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CAN FINANCIAL STATEMENTS PREDICT STRESS TEST RESULTS? EVIDENCE FROM THE SPANISH CASE

Abstract: *In the aftermath of the 2008 financial crisis, the Spanish banking system faces a situation in which levels of capital higher than previously are required. As a result, most of its institutions have been involved in a process of restructuring and/or refinancing, as well as having been submitted to stress testing so that their solvency and resilience against potentially worse economic conditions be determined.*
This study aims to analyse the degree to which the solvency status of each institution as given by the stress tests could have been predicted on the basis of data obtained from financial statements. The stress test results are used to define the dependent variable in terms of either capital shortfall/surplus, or the ratio of tier 1 capital. Logit and regression models with financial ratios as predictors are used. The models based on the equity-to-debt ratio as the explanatory variable provide a good fit in both scenarios considered by the stress tests.
Keywords: *banking sector, stress test, accounting ratios, regression models.*

JEL Classification: C21, G21, G28

1. Introduction

The recent financial crisis and its effects on the real economy, along with the European sovereign debt crisis, have underlined the importance of banking regulation and supervision as control mechanisms in this important economic sector, a sector whose behaviour clearly affects the economic cycle, either through mitigating or sharpening it. Whether in order to avoid the necessity of the intervention of the central banks as suppliers of liquidity, or to enhance their ability to act, the control of solvency through minimum capital requirements has been shored up by the new solvency rules based on the international Basel Accords.

The Basel II Accord was published in 2004 and implemented in the European Union from 2007. It was thus in force at the outbreak of the crisis, making it impossible not to link the two events. Despite the Accord's apparent complexity and thorough risk detection mechanisms, its weaknesses led to its amendment in the form of Basel III, which came into force in 2013.

In the European context, these changes in the banking solvency rules coincided with EU-wide stress tests, whose results have not always detected real weaknesses in the banking sector, e.g. in the Irish case. In Spain, a similar stress test was conducted in the summer of 2012. In June 2012 the results of a previous external analysis were made public and its conclusions caused the Spanish government to ask for financial help in order to restructure and recapitalise the banking system, a request which took the form of the Memorandum of Understanding signed with the European Commission (with the assistance of the European Central Bank and the International Monetary Fund). Among the agreed conditions, the Memorandum required the identification of capital requirements through stress testing, as well as the recapitalisation, restructuring and/or resolution of non-viable banks, and ring-fencing toxic assets under the auspices of an external Asset Management Company.

The stress test used both data provided by the credit institutions and the Spanish Central Bank (Bank of Spain), as well as auditor data concerning asset portfolios and real estate losses, and business plan revisions, focused in December 2011. Since the estimates and projections in the report were uncertain, macroeconomic data were used to help define a baseline and an adverse scenario for the 3-year period 2012-2014. The results, released in September, predicted capital requirements of between 16 billion euros in the baseline and more optimistic scenario,and 62 billion euros in the adverse scenario.

The aim of this paper is to determine if data from financial statements could have predicted the stress test results in two different ways: firstly in terms of capital shortfall or surplus, and secondly in terms of the core tier 1 ratio. To do this, the paper is structured as follows. Firstly, banking solvency is analysed through the context of the international regulatory framework and previous research on banking crises, reviewing the academic literature that constitutes the ‘state of the art’ in this field. Then, the restructuring process in the Spanish banking sector is briefly summarised. Following this, the stress tests conducted in the European Union (2011) and Spain (2012) are described with the intention of determining if the conclusions of these could also have been drawn using the empirical data obtained from indicators obtained from financial statements. Finally, the main conclusions of the research are presented.

2. Literature review

2.1. International regulation of banking solvency: The Basel Accords

The first attempts to develop an international financial supervisory framework, especially in the banking sector, begun after the Great Depression, which brought about regulatory changes in order to develop a deposit insurance system and to ensure that institutions maintained minimum capital requirements. This regulation in terms of capital and the definition of the solvency ratio was the central idea emerging from the Basel Committee on Banking Supervision, whose Accords, although not compulsory, have eventually been adopted by the majority of national or regional regulators.

The Basel II Accord replaced the first international convergence on capital standards, and combined three different models of international supervision (norms, supervisory review and market discipline), and considered capital requirements to cover credit, market and operational risk, allowing credit institutions use both standard and internal advanced models (the first pillar). This framework was complemented by regulatory review of capital adequacy (the second pillar) and a greater degree of information disclosure, with market discipline reinforcement (the third pillar).

The beginning of the implementation of Basel II coincided with the start of the current financial crisis, which makes it very difficult to establish a causal relationship between the two events. However, the Accord's limitations and procyclicality, along with the financial problems underlined with the fall of Lehman Brothers, led to the convocation of several Summits on Financial Markets and the World Economy, in one of which the new Basel III Accord was endorsed. This Accord, finally published in December 2010, focused on strengthening solvency and adding liquidity measures (BCBS, 2010a; BCBS, 2010b). Basel III is intended to be a systemic framework that combines capital ratio with other standards. Its aim is to require greater and better-quality capital, so that core capital reach 7%. Moreover, in an attempt to eliminate one of Basel II's inconsistencies, since June 2013 credit companies have had to report on capital composition. In addition, a tier 1 capital leverage ratio of 3% was introduced to prevent both arbitrage and model risk.

