293 billion Euros were utilized in guarantee and liquidity measures (9,3% of 2014 GDP of the EU-28)[1].

Given the importance of the subject, it is not surprising that researchers have focused on the causes of many banking crises and especially the more recent one. The main aim of such research is to identify a set of factors, at the micro and macro - economic level that might cause bank distress. Such a set of factors would be particularly useful for regulatory and government authorities as they can take timely measures to prevent such crisis, but also to corporations, households, shareholders, bondholders, and rating agencies. Most such studies have focused on the US due to more and better quality data availability; for example, Estrella et. al. (2000), Wheelock and Wilson (2000), Cebula (2010), Cole and White (2012), and Mayes and Stremmel (2013). In Europe, it is more difficult to compile a dataset of banks in distress and as such, studies have been scarcer; for example, Mannasoo and Mayes (2009), Poghosyan and Cihak (2011), and Betz et. al. (2014).

[1] http://ec.europa.eu/competition/state_aid/scoreboard/financial_economic_crisis_aid_en.html

Motivated by the "cataclysmic" developments in the European Union banking sector during the recent financial crisis, this paper aims to contribute to existing literature by considering a set of factors that may contribute towards the explanation (and possibly the prediction) of bank distress in the EU. To address the issue, a unique dataset of European banks that faced distress during 2008-2015 is constructed and the behavior of key financial, macroeconomic and banking sector variables is examined, one and two years prior to the actual distress. Effectively, we ask the following questions: How do banks that faced distress differ from those that did not? What are the main weaknesses that led to distress? Under the prism of these questions we pay special attention on issues such as absolute and systemic size and revenue diversification. As such, we also ask the following questions: Were large and possibly "systemic" banks subjected to a higher probability of distress? Were banks engaging more in less traditional lines of business (i.e. activities generating non-interest income) associated with a higher probability of distress? These questions are particularly interesting given the tendency of new bank regulations to focus on capital surcharges on large banks (Basel III) and on measures to reduce their market-based activities (the Volcker rule in the US and the Vickers and Liikanen reports in Europe).

Following that, we divide our sample period and use 2/3 of our observations to establish a "training model" based on which, we perform "out-of-the-sample" forecasts for the remaining 1/3 of our observations. This enables us to assess whether the model developed in this paper can be used to predict the probability of bank distress, i.e. issuing warning signals prior to distress.

This paper differs from those that preceded it in a number of ways, such as the definition of bank distress, the inclusion of only bank parent companies and the emphasis given to the size and revenue diversification parameters. Moreover, it includes additional analysis to test whether the determinants of the probability of bank distress in countries that faced serious problems (Greece, Ireland, Italy, Portugal, Spain, and Cyprus)[2] were different prior to distress, to those of other EU countries.

[2] These are EU countries, which during the global financial crisis were either unable to refinance their government debt or to support (i.e. "bail out") their troubled banking sector and as such applied for rescue packages (these countries – excluding Cyprus - are referred to as GIIPS).

This latter part of the analysis could be particularly interesting given the fact that, on some occasions, unprecedented measures were taken in the case of these countries; for example, in the case of Cyprus, for the first-time uninsured depositors were called to recapitalize the two largest banks for an estimated amount of 7 billion Euros, while, again for the first time, capital controls needed to be imposed (Michaelides, 2014).

The remainder of the paper is structured as follows: section 2 provides a review of the literature; section 3 describes how our sample was constructed, presents the variables used and the methodology employed; section 4 presents our results, additional analysis regarding GIIPS plus Cyprus and the “out-of-sample” forecasting performance of our model and section 5 concludes.

2. Literature Review

There are several papers that have addressed the issue of bank distress. These typically utilize a set of regressors, which consists of bank-specific variables (micro-variables) augmented on several occasions by country-specific macroeconomic and banking sector variables (macro-variables) to explain bank distress. The micro-variables employed usually refer to the “CAMEL rating system”, which was introduced by US regulators in 1979 as an internal supervisory tool consisting of balance sheet and income statement ratios[3]. Such ratios focus on (C)apital adequacy, (A)sset quality, (M)anagement quality, (E)arnings and (L)iquidity. Since 1996 the system has been augmented to include “(S)ensitivity to market risk”.

Most of the papers surveyed focus on the US due to its richness of high-quality data regarding bank distress. For example, Campbell et. al. (2008) and Arena (2008) documented that the CAMEL variables, along with market and macroeconomic indicators contain useful predictive information regarding bank distress.

As has been clearly demonstrated during the recent financial crisis, the deterioration of the capital ratio can be one of the most important determinants of bank distress. Some popular ratios that have been used in the literature to test this

[3] https://www.fdic.gov/regulations/laws/rules/5000-900.html

hypothesis are the simple leverage ratio, the tier 1 and total capital ratios as defined by the Basel Committee on Banking Supervision; see for example Wheelock and Wilson (2000), Estrella et. al. (2000), and Samad (2011).

In a more recent paper, Mayes and Stremmel (2013) focus on bank distress in the US for the period 1992-2012 and find that CAMEL indicators along with GDP growth have good predictive power. Moreover, they find that a simple measure of capital outperforms the more complex risk-weighted measures. An interesting argument put forward in this paper is that risk-weighted capital ratios can be open to manipulation and may provide space for discretion to "hide" the real financial condition of the bank. Furthermore, Mayes and Stremmel (2013) presented evidence that the determinants of bank distress during the recent financial crisis have not been different from previous ones; the CAMEL plus country-specific variables "recipe" appears to work quite well over time.

In addition to capital ratios, asset quality ratios, management quality, earnings and liquidity ratios complement the CAMEL set of variables. Asset quality is typically measured by various loan quality ratios focusing on non-performing loans or loan loss reserves; see for example Schaffer (2012), Samad (2012) and Cole and White (2012). Management quality is usually measured by the efficiency ratio (operating expenses divided by operating income); see for example Wheelock and Wilson (2000), and Mayes and Stremmel (2013). Earnings ability is measured by return on assets (ROA), return on equity (ROE) and net interest margin (NIM); see for example Tatom and Houston (2011) and Cole and White (2012). Liquidity is measured by ratios such as liquid assets to total assets; see for example Cole and White (2012), and Shim (2013). Regarding the sensitivity to market risk variable, many researchers have proposed the use of the size of the bank, as measured by its total assets; see for example Kolari et. al. (2002), and Avkiran and Cai (2014).

Size is a variable that has been broadly discussed in the context of the recent financial crisis. The key issue that has been put forward relates to the "too-big-to-fail" or "too-systemic-to-fail" arguments, which point out that the failure of a large bank is likely to have disastrous consequences for the economy. As such, governments would have an incentive to "bail out" large banks to avoid an even worse outcome. For example, Rose and Wieladek (2012) focused on government interventions in the UK and found that bank size is the key explanatory variable for various types of support measures that were granted. This might imply that banks that consider themselves "too-big-to-fail" or "too-important-to-fail" have an incentive to misbehave; hence one might expect a positive relationship between size and probability of distress, due to this "too-big-to-fail subsidy". Another view regarding bank size is that it is a result of management "empire-building" and that large banks may be suffering from insufficient corporate governance; for example, Gabaix and Landier (2008) argue that managers may strive for size to receive a larger salary and Jensen (1986) points out that they may wish to enjoy the prestige stemming from running a large company.

Laeven et. al. (2014) document that large banks, on average, create more systemic risk in comparison to smaller ones and that today's large banks might be too large from a social welfare perspective. They moreover point out that additional regulation that is related to large banks and that has to do either with capital surcharges or measures to reduce their involvement in market-based activities is justified in order to deal with the potential externalities of distress of large banks.

Another issue that has also been broadly discussed in the context of the recent crisis is revenue diversification and more specifically the proportion of income generated from non-interest income activities relative to the bank's total income. Income generated from non-interest activities includes fee and commission income and trading income. As such, this variable is typically measured by the ratio of non-interest income to total income; see for example Lepetit et. al. (2008), and Laeven et. al. (2014). Empirical evidence so far appears to move along two dimensions regarding this issue. On the one hand, there are studies such as Kwast (1989), Gallo et. al. (1996), and Uzun and Webb (2007), which focus on US banks that argue that bank expansion into non-interest income activities helps banks to diversify away risk, at least partially. Along the same lines, in a recent paper focusing on the EU banking sector, Kohler (2015) argued that banks are likely to be more stable and profitable if they diversify into non-interest income activities. On the other hand, other studies suggest that there is a positive relationship between higher reliance on non-interest income activities and risk; see for example De Young and Roland (2001), Stiroh (2006), DeJonghe (2010), Demirguc-Kunt and Huizinga (2010) (these papers focus on US banks) and Lepetit et. al (2008) (this paper focuses on the EU). Moreover, some studies also argue that potential diversification benefits of non-interest income activities are not that much, as the two seem to be correlated; see for example Stiroh (2004) and Stiroh and Rumble (2006). A number of explanations were put forward to explain the above finding, for example De Young and Roland (2001) cited high competition on non-interest income activities, fixed costs associated with fee-based activities and lack of sufficient regulation on non-interest income activities. Stiroh (2004) and Stiroh and Rumble (2006) suggested that this might be due to the possibility of cross-selling different products to the same customer. In an interesting recent paper, De Young and Torna (2013) examined whether income from non-traditional banking activities contributed to the failure of banks in the US during the recent financial crisis and documented that the probability of bank distress declined with pure fee-based activities (e.g. securities brokerage, insurance sales) but increased with asset-based activities (e.g. investment banking).