The regulatory changes incorporate liquidity risk coverage, demanding both short and long term standards. The former–a liquidity coverage ratio–will take effect in 2015 and the latter–a net stable funding ratio–in 2018. However, the 2008 liquidity crisis demonstrated that these entities need longer time frames to work with and that liquidity demands can restrict private sector credit, worsening credit crunches.

Finally, given its potential impact, the Accord itself outlines a transitional period for its own implementation. The estimated effect of higher levels of necessary capital on GDP is also noteworthy. According to the Basel Committee itself, a 1% increase in the core capital ratio would lead to 0.19% reduction in GDP within a time frame of four-and-a-half years. Moreover, a 25% increase in liquid assets held over a 4-year-period would mean a decrease in GDP of 0.08%. In both cases, the impact will be higher the longer the time frame is.

2.2. Research on the banking sector: an overview

As has already been indicated, the banking sector is under study because of its importance in the financial system and its effects on the real economy. In particular, attempts to predict and explain banking insolvency focus on finding a set of indicators which would permit early detection and which would allow the discrimination between healthy banks and those in difficulties, with the final aim of reducing the costs arising from a potential bankruptcy.

Among the wide variety of research on this subject, that related to early warning systems (EWS) stands out. They have been extensively reviewed by Gaytán and Johnson (2012), and have been applied in contexts both global (Sahajwala and Van den Bergh, 2000; Davis and Karim, 2008b; Barrell et al., 2010) and partial, in emerging markets (Bussiere and Fratzscher, 2006), in the Asian crisis of 1997-1998 (Berg and Pattillo, 1999; Edison, 2003), and the subprime crisis (Davis and Karim, 2008a).

Another branch of the academic literature has tried to assess the importance of variables included in the CAMEL model as early-warning indicators in relation to systemic banking difficulties. The CAMEL model (whose initials stand for *Capital*, *Assets*, *Management*, *Earnings*, *Liquidity*) has been used to explain and forecast banking problems in the case of Argentina (Dabos and Sosa Escudero, 2004), Croatia (Kraft and Galac, 2007), the US (Weelock and Wilson, 2000; Jin et al., 2011) and Southeast Asia (Arena, 2008), among others. These studies show that the reasons for banking failure include several factors and that financial ratios could offer relevant firm-specific information. From the regulatory perspective, Estrella et al. (2002) find that simple capital ratios have as much capacity to predict banking failure as weighted and complex indicators, thus contradicting the definition of capital ratios in Basel II.

2.3. Spanish banking restructuring and recapitalisation

The solvency rules adopted by the Bank of Spain in 2008 are similar to those of Basel II: they insist on minimum capital requirements to be covered against credit, market and operational risk, allowing institutions to apply their own internal methods under the condition that these meet with regulatory approval. The new rules also raised the level of information to be submitted to the Bank of Spain, from the previous norm of eight financial statements to twenty-three.

Nevertheless, these solvency rules have been converted into a minimum regulatory framework, since they have been superseded by a new set of norms derived from the Spanish banking recapitalisation process, which, from 2013, has required a minimum 9% core capital ratio, defining its components according to the European Banking Authority (EBA), and requiring quarterly information oncore capital.

In addition, since 2009, when the Fund for Orderly Bank Restructuring (FOBR[1]) was created, the restructuring process has mainly affected saving banks–focusing on readjusting their business networks and resizing their assets–with the intention of improving their level of solvency.

[1]In Spanish, *Fondo de Reestructuración Ordenada Bancaria* (FROB).

3. Materials and methods

3.1. Context: bank stress tests

Stress tests have become one of the main tools to assess banking solvency. They have been conducted not only in the context of the European Union but also in the Spanish case as a consequence of the commitments included in the financial assistance programme agreed in the summer of 2012.

In the European area, the first stress test was conducted in July 2010 with the aim of assessing capital levels and loss predictions under severe scenarios. This EU-wide stress test required 6% tier 1 capital and the results were apparently satisfactory–despite the Irish case–although they warned of the need for higher capital requirements. One year later, the EBA published the results of a new stress test exercise, applied to 90 institutions from 21 countries, considering their figures at the end of 2010 and making projections for a two-year period. In this case, the test required a minimum 5% core tier 1 ratio (*ct*1*r*).

Eight credit institutions did not meet the capital requirements. Five of them were Spanish: four saving banks (CAM, Caja3, Unnim, CatalunyaCaixa) and a commercial bank (Pastor), and the average core capital ratio for the Spanish entities was 7.3%.

As a consequence of these results, the EBA recommended that national regulators ask non-complying institutions to increase their levels of capital, and those institutions with excessive sovereign exposure to strengthen their capital base and restrict dividend payments and leverage.