To the best of our knowledge, and contrary to what has been observed for US banks, there are only a few papers that deal with the issue of the determinants of bank distress in Europe. Mannasoo and Mayes (2009) focused on defaults in Eastern European banks by utilizing the CAMEL variables and other banking sector and macroeconomic factors. Podpiera and Otker (2010) also focused on bank distress events in Europe by using Credit Default Swaps to identify default events.

There are, nonetheless, two papers on the EU banking sector, which are related to ours; the first one is by Poghosyan and Cihak (2011), who analysed bank distress in the EU during the period 1997-2007 and the second one is by Betz et. al. (2014), who also focus on bank distress in the EU during the period 2008-2013.

Poghosyan and Cihak (2011) identify bank distress based on media reports including words such as “rescue”, “bailout”, “financial support”, “liquidity support”, “government guarantee” and “distressed merger”. They employed a logistic model and documented that a capital adequacy indicator is not enough to capture bank distress; other determinants such as asset quality, profitability and market discipline are also important. In addition, they argued that by including macroeconomic variables the fit of the model improves.

Betz et. al. (2014) define distress events as bankruptcies, defaults, mergers in distress and state intervention on the asset side. They also use a logistic model and document that banks with higher capital levels and a bigger share of deposit funding were less likely to experience distress. They also argue that a model that incorporates CAMEL variables as well as macroeconomic and banking sector variables performs better.

Our paper aims to enrich the limited existing literature on bank distress in the EU. In addition to employing a more recent data set, it is different from the above-mentioned papers in several ways. Firstly, when considering banks that were in distress and received state support, in contrast to Betz et. al. (2014) who consider only intervention on the asset side, we also take account of banks that received state support on the liability side too. Secondly, our sample of banks includes only parent companies; the reasoning behind this is that state support in the EU is given at the parent level. Thirdly, we only consider the first instance that a bank experienced distress; the idea here is to identify determinants of the probability of distress as at the start of the distress. Fourthly, we address the issue of bank systemic size, both in terms of the economy of the home country and the EU, as well as the issue of revenue diversification, as measured by the percentage of non-interest income to total income. Finally, our paper also compares banks in distress in the EU countries that were mostly affected by the recent financial crisis (GIIPS and Cyprus) to those in the rest of the EU. To the best of our knowledge, no other paper has attempted such a comparison so far.

3. Data and Methodology

3.1 Data

We construct our dataset based on data availability of the financial statements of banks in the EU that faced distress in the period 2008-2015. Our main source of information regarding this is Bureau Van Dijk’s BankScope from which we exported financial ratios and other information for the banks in our sample[4]. Our second source of information is Eurostat from which we extract macroeconomic and banking sector data for each of the EU-28 countries.

Actual bank failures have been rare in the EU and as such it is quite challenging to build a sample of banks in distress. We should note that, to the best of our knowledge, an official comprehensive data set of such banks has not been compiled yet. As far as existing literature is concerned, Podpiera and Otker (2010) identified bank distress by looking at credit default swaps (CDS), Poghosyan and Cihak (2011) by looking at media reports and searching for words that indicate distress, such as "bailout", "rescue" etc. and Betz et. al. (2014) by focusing on bankruptcies, defaults, and state interventions on the asset side and mergers in distress.

Arguably, during the recent financial crisis in the EU, state intervention has been the primary indicator of bank distress. Approved state measures in the EU can be classified into measures on the asset side and the liability side. On the asset side, government intervention occurs through recapitalization or asset relief measures. Recapitalizations aim to improve the capacity of banks to absorb losses and asset relief measures involve taking "bad assets" off the balance sheets of banks and moving them to a so-called "bad bank". On the liability side, government intervention occurs through liquidity measures and liability guarantees. Such measures effectively provide "insurance" against default on bank debt and deposits. Both types of state intervention are important and this can be documented by looking at the vast amounts that have been spent to support the banking sector in the EU. On the asset side, state support exceeded 641,8 billion Euro (4,6% of 2014 GDP of the EU-28) and on the liability side, state support comprising of guarantees and liquidity measures amounted to 1,293 billion Euro (9,3% of 2014 GDP of the EU-28)[5].

To define banks in distress in our paper, we identify banks in the EU, which have received state support, either on the asset side or the liability side of their

[4] The banks that were selected had a minimum of Euro 1 billion in total assets during the period under examination.
[5] http://ec.europa.eu/competition/state_aid/scoreboard/financial_economic_crisis_aid_en.html

balance sheet. We further augment our sample by including banks that went bankrupt and others that have been acquired while in distress.

Regarding the identification of banks that received state support, we started by collecting information from the European Commission and then did a case-by-case search to determine when the intervention took place. This search utilized sources such as the European Commission itself, bank annual reports and market sources such as Reuters and Bloomberg. On several occasions, banks received state support on more than one occasion; our sample takes account only of the first time a bank received state support, so effectively we are looking at individual banks and not events of distress. By doing this we aim to uncover the determinants of the probability of distress right at the beginning as it is possible that subsequent periods of distress might distort the picture as the determinants of the probability of distress may have deteriorated.

Figure 1 presents our total sample of banks in distress, during the period 2008-2015, and shows the type of distress identified. The dominance of state intervention is clear, particularly in the early years of the financial crisis. Overall, our sample comprises of 135 banks in distress. An important characteristic of our sample is that the banks selected are all parent companies (we exclude subsidiaries). The main argument behind this is that it is the strength of the parent bank and the "safety net" provided by the home country of the parent bank that determine the strength of each subsidiary rather than that of the host country; see for example Sebnem Kalemli-Ozcan et.al. (2015).

<Insert Figure 1>

3.2 Dependent and Independent Variables

Our dependent variable indicates whether, during the period 2008-2015, a bank has been in distress or not. We therefore generate a dummy variable that takes the value of "1" if a bank has been in distress in the above-mentioned period and the value of "0" otherwise.

As far as the explanatory variables are concerned, this paper uses two broad categories of indicators to assess the diverse aspects of banks' distress. The first category focuses on bank specific indicators taken from banks' financial statements. Following the literature, we use the CAMEL rating system, as in Poghosyan and Cihak (2011), Mayes and Stremmel (2013) and Betz et. al. (2014), augmented by size (absolute and systemic) and revenue diversification variables. We must note that as far as the CAMEL indicators are concerned, there is not a single "recipe" and that several proxies for each letter in the acronym have been used in the literature. The second category focuses on country-specific macroeconomic and banking sector indicators, which have been used in the literature, and on some occasions, for example in the papers of Poghosyan and Cihak (2011) and Betz et. al. (2014), appeared to increase the reliability of the model.

In our paper, for capital (C) we employ three indicators; equity to total assets, as in Poghosyan and Cihak (2011) and Mayes and Stremmel (2013), tier 1 capital ratio and total capital ratio, as in Betz et. al. (2014). Studies so far have documented a negative relationship between the level of capitalization and the probability of distress of a bank; see for example Poghosyan and Cihak (2011), Mayes and Stremmel (2013), Betz et. al. (2014) and Samad (2011).

Regarding asset quality (A), we employ the loan loss reserves to gross loans ratio as in Cole and White (2012); we expect a positive relationship with the probability of distress. Having said that, empirical evidence regarding loan loss reserves appears to be contradictory on some occasions; for example, Arena (2008) finds a positive relationship, while Cole and White (2012) find a negative one.

For management quality (M), we use the cost to income ratio, as in Betz et. al. (2014), Poghosyan and Cihak (2011) and Mayes and Stremmel (2013). Typically, lower values of this ratio indicate better management quality, hence, possibly lower probability of distress.

As far as earnings ability (E) is concerned, most papers reviewed use measures such as ROE and NIM; see for example Betz et. al. (2014), Poghosyan and Cihak (2011) and Mayes and Stremmel (2013). In our paper, we employ a new variable, the recurring earnings power of the bank. This ratio is a measure of after-tax profits plus provisions for bad debts, expressed as a percentage of total assets; effectively the return on assets before subtracting provisions. We expect this variable to be negatively related to the probability of bank distress.

Finally, regarding liquidity (L) we use the ratio of liquid assets to deposits & short term funding, as in Poghosyan and Cihak (2011). This ratio focuses on the percentage of customer and short-term funds that could be met if they were withdrawn suddenly. Therefore, the higher this percentage is the more liquid the bank is and hence less vulnerable to a "bank run" and possible distress.

We also include size in our model measured along two dimensions, absolute size, and systemic size in terms of the economy of the home country and the EU. The former is measured as the logarithm of total assets, as in Cole and White (2012), while the latter is measured as the ratio of total bank assets to the GDP of the home country and the EU, respectively.

In addition to the above, we also consider whether a bank is listed on the stock market or not. This is captured by including a dummy variable in our model, which takes the value of "1" if a bank is listed and "0" otherwise. The logic behind the inclusion of this dummy variable is that if a bank is listed, then it should exhibit better corporate governance, which should possibly lead to lower probability of distress.

The final bank-specific variable that we include in our model is revenue diversification, measured by the percentage of non-interest income to total income, as in Lepetit et. al. (2008). This variable is included to identify whether banks that have diversified away from traditional interest income were associated with a higher probability of distress. Empirical evidence so far appears to be divided on the issue as some papers, such as Uzun and Webb (2007) and Kohler (2015), document that there are diversification benefits whereas others, such as De Young and Roland (2001) and Lepetit et. al. (2008) argue that expansion into non-interest activities is associated with higher risk. As such we have no a-priori expectation regarding this variable.

The second category of explanatory variables that we include in our model are country-specific macroeconomic and banking sector indicators. Towards this direction, we employed a number of variables in the spirit of Betz et. al. (2014), such as the long-term government bond yield, real GDP growth and unemployment. In addition, we also included the total change of loans in the economy over the previous year, as in Borio and Drehman (2009). Based on prior literature and intuition, in all cases except real GDP growth, we expect a positive relationship between the probability of bank distress and the macroeconomic and banking sector indicators mentioned above.

Tables 1 and 2 describe all explanatory variables, their method of measurement and the expected direction of each one in relation to the probability of bank distress. All data regarding the variables depicted in tables 1 and 2 have been collected from BankScope and Eurostat, respectively.

< Insert Table 1>

<Insert Table 2>

3.3 Two Sample Mean Tests

In table 3 we present summary statistics and carry out comparisons of the means of the explanatory variables for banks that faced distress vs. those that did not. Effectively, we divide our sample into two sub-samples, banks that faced distress *(y=1)* and banks that did not face distress *(y=0)* and then we test whether the mean of each explanatory variable, lagged by one year, is different across the two sub-samples.

As far as the CAMEL variables are concerned, on average, the banks that faced distress had a lower capital base in terms of all 3 measures used (tier 1, total capital and equity to total assets ratios), the difference ranging from 3% to 3,7% depending on the measure used. Moreover, they had assets of lower quality (higher loan loss reserves to gross loans), had lower quality of management (higher cost to income ratio), lower earnings ability (lower recurring earnings power), and were in a weaker liquidity position (lower liquid assets / deposits & ST funding).

Furthermore, it appears that banks that experienced distress during the period under investigation were bigger in absolute terms but also in terms of their systemic size. Interestingly, the average systemic size of banks in distress was 24.8% of home country GDP while that of banks not in distress was only 8.9%. Moreover, it appears that banks in distress exhibited less revenue diversification, as reflected by the lower proportion of non-interest income relative to total income (26.7%) in comparison to those that did not experience distress (40%). Finally, it appears that banks that were listed on the stock exchange faced a higher probability of distress in comparison to those that were not.

As far as the macroeconomic and banking sector variables are concerned, banks that experienced distress appear to be in countries where the long-term government bond yield was higher, real GDP growth was lower, unemployment was higher and the rate of growth of total loans over the previous year was higher.

< Insert Table 3>

3.4 Regression Methodology

In line with most recent studies on bank distress, such as Arena (2008), Poghosyan and Cihak (2011), Cole and White (2012), Mayes and Stremmel (2013), and Betz et. al. (2014), we employ a logistic probability model.

The dependent variable, Y_{it}, in the logistic model is a binary variable and as such can only take two values, *"1"* if the bank experiences distress and *"0"* otherwise. The probability of distress can then be estimated as a function of lagged explanatory variables, X_{it-1}[6]. Mathematically, the logistic model can be represented as follows:

$$\log \frac{P_{it}}{1-P_{it}} = b_0 + \sum_{k=1}^{K} b_k X_{k,it-1}$$

Where: $P_{it} = Prob\ (Y_{it} = 1/X_{it-1})$ is the probability that bank *i* will experience distress in period *t*, given a vector of *k* explanatory variables at time *t-1*.

[6] In our baseline estimate, we lag the explanatory variables by one year. We also re-run our model by using a two-year lag.

The left-hand side of the equation can be thought of as the log odds ratio; this measures the probability of bank distress relative to the probability of no distress. The above equation indicates that the slope coefficients b_k measure the linear impact of each explanatory variable on the log odds ratio. Furthermore, the intercept, b_0 can be thought of as the remaining probability of bank distress, after considering the impact of the explanatory variables.

Given the above equation, the impact on the probability of distress of bank *i*, P_{it}, can be estimated according to the following equation. This probability depends on the initial values of the explanatory variables and their estimated coefficients.

$$P_{it} = \frac{1}{1 + e^{-\left(b_0 + \sum_{k=1}^{K} b_k X_{ki,t-1}\right)}}$$

4. Results

The aim of this section is twofold: firstly, to identify the main variables that lead to bank distress and secondly, based on these variables, to try to assess whether distress could have been predicted before happening. We start by presenting our baseline multivariate models of bank distress focusing, apart from the traditional CAMEL and macroeconomic variables, on issues such as absolute and systemic bank size and revenue diversification. We also carry out a comparison of the determinants of the probability of distress of banks in GIIPS plus Cyprus vs. other EU countries. We then divide our sample period and re-run our baseline model for 2/3 of our observations. Based on the model derived, we perform “out-of-the-sample” forecasts for the remaining 1/3 of our observations and assess the predictive performance of the model.

4.1. Multivariate Regression Models

Table 4 presents the results of our multivariate logit regression analysis; all explanatory variables have been lagged by one year. The first model includes the CAMEL variables, absolute size, the revenue diversification variable, and the country-specific macroeconomic and banking sector variables.

<insert table 4>

Regarding the CAMEL variables, all come out as statistically significant except the cost-to-income ratio. As expected, the higher the capital ratio of a bank, the lower the probability of distress. Furthermore, the probability of distress is also lower if the recurring earnings power is stronger and the bank's funding structure comprises of more liquid assets. Regarding asset quality, a higher ratio of loan loss reserves to loans increases the probability of distress. Our results regarding the CAMEL indicators appear to be as expected and consistent with the discussion in section 2.

Regarding the absolute size variable, we find a positive relationship, which indicates that the larger the bank is, the higher its probability of distress. The literature regarding this variable seems to be divided as some studies document a positive relationship while, others, document a negative one; for example, Schafer (2012) finds that in the eighties a smaller bank was more likely to face distress but during the 2007/08 crisis this was reversed. Given the period of our analysis, our results appear to be consistent with the latter proposition.

In the next column of table 4, we re-run our model but replaced the size variable with a dummy variable that takes the value of "1" if the bank is listed and "0" otherwise. Results appear to be broadly the same as before but the sign of the listed vs. non-listed dummy variable is quite interesting as it comes out as positive and statistically significant, thus suggesting that banks that were listed had a higher probability of distress. Listed banks are supposed to adhere to corporate governance standards which should, if anything, reduce the probability of distress; our results here seem to suggest otherwise.

The revenue diversification variable is statistically significant and comes out with a negative sign across all our models. As such, it appears that during the recent financial crisis, banks which had a higher share of non-interest to total income faced a lower probability of distress[7]. This result is in line with papers such as Gallo et. al. (1996) and Uzun and Webb (2007), who addressed the issue for US banks and Kohler (2015), who did likewise for the EU; all three papers documented that there are diversification benefits for banks expanding into non-traditional (i.e. non-interest income) banking activities. Our findings, however, contrasts with De Young and Roland (2001) and Lepetit et. al. (2008), who addressed the issue for US and EU banks, respectively. Both papers documented that banks expanding into non-interest income activities present higher insolvency risk.

We further explored this variable by substituting it with an interaction variable consisting of absolute size times non-interest income (lnAssets*Revenue diversification). The new variable remains significant but its sign changes, it now becomes positive thus indicating that the larger banks that had a bigger share of non-interest income were exposed to higher probability of distress. This finding may be related to DeYoung and Torna (2013) who documented that, during the recent crisis, banks in the US which engaged in pure fee-based non-traditional activities had a lower probability of distress, whereas banks which engaged in asset-based non-traditional activities had a higher probability of distress. It might be the case that in the EU, the latter set of banks were mostly large banks that engage more in market-based activities, which in turn are associated with high leverage and unstable short-term funding (e.g. use of securities as collateral in repos). Another possible explanation is that large banks tend to respond to the perception that they will be bailed out in case of distress and are thus more willing to engage in risky market-based activities. As such, based on this finding, calls to reduce the "too-big-to-fail" subsidy appear to be justified; see for example Farhi and Tirole (2012) and Stein (2013).

We next considered the issue of systemic size and its potential relationship with the probability of distress. This issue is related to the "too-big-to-fail" and "too-systemic-to-fail" arguments, which refer to situations where the failure of one or more such banks would produce significant negative externalities onto the rest of the

[7] We cross-checked and confirmed this result by also including interest income to total income (in place of non-interest income to total income) and, as expected, found a positive relationship between this variable and the probability of default.

financial system or the real economy; see for example Bernanke (2009), De Nicolo et. al. (2012). To take account of systemic size in our model, we replace absolute size with systemic size, defined as the ratio of the total assets of the bank to the GDP of its home country and the EU as a whole. Results indicate that there is a positive relationship between the systemic size of a bank, both in terms of its home country and the EU as a whole, and its probability of distress. This in turn supports the view that during the recent financial crisis, the larger and potentially systemically important financial institutions have been clearly subjected to higher probability of distress.

We further explored this variable too by including the interaction variable systemic size times non-interest income to total income (Systemic*Revenue diversification). Again, we documented a positive and statistically significant relationship with the probability of distress, which means that large and possibly systemically important banks that engage more in non-interest income activities are subjected to a higher probability of distress. This in turn implies that the changes in bank regulation that have been occurring after the recent financial crisis such as capital surcharges on large systemic banks (Basel III), reduction of "too-big-to-fail" subsidies and measures to reduce involvement in market-based activities (Vickers and Liikanen reports in the UK and Europe, respectively) seem to be justified.

As far as the macroeconomic and banking sector variables are concerned, long-term government bond yield, total loans change y-o-y and the unemployment rate seem to be positively related to the probability of bank distress (these findings are consistent across all our models). Therefore, in line with prior literature, for example Betz et. al. (2014), CAMEL variables, supplemented by country-specific macroeconomic and banking sector variables, seem to work well in explaining the probability of bank distress.

We next re-run our model but lagged our explanatory variables by 2 years. The results are presented in table 5.

<insert table 5>

Regarding the CAMEL variables, there are two differences in comparison to the earlier model; liquidity and recurring earnings power (in two of the three models) now become statistically insignificant. As far as the former is concerned, it seems that the liquidity position of a bank in distress deteriorates in the 12 months before actual distress but not earlier, at least in a way that would significantly increase the probability of distress. The earnings variable appears not to influence the probability of distress substantially, two years before distress. Regarding the macroeconomic and banking sector variables, there is one change in relation to the earlier model; the increase in total loans y-o-y, which remains statistically significant but changes sign (it now becomes negative). This may suggest that two years prior to distress, an increase in total loans decreases the probability of bank distress but this is reversed one year prior to distress. Given the fact that most banks in the EU experienced distress in 2008 and 2009, it is possible that two years before that (i.e. 2006 and 2007), when the economies of the countries in the EU were doing much better, an increase in total loans y-o-y was having a positive effect on the financial condition of banks, thus decreasing the probability of distress.

The absolute size variable comes out with a positive sign and is statistically significant again. Also, the listed variable maintains its positive sign and statistical significance. As such, it seems that larger or listed banks exhibited a higher probability of distress two years prior to the actual distress. The revenue diversification variable comes out again with a negative sign but its statistical significance deteriorates substantially. Finally, the systemic size variable also maintains its positive sign both in terms of the home country and EU economies, but its magnitude and statistical significance also deteriorate relative to that of one year prior to distress.

It seems that when running the t-2 model, the magnitude of the coefficients of some of the explanatory variables and their statistical significance deteriorates, thus suggesting that their explanatory power two years prior to distress might not be so strong. Clearly, this does not hold for the capitalization variable (equity / total assets ratio), which remains highly statistically significant across all models two years prior to distress.

Given its importance and prominence in the literature, we did some additional tests regarding the capitalization variable; table 6 presents variations of our baseline model by using alternative capitalization variables, one year prior to distress. More specifically, apart from the simple equity to total assets ratio, we also use the tier 1 and the total capital ratios, as defined by the Basel Committee on Banking Supervision. Results suggest that the simple equity to total assets ratio employed in our baseline model is more influential in explaining the probability of bank distress. This result is interesting and consistent with previous literature, such as Estrella et. al. (2000), Blundell-Wignall and Roulet (2013), and Mayes and Stremmel (2013), and lends support to the latest version of Capital Adequacy Rules (Basel III), which for the first time require banks to maintain a certain percentage of capital relative to their total assets and not only to the risk-weighted ones (according to the new set of rules, this ratio must be at least 3%[8]).

Our results become even more interesting when we look at the various capitalization variables two years prior to distress (table 7). The dominance of the simple equity to total assets variable is more profound as it maintains its statistical significance at the 1% level, while the tier 1 ratio becomes significant only at the 10% level and the capital ratio becomes statistically insignificant. Hence, it can be argued that the simple capital ratio appears to give not only stronger but also earlier warning signals regarding the probability of bank distress.

<InsertTables 6 and 7>

4.3 “GIIPS” and Cyprus vs. Other Countries

There is little doubt that the recent crisis in the EU “divided” the continent into economically “healthy” and “problematic” countries with the former being in the Northern part of the continent and the latter being (mostly) in the South. For the purposes of our analysis we include Greece, Ireland, Italy, Portugal, Spain (GIIPS), and Cyprus in the category of countries which faced serious economic problems during the crisis.

The reasons why the above countries experienced troubles vary. For example, in Spain and Ireland, the crisis originated from banks granting large loans to the real estate sector, thus helping to create a housing “bubble”. In the case of Greece, lack of

[8] It is interesting to note that the mean equity to total assets ratio of the banks that faced distress in our sample is 5,143%, which is substantially higher than the minimum threshold of 3%.

fiscal discipline from the public sector, whose debt was primarily held by commercial banks, was at the heart of the crisis.

Table 8 presents our model for banks in these countries and compares its results with those of banks in the remaining EU countries. We present our model both with absolute and systemic size. Results in GIIPS plus Cyprus are clearly different to those of other EU countries. Firstly, in the case of these countries, as far as the CAMEL variables are concerned, they do not appear to have significant explanatory power over the probability of distress. This is contrary to other EU countries where we clearly see the prominence of variables such as capital and asset quality and to a lesser extent earnings and liquidity.

Secondly, in the case of GIIPS and Cyprus, both the absolute and systemic size variables come out as positive and statistically significant; clearly, larger banks in these countries faced a higher probability of distress. Moreover, it is worth noting that the systemic size of banks in these countries is highly significant, in contrast to other EU countries.

Thirdly, the revenue diversification variable comes out as negative and statistically significant, thus suggesting that banks in GIIPS plus Cyprus that had a lower share of non-interest income (relative to total income) – or, to put it another way, a higher share of interest income – were associated with a higher probability of distress. This implies that revenue diversification was an issue in these countries and that if banks had diversified their income streams (away from traditional interest income) they could have possibly had diversification benefits, as suggested by Kwast (1989), Gallo et. al. (1996), Uzun and Webb (2007), and Kohler (2015). Interestingly, this variable does not come out as statistically significant in the other EU countries, thus indicating that it was not an important determinant of bank distress in these countries during the period examined.

Fourthly, regarding the macroeconomic and banking sector variables, the probability of bank distress in GIIPS plus Cyprus is positively affected by the change in total loans in the economy y-o-y and by the rise of the unemployment rate. In the case of the other EU countries, the prime macroeconomic determinant of bank distress was the long-term government bond yield.

Effectively, the results in GIIPS plus Cyprus seem to suggest that, given deteriorating economic conditions, it became very difficult for these states to support ("bail-out") their banking sector, which at the same time was not diversifying its revenue basis and increasing its loan book. Consider the cases of Spain and Ireland, where, as already mentioned, large loans were granted to the real estate sector thus "facilitating" a housing "bubble". When the "bubble" burst, the banks (and the state) faced severe problems[9]. The problem became even more acute when these countries lost access to international financial markets; see for example the case of Cyprus in Michaelides (2014). As such, it is not surprising that banks in these countries, especially the larger and more systemic ones, experienced higher probability of distress.

To add to the above, one must also consider that banks typically hold large amounts of sovereign bonds of their home country; since the economic condition of these countries was deteriorating, the value of such bonds was decreasing. For example, according to Michaelides (2014), in the case of Greece, following the PSI program of October 2011, holders of Greek sovereign bonds experienced a "haircut" as high as 79% in present value terms. This feedback loop (from the state to the banking sector) was putting even more pressure on the balance sheets of banks either through "haircuts" in the value of sovereign bonds used as collateral, or by "alarming" depositors and other market participants and laying the seeds for possible "bank-runs".

In conclusion, the "big picture" comment that can be made regarding the above results is that, in the case of GIIPS plus Cyprus, the local economic conditions, as reflected by macroeconomic and banking sector variables, in conjunction with bank size and little revenue diversification, appear to have positively influenced the probability of bank distress. On the other hand, in the case of the other countries, the CAMEL variables appear to play a much more prominent role.

[9] The State had to intervene and run up government debt to rescue its troubled banks.

<Insert Table 8>

4.4 "Out of Sample" Forecasts

A useful property of the logit model is its ability to measure Type I and Type II errors. We attempt to exploit this property by using the model to produce "out-of-sample forecasts" employing explanatory variables at *t-1*. Towards this direction, we utilise two models to take account of both absolute and systemic size. In both cases, to generate the "training model" and the "testing model", we need to split our sample. For the "training model", we utilize data between 2008-2011 comprising of 195 banks, 114 of which are healthy and 81 in distress. For the "testing model", we focus on the period 2012-2015 and use 82 banks (58 healthy and 24 in distress). In simple words, we "build" a model based on 195 banks and given this model, we try to estimate the probability of distress of 82 banks.

A summary of our results can be seen in tables 9 (model with absolute size) and 10 (model with systemic size). Both models give identical forecasting results; more specifically, out of 58 healthy banks, 54 (93,1%) were categorized correctly whereas, out of 24 banks in distress, 23 (95,8%) were categorized correctly. An incorrect prediction may occur in 2 forms and, as such, we may have Type I and Type II errors. Type I error occurs when a bank is predicted to be healthy, but is in distress and Type II error occurs when a bank is predicted to be in distress, but is healthy, a so called "false alarm". Obviously, from the perspective of interested stakeholders and regulators, the most important and serious of the two is Type I error. In the case of both models, our "out-of-sample forecasts" exhibit Type I and Type II errors of 4,17% and 6,90%, respectively.

<Insert Table 9 and 10>

We also present the sensitivity of our "testing model" to various probability thresholds with the Receiver Operating Characteristic (ROC) curve[10] (figures 2 and 3).

[10] The ROC curve plots sensitivity vs. (1 – specificity) where sensitivity is the percentage of correctly predicted banks in distress (in terms of the total number of banks in distress) and specificity is the percentage of correctly predicted healthy banks (in terms of the total number of healthy banks). Sensitivity is equal to (1 – Type I error) and Specificity is equal to (1 – Type II error).

The area under the ROC curve can provide insight regarding the predictive ability of the model. If it is equal to 0,5, the model can be thought of as predicting at random. The closer the area is to 1, the better the model. This can be measured by the Gini coefficient[11], which equals 84,80% for the first model and 83,60% for the second one.

<Insert Figures 2 and 3>

5. Conclusion

In this paper, we employ a unique sample of banks in the EU that experienced distress during the period 2008-2015 to provide empirical evidence regarding the relationship between bank-specific, micro-variables such as the CAMEL indicators, size and revenue diversification and country-specific, macroeconomic and banking sector variables, with the probability of bank distress. Our results indicate that a combination of the above variables, lagged by one and two years (to a lesser extent), explains the probability of bank distress quite well.

More specifically, our results suggest that when banks have more capital, stronger recurring earnings power and liquidity, their probability of distress is lower. On the other hand, when banks have assets of lower quality, then their probability of distress rises. An important finding here is that the simple capital ratio, as measured by equity to total assets, appears to be more influential in identifying bank distress when compared with other, more complicated measures, usually employed by regulators. Furthermore, it seems that this simple capital ratio is also able to give earlier warnings signals as it is the only one of the three capital ratios used that comes out as significant two years before distress. As such, we may argue that the latest version of Capital Adequacy Rules (Basel III) is right to require banks to maintain a certain percentage of capital relative to their total assets and not only to the risk-weighted ones.

We moreover document that during the period 2008-2015, larger and systemic banks (both in terms of the home country and the EU) were more likely to experience distress and so were banks whose shares were listed. The finding regarding size also

[11] Gini Coefficient = 2 x AUC – 1, where AUC = area under the curve.

lends support to the Basel III rules, which require large systemic banks to hold additional capital and is also aligned with the argument of reducing the "too-big-to-fail" subsidies. The finding regarding listed banks may imply that corporate governance standards should be reviewed yet again.

In addition, our results suggest that banks with a lower share of non-interest income relative to total income exhibited a higher probability of distress. This finding suggests that there might be diversification benefits for banks moving away from traditional interest income and into other non-interest income activities, such as fees and commissions. An interesting twist in the above result is that our findings are reversed when we address the question in the context of larger and systemic banks. Again, this latter finding seems to lend support to new regulatory measures, such as the Volcker rule in the US and the Vickers and Liikanen reports in Europe, aimed at the reduction of the involvement of banks in market-based activities in an attempt to mitigate systemic risk.

As far as the macroeconomic and the banking sector variables are concerned, we find a positive relationship between the long-term government bond yield, the unemployment rate, the change in total loans in the economy y-o-y and the probability of bank distress.

We next compared our baseline model for banks in EU countries that faced serious economic problems during the crisis and the remaining countries in the EU. Interestingly, the results regarding GIIPS plus Cyprus are different to those of other EU countries. Firstly, the CAMEL variables appear not to have a significant role in explaining the probability of distress, in contrast to the other EU countries. Secondly, absolute, and systemic size variables came out as significant predictors of bank distress in GIIPS plus Cyprus but not so for the other EU countries. Thirdly, banks in these countries, which exhibited more revenue diversification were associated with a lower probability of distress (unlike those in other EU countries). Finally, at the macro-level, in GIIPS plus Cyprus, the increase in loans y-o-y was positively related to bank distress and so was unemployment; in the case of the other EU countries, the long-term government bond yield was the dominant variable. Overall, it seems that in the case of GIIPS plus Cyprus, the deterioration of local economic conditions, in conjunction with size and little revenue diversification, have positively influenced the probability of bank distress.

We finally attempted to exploit the property of the logit model to measure Type I and Type II Errors by running a "training model" and then using it to make out-of-sample forecasts (the "testing model"). Our results show a probability of Type I error (a bank is predicted to be healthy, but is in distress) of 4,17% and a probability of Type II error (a bank is predicted to be in distress, but is healthy) of 6,90%%.

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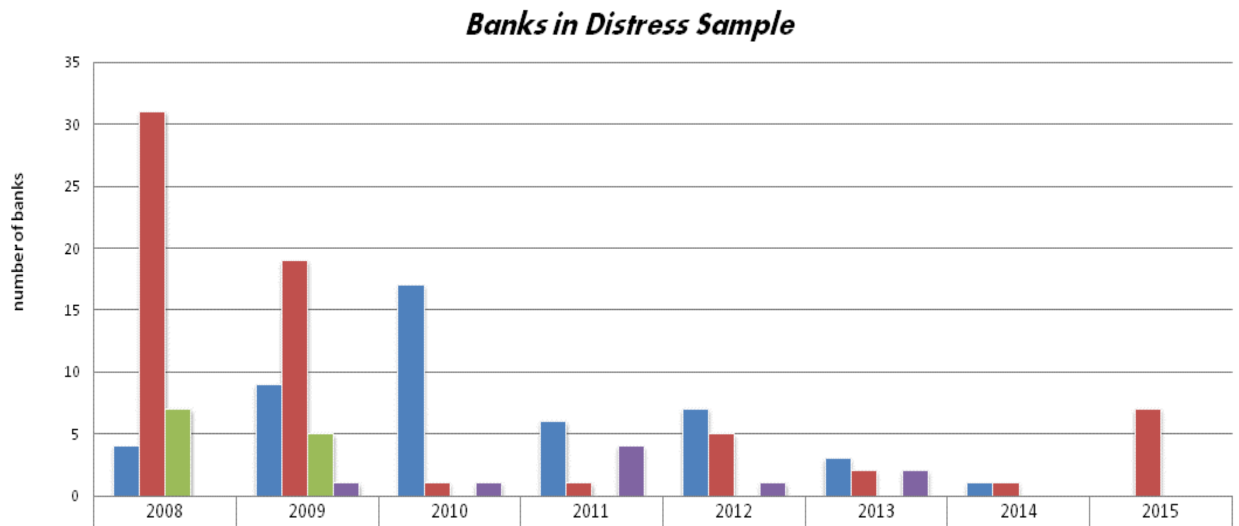
Figures and Tables

Figure 1: Number of banks in distress (2008-2015)



	2008	2009	2010	2011	2012	2013	2014	2015
Acquired	4	9	17	6	7	3	1	0
Asset side intervention	31	19	1	1	5	2	1	7
Liability side intervention	7	5	0	0	0	0	0	0
Bankruptcy	0	1	1	4	1	2	0	0

Note: Chart depicts banks in distress / type of distress; calculation by authors.

Table 1: *CAMEL and other explanatory variables used in the analysis*

Category	***Variable Name***	***Method of Measurement***	***Expectation***
(C)apitalization	**Equity / Total Assets**	**Total equity / total assets**	**-**
	Tier 1 Ratio	**Shareholder funds + perpetual non-cumulative preference shares / Risk Weighted Assets**	**-**
	Total Capital Ratio	**Tier 1 capital + Tier 2 capital (includes subordinated debt, hybrid capital, loan loss reserve and the valuation reserves) / Risk Weighted Assets**	**-**
(A)sset quality	**Loan loss Res / Gross loans**	**Loan loss reserve / (total loans + loan loss reserve)**	**+**
(M)anagement	**Cost to Income Ratio**	**Operating expenses / net interest revenue + other operating Income**	**+**
(E)arnings Ability	**Recurring Earnings Power**	**Profit after tax + provision for bad debts / total assets**	**-**
(L)iquidity	**Liquid Assets / Dep & ST Funding**	**Liquid assets / deposits & short term funding**	**-**
Other variables	**Absolute Size**	**LN (total assets)**	**+**
	Listed	**If bank is listed ="1" Otherwise="0"**	**?**
	Systemic Size	**Total assets / GDP home country (or GDP EU)**	**+**
	Revenue Diversification	**Total non – interest operating income / total operating income**	**?**

Note: Table presents the CAMEL and other micro-variables used in the study, their method of measurement and the expected sign of their relationship with the probability of distress. Expectations are based on prior literature and intuition. Capital, Earnings, and Liquidity are inversely related to the probability of bank distress whereas inferior Asset quality and Management are positively related to the probability of bank distress. We expect a positive relationship between Size and the probability of bank distress (due to the "too-big-to-fail" and "too-systemic-to-fail" arguments) whereas we have no a-priori expectation regarding the "Listed" and "Revenue Diversification" variables.

Table 2: *Macro-economic and banking sector variables used in the analysis*

Category	*Variable Name*	*Method of Measurement*	*Expectation*
MACRO AND BANKING SECTOR	**Long-term government bond yield**	**Central government bond yield on the secondary market, gross of tax (10-year maturity)**	**+**
	Real GDP growth rate	**(GDPt – GDPt-1) / GDPt-1**	**-**
	Total loans in economy, change over previous year (y-o-y)	**(total loans in year t / total loans in year t-1) / total loans year in t-1**	**+**
	Unemployment rate	**Number of unemployed persons as a percentage of the labour force based (ILO)**	**+**

Note: Table presents the macro-economic and banking sector variables used in the study, their method of measurement and the expected sign of their relationship with the probability of distress. As before, expectations are based on prior literature and intuition. Real GDP growth rate is inversely related to the probability of bank distress whereas long-term government bond yield, change in total loans y-o-y and unemployment are positively related to the probability of bank distress.

Table 3: *Summary statistics and mean comparison tests one year prior to distress*

		Y=0			*Y=1*			*Mean t-test*		
		Obs	*Mean*	*Standard Deviation*	*Obs*	*Mean*	*Standard Deviation*	*Mean difference*	*Std. Error difference*	*t*
C	*Equity / Total Assets*	188	8,831	5,655	114	5,143	2,640	3,687	0,480	7,667
	Total Capital Ratio	131	14,267	7,857	93	11,124	2,604	3,143	0,738	4,260
	Tier 1 Ratio	119	11,902	8,154	95	8,305	2,712	3,597	0,798	4,511
A	*Loan Loss Res / Gross Loans*	175	2,326	2,310	107	3,594	3,433	-1,268	0,375	-3,379
M	*Cost to Income Ratio*	186	62,198	19,479	113	72,003	39,130	-9,805	3,948	-2,483
E	*Recurring Earning Power*	188	1,704	2,836	114	0,813	0,742	0,891	0,218	4,084
L	*Liquid Assets / Dep & ST Funding*	186	30,158	31,073	114	23,538	21,461	6,620	3,038	2,179
MACRO AND BANKING SECTOR	*Long term government bond yield*	188	3,707	1,139	123	4,710	1,583	-1,003	0,165	-6,074
	Real GDP growth rate	188	1,539	2,291	123	0,361	2,903	1,178	0,310	3,796
	Total loans in economy, change over previous year	188	9,632	12,509	123	13,073	18,890	-3,441	1,932	-1,781
	Unemployment rate	188	5,977	2,250	123	9,290	5,705	-3,313	0,539	-6,136
OTHER	*Systemic Size*	188	0,089	0,239	123	0,248	0,432	-0,159	0,042	-3,711
	Listed	188	0,300	0,461	123	0,490	0,502	-0,190	0,056	-3,275
	Revenue Diversification	186	0,400	0,285	113	0,267	0,413	0,133	0,044	3,006
	LN(total Assets)	188	23,157	1,625	114	24,460	1,824	-1,303	0,207	-6,264

Note: Table presents mean comparison tests of banks in distress *(Y=1)* vs. banks not in distress *(Y=0)* for all explanatory variables lagged by one year.

Table 4: *Multivariate regression analysis (one year prior to distress)*

	BASELINE MODEL LN(total Assets)	***BASELINE MODEL Listed***	***BASELINE MODEL Systemic Size***	***BASELINE MODEL Systemic Size * Revenue Divers.***	***BASELINE MODEL LN(total Assets) * Revenue Divers.***
Equity / Total Assets	-0,295***	-0,354***	-0,306***	-0,313***	-0,292***
	(0,099)	(0,101)	(0,098)	(0,092)	(0,093)
Loan Loss Res / Gross Loans	0,393***	0,336***	0,357***	0,363***	0,380***
	(0,124)	(0,114)	(0.118)	(0,113)	(0,116)
Cost to Income Ratio	-0,005	-0,008	-0,005	0,002	0,001
	(0,012)	(0,009)	(0,010)	(0,008)	(0,008)
Recurring Earning Power	-0,900**	-1,105***	-0,985***	-1,020***	-1,093***
	(0,407)	(0,410)	(0,400)	(0,370)	(0,388)
Liquid Assets / Dep & ST Funding	-0,016*	-0,009	-0,010	-0,014*	-0,014*
	(0,009)	(0,008)	(0,008)	(0,008)	(0,008)
LN(total Assets)	0,447***				
	(0,119)				
Systemic size (GDP)			1,901***		
			(0,608)		
Systemic Size * Revenue Diversification				2,701**	
				(1,298)	
LN(total Assets) * Revenue Diversification					
					0,069***
Listed		1,343***			(0,023)
		(0,398)			
Revenue Diversification	-1,795**	-1,638**	-1,592**		
	(0,801)	(0,763)	(0,756)		
Long term government bond yield	1,144***	1,191***	1,187***	1,131***	1,150***
	(0,293)	(0,292)	(0,288)	(0,265)	(0,272)
Real GDP growth rate	0,011	0,001	-0,008	-0,035	-0,038
	(0,086)	(0,087)	(0,084)	(0,082)	(0,082)
Total loans in economy, change over.	0,030***	0,020*	0,026**	0,026**	0,027**
	(0,012)	(0,012)	(0,012)	(0,011)	(0,011)
Unemployment rate	0,287***	0,290***	0,304***	0,241***	0,266***
	(0,070)	(0,072)	(0,072)	(0,063)	(0,066)
Constant	-15,610***	-4,514***	-5,137***	-4,956***	-5,398***
	(3,359)	(1,460)	(1,488)	(1,366)	(1,426)
R Square	65,10%	63,90%	63,80%	61,30%	62,80%
No of banks	277	277	277	277	279
Log likelihood	187,495	192,176	192,554	202,856	197,938

Note 1: Banks in distress during the period 2008-2015 are pooled at the time of distress *(t)*. Multivariate regressions on all explanatory variables at time *t-1* are then carried out.
Note 2: R-square refers to Nagelkerke's pseudo R-squared (inversely related to log likelihood).
Note 3: Numbers in brackets are standard errors.
Note 4: ***: p<1%; **: p<5%; *: p<10%.

Table 4 (continued):

	BASELINE MODEL *Systemic_Size (EU)*
Equity / Total Assets	-0,333***
	(0,095)
Loan Loss Res / Gross Loans	0,330***
	(0,112)
Cost to Income Ratio	-0,007
	(0,010)
Recurring Earning Power	-0,869**
	(0,373)
Liquid Assets / Dep & ST Funding	-0,012
	(0,008)
LN(total Assets)	
Systemic_EU	14,234*
	(7,371)
Revenue Diversification	-1,718**
	(0,757)
Long term government bond yield	1,132***
	(0,272)
Real GDP growth rate	0,024
	(0,082)
Total loans in economy, change over.	0,024**
	0,011)
Unemployment rate	0,272***
	(0,067)
Constant	-4,148***
	(1,385)
R Square	61,80%
No of banks	277
Log likelihood	200,102

Table 5: *Multivariate regression analysis (two years prior to distress)*

	BASELINE MODEL LN(total Assets)	*BASELINE MODEL Listed*	*BASELINE MODEL Systemic Size*	*BASELINE MODEL Systemic Size * Revenue Divers.*	*BASELINE MODEL LN(total Assets) * Revenue Divers.*
Equity / Total Assets	-0,369***	-0,430***	-0,407***	-0,401***	-0,447***
	(0,104)	(0,102)	(0,101)	(0,099)	(0,099)
Loan Loss Res / Gross Loans	0,367***	0,297***	0,316***	0,322***	0,308***
	(0,111)	(0,111)	(0,108)	(0,107)	(0,105)
Cost to Income Ratio	-0,019	-0,023	-0,020	-0,027*	-0,028*
	(0,016)	(0,015)	(0,015)	(0,014)	(0,015)
Recurring Earning Power	-0,505	-0,745*	-0,569	-0,714*	-0,649*
	(0,393)	(0,398)	(0,378)	(0,369)	(0,366)
Liquid Assets / Dep & ST Funding	-0,005	0,001	-0,001	-0,006	-0,003
	(0,007)	(0,007)	(0,007)	(0,007)	(0,007)
LN(total Assets)	0,451***				
	(0,134)		0,017**		
Systemic Size (GDP)			(0,007)		
Systemic Size * Revenue Diversification				0,035**	
				(0,017)	
LN(total Assets) * Revenue Diversification					-0,001
					(0,063)
Listed		0,929**			
		(0,432)			
Revenue Diversification	-2,515*	-1,860	-1,677		
	(1,333)	(1,275)	(1,247)		
Long term government bond yield	1,818***	1,772***	1,909***	1,938***	1,880***
	(0,400)	(0,371)	(0,402)	(0,399)	(0,381)
Real GDP growth rate	-0,040	-0,013	-0,032	-0,018	0,016
	(0,086)	(0,088)	(0,085)	(0,084)	(0,082)
Total loans in economy, change over.	-0,081***	-0,083***	-0,086***	-0,086***	-0,093***
	(0,023)	(0,023)	(0,023)	(0,023)	(0,023)
Unemployment rate	0,238**	0,226**	0,256***	0,236***	0,216**
	(0,093)	(0,089)	(0,091)	(0,087)	(0,085)
Constant	-11,697***	-3,459**	-4,619*	-4,529*	-3,691**
	(3,118)	(1,705)	(1,860)	(1,806)	(1,744)
R Square	65,40%	63,33%	64,00%	63,33%	61,70%
No of banks	257	257	257	257	257
Log likelihood	178,437	186,292	183,764	186,074	191,906

Note 1: Banks in distress during the period 2008-2015 are pooled at the time of distress *(t)*. Multivariate regressions on all explanatory variables at time *t-2* are then carried out.

Note 2: R-square refers to Nagelkerke's pseudo R-squared (inversely related to log likelihood).

Note 3: Numbers in brackets are standard errors.

Note 4: ***: p<1%; **: p<5%; *: p<10%.

Table 5 (continued):

	BASELINE MODEL ***Systemic_Size (EU)***
Equity / Total Assets	**-0,413*****
	(0,101)
Loan Loss Res / Gross Loans	**0,315*****
	(0,106)
Cost to Income Ratio	**-0,023**
	(0,015)
Recurring Earning Power	**-0,567**
	(0,371)
Liquid Assets / Dep & ST Funding	**-0,003**
	(0,007)
LN(total Assets)	
Systemic_EU	**0,188***
	(0.099)
Revenue Diversification	**-1,859**
	(1,281)
Long term government bond yield	1,834***
	(0,381)
Real GDP growth rate	0,009
	(0,082)
Total loans in economy, change over.	-0,090***
	(0,023)
Unemployment rate	0,229***
	(0,087)
Constant	-3,763**
	(1,761)
R Square	63,10%
No of banks	**257**
Log likelihood	186,844

Table 6: *Model variations according to capitalization measure (one year prior to distress)*

	BASELINE MODEL LN(total Assets)	***BASELINE MODEL Total Capital Ratio***	***BASELINE MODEL Tier 1 Ratio***
Equity / Total Assets	-0,295***		
	(0,099)		
Total Capital Ratio		-0,219**	
		(0,099)	
Tier 1 Ratio			-0,265***
			(0,095)
Loan Loss Res / Gross Loans	0,393***	0,433***	0,353**
	(0,124)	(0,144)	(0,144)
Cost to Income Ratio	-0,005	-0,012	-0,003
	(0,012)	(0,011)	(0,013)
Recurring Earning Power	-0,900**	-1,245***	-1,215***
	(0,407)	(0,420)	(0,441)
Liquid Assets / Dep & ST Funding	-0,016*	-0,008	-0,009
	(0,009)	(0,009)	(0,009)
LN(total Assets)	0,457***	0,498***	0,407***
	(0,119)	(0,134)	(0,138)
Revenue Diversification	-1,795**	-1,917**	-1,530*
	(0,801)	(0,861)	(0,845)
Long term government bond yield	1,144***	0,920***	0,907***
	(0,293)	(0,307)	(0,291)
Real GDP growth rate	0,011	-0,025	0,054
	(0,089)	(0,093)	(0,096)
Total loans in economy, change over.	0,030**	0,032**	0,029**
	(0,012)	(0,013)	(0,012)
Unemployment rate	0,287***	0,257***	0,280***
	(0,070)	(0,075)	(0,077)
Constant	-15,610***	-14,037***	-12,678***
	(3,359)	(3,906)	(3,862)
R Square	65,10%	60,20%	59,80%
No of banks	277	213	205
Log Likelihood	187,495	163,168	160,425

Note 1: Banks in distress during the period 2008-2015 are pooled at the time of distress *(t)*. Multivariate regressions including different capitalization measures at time *t-1* are then carried out.
Note 2: R-square refers to Nagelkerke's pseudo R-squared (inversely related to log likelihood).
Note 3: Numbers in brackets are standard errors.
Note 4: ***: p<1%; **: p<5%; *: p<10%.

Table 7: *Model variations according to capitalization measure (two years prior to distress)*

	BASELINE MODEL LN(total Assets)	***BASELINE MODEL Total Capital Ratio***	***BASELINE MODEL Tier 1 Ratio***
Equity / Total Assets	-0,369***		
	(0,104)		
Total Capital Ratio		-0,096	
		(0,078)	
Tier 1 Ratio			-0,178*
			(0,094)
Loan Loss Res / Gross Loans	0,367***	0,512***	0,490***
	(0,111)	(0,135)	(0,138)
Cost to Income Ratio	-0,019	-0,031	-0,026
	(0,016)	(0,020)	(0,021)
Recurring Earning Power	-0,505	-1,285***	-1,171**
	(0,393)	(0,454)	(0,472)
Liquid Assets / Dep & ST Funding	-0,005	-0,012	-0,013
	(0,007)	(0,010)	(0,011)
LN(total Assets)	0,451***	0,585***	0,538***
	(0,134)	0,166)	(0,175)
Revenue Diversification	-2,515*	-1,684	-0,966
	(1,333)	(1,571)	(1,676)
Long term government bond yield	1,818***	1,746***	1,946***
	(0,400)	(0,482)	(0,555)
Real GDP growth rate	-0,040	-0,003	0,003
	(0,086)	(0,093)	(0,094)
Total loans in economy, change over.	-0,081***	-0,091***	-0,093***
	(0,023)	(0,025)	(0,026)
Unemployment rate	0,238**	0,240**	0,258**
	(0,093)	(0,102)	(0,110)
Constant	-11,697***	-13,591***	-13,793***
	(3,118)	(4,027)	(4,306)
R Square	65,40%	62,50%	63,60%
No of banks	257	197	187
Log Likelihood	17,437	148,177	138,134

Note 1: Banks in distress during the period 2008-2015 are pooled at the time of distress *(t)*. Multivariate regressions including different capitalization measures at time *t-2* are then carried out.
Note 2: R-square refers to Nagelkerke’s pseudo R-squared (inversely related to log likelihood).
Note 3: Numbers in brackets are standard errors.
Note 4: ***: p<1%; **: p<5%; *: p<10%.

Table 8: GIIPS plus Cyprus vs. Other EU Countries

	BASELINE MODEL PIIGS + CYPRUS (Systemic Size)	*BASELINE MODEL OTHER (Systemic Size)*	*BASELINE MODEL PIIGS + CYPRUS (LN(Total Assets))*	*BASELINE MODEL OTHER (LN(Total Assets))*
Equity / Total Assets	0,202	-0,580***	-0,053	-0,527***
	(0,178)	(0,168)	(0,191)	(0,170)
Loan Loss Res / Gross Loans	0,141	0,466***	0,202	0,491***
	(0,168)	(0,170)	(0,186)	(0,173)
Cost to Income Ratio	0,015	-0,004	0,005	-0,005
	(0,052)	(0,013)	(0,042)	(0,013)
Recurring Earning Power	-2,825	-0,942*	-2,456*	-0,880
	(0,180)	(0,560)	(1,430)	(0,556)
Liquid Assets / Dep & ST Funding	-0,027	-0,013	-0,010	-0,018*
	(0,024)	(0,010)	(0,020)	(0,010)
LN(total Assets)			1,187***	0,296**
			(0,396)	(0,150)
Systemic Size (GDP)	8,181***	1,030		
	(2,390)	(0,646)		
Revenue Diversification	-8,048**	-1,399	-6,727**	-1,466
	(3,486)	(0,901)	(3,161)	(0,919)
Long term government bond yield	0,496	1,412***	0,810	1,316***
	(0,621)	(0,377)	(0,558)	(0,381)
Real GDP growth rate	-0,330	0,177	-0,343	0,204*
	(0,219)	(0,121)	(0,225)	(0,124)
Total loans in economy, change over.	0,094***	-0,020	0,105***	-0,019
	(0,032)	(0,024)	(0,035)	(0,025)
Unemployment rate	0,328**	0,161	0,250**	0,117
	(0,134)	(0,168)	(0,123)	(0,163)
Constant	-3,273	-3,670**	-30,233***	-10,226**
	(5,633)	(0,180)	(10,382)	(4,040)
R Square	80,30%	57,20%	78,10%	57,90%
No of banks	104	173	104	173
Log likelihood	46,776	111,195	50,930	109,837

Note 1: Banks in distress during the period 2008-2015 are divided according to country ("GIIPS plus Cyprus" vs. Other EU Countries) and pooled at the time of distress *(t)*. Multivariate regressions on all explanatory variables at time *t-1* are then carried out.
Note 2: R-square refers to Nagelkerke's pseudo R-squared (inversely related to log likelihood).
Note 3: Numbers in brackets are standard errors.
Note 4: ***: p<1%; **: p<5%; *: p<10%

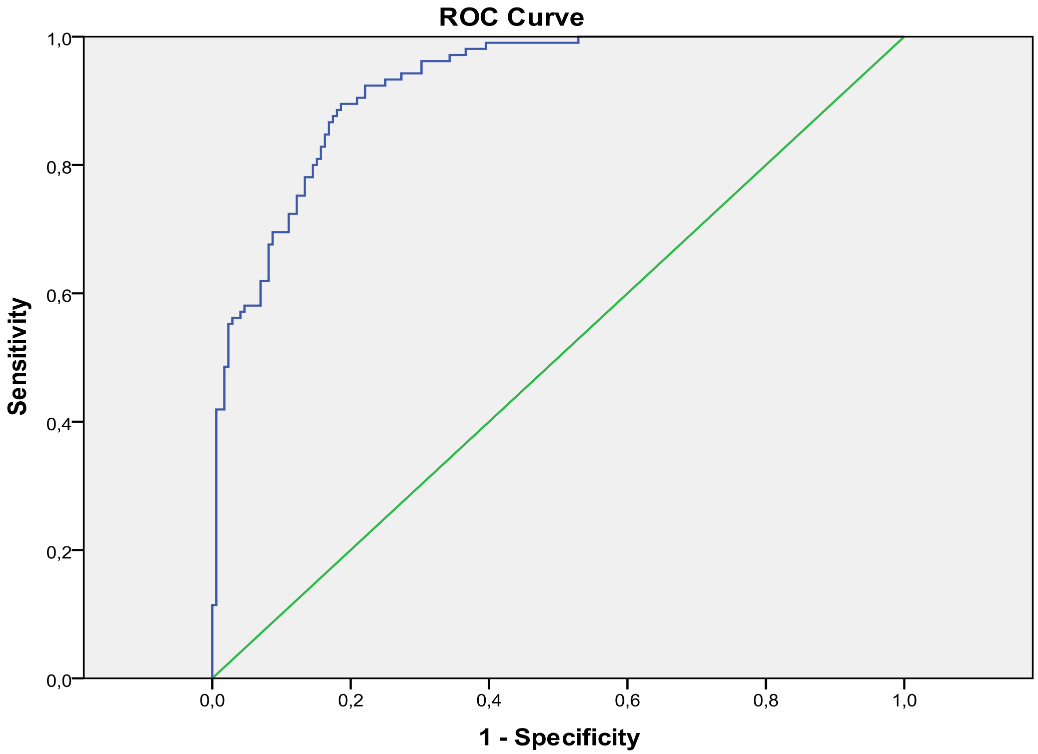
Table 9: *Results for the "training" and "testing" models (Absolute size)*

			Predicted* at t-1					
			Training dataset (n=195) 2008-2011			*Forecating dataset (n=82)* 2012-2015		
			No	*Yes*	*% Correct*	*No*	*Yes*	*% Correct*
Observed	*failure*	*No*	94	20	82,50	54	***4***	93,10
		Yes	22	59	72,80	***1***	23	95,80
	Overall Percentage				**78,50**			**93,90**
	Type I error					4,17%		
	Type II error						6,90%	

Note 1: Type I error: A bank in distress is wrongly classified as healthy; Type II error: A healthy bank is wrongly classified as in distress.

Note 2: Explanatory variables lagged by one year.

Figure 2: ROC Curve (model with Absolute size)



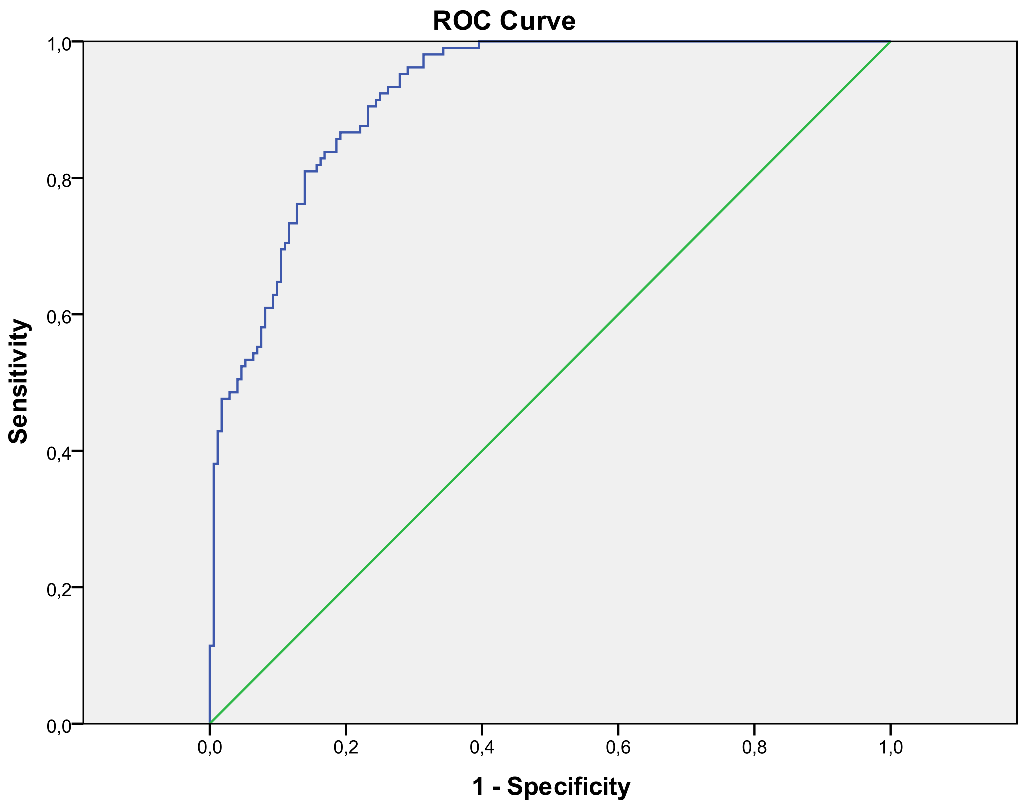
Note 1: Sensitivity is the percentage of correctly predicted banks in distress and specificity is the percentage of correctly predicted healthy banks.
Note 2: The green line represents an area of 50%; the model is predicting at random.

Table 10: *Results for the “training” and “testing” models (Systemic Size)*

			Predicted* at t-1					
			Training dataset (n=195) *2008-2011*			*Forecating dataset (n=82)* *2012-2015*		
			No	*Yes*	*% Correct*	*No*	*Yes*	*% Correct*
Observed	*failure*	*No*	94	20	82,50	54	***4***	93,10
		Yes	20	61	75,30	***1***	23	95,80
	Overall Percentage				**79,50**			**93,90**
	Type I error					4,17%		
	Type II error						6,90%	

Note 1: Type I error: A bank in distress is wrongly classified as healthy; Type II error: A healthy bank is wrongly classified as in distress.
Note 2: Explanatory variables lagged by one year.

Figure 3: ROC Curve (model with Systemic size)



Note 1: Sensitivity is the percentage of correctly predicted banks in distress and specificity is the percentage of correctly predicted healthy banks.
Note 2: The green line represents an area of 50%; the model is predicting at random.