Following these analyses, in October 2012 the EBA published the results of a study of European banking recapitalisation that included 61 entities to evaluate if they met a 9% core tier 1 ratio in June 2012. A new stress test exercise will be conducted in 2014. The capital benchmark will be an 8% core tier 1 ratio and it will be applied to 130 credit institutions deemed to be ‘significant’ and supervised directly by the ECB.

In Spain, as a complement to previous top-down assessments, an independent evaluation of the banking sector was conducted in the summer of 2012, complying with one of the commitments of the financial assistance programme signed between the Spanish government and the Eurogroup. Fourteen banking groups, representing 90% of banking sector assets, were under study. This bottom-up exercise was carried out under two economic scenarios (baseline and adverse) using information from the banks’ confidential statements of 31st December 2011, real-estate valuations, credit portfolios, business plans and other data facilitated by the credit institutions and by the Bank of Spain.

Capital requirements were set at 9% and 6% under the baseline and adverse scenarios respectively, using the standard core tier 1 ratio. The seven banking groups that met the capital requirements amounted to 62% of the revised credit portfolio.

As a result of this test, those entities unable to recapitalise on their own had to present restructuring plans to the Bank of Spain and the European Commission. The Eurogroup announced in December 2012 that the European Financial Stabilisation Mechanism would pay 39,500 million euros to help credit institutions where the FOBR has a majority holding (group 1) and, later on, a second tranche of 1,864 million euros was released for institutions with approved restructuring or resolution plans (group 2). Group 3companies were considered able to meet capital needs on their own and Group 0 comprised companies with a capital surplus.

Finally, this process of the definition of capital requirements, and of restructuring, recapitalisation and resolution plans, was completed with the segregation of impaired assets to an external Asset Management Company (SAREB).

3.2. Data and variables

The capital requirements detected by the stress tests are determined by expected credit losses, and the capacity to absorb these losses (through reserves, asset protection schemes, profit generation and capital buffers). In order to estimate these variables, the stress tests make use of information supplied from the credit institutions' own accounts, the Bank of Spain, audit analyses, evaluation of foreclosed assets, and estimates of macroeconomic data.

However, this study aims to determine whether the individual solvency status of each institution estimated by the stress test could have been predicted just on the basis of data obtained from financial statements.

Table 1.Values for the dependent variables

Credit institutions	**Analysis #1** Capital shortfall/surplus (1/0)		**Analysis #2** Core tier 1 ratio (%)	
	Baseline scenario	Adverse scenario	Baseline scenario	Adverse scenario
Banco de Valencia	1	1	-7.0	-27.7
Bankinter	0	0	10.4	7.4
BBVA	0	0	10.9	9.2
Unnim	1	1	7.8	4.5
Bankia - BFA	1	1	-2.3	-17
Banco Mare Nostrum	1	1	7.9	-1.1
Caixabank	0	0	8.1	6.4
BancaCívica	0	0	8.2	5.6
Caja 3	1	1	7.3	-1.5
Catalunya Bank	1	1	-10.2	-29.6
CEISS	1	1	2.6	-5.2
Ibercaja	0	1	10.9	4.8
Liberbank	0	1	9.4	0.6
NGC Banco	1	1	-3.7	-19.6
Popular	0	1	7.5	5.3
Pastor	1	1	7.3	3.3
Sabadell	0	0	7.5	5.7

CAM	1	1	6.4	3.0
Santander	0	0	12.6	10.8
Unicaja	0	0	14.1	8.6
BBK Bank	0	0	10.5	8.8
Kutxa	0	0	12.7	10.1
Caja Vital	0	0	11.2	8.7

To do this, the stress test results are used to define the dependent variable either as a binary variable that has a value of 1 for banking institutions with capital shortfall and a value of 0 for those having capital surplus (analysis #1), or as the quantitative variable of the core tier 1ratio (analysis #2). The two macroeconomic scenarios defined in the stress test exercise will also be considered in both analyses; four models will thus be set out.

For all of these, the sample consists of the 23 stand-alone institutions that constitute the 14 stress-tested banking groups. Whenever the institution is part of a banking group[2] and it is not the parent company, the value for the dependent variable used in analysis #1 will come from the EU-wide stress test results. For analysis #2, the values for the dependent variable come from the Spanish stress test results where possible, or, if not, from the EU-wide results. It should be noted that these data refer to different time horizons (2014 in the Spanish stress test and 2012 in the EU-wide one).Table 1 shows the 23 credit institutions under analysis and the value of the corresponding dependent variable in the two proposed analyses, considering both baseline and adverse scenarios.

Table 2. Explanatory variables

	Variables and definitions
Profitability	$roa = Return\ on\ assets = \frac{Net\ income}{Assets}$
	$roe = Return\ on\ equity = \frac{Net\ income}{Equity}$
	$r3\ (Return\ on\ lending) = \frac{Interest\ received\ and\ similar\ income}{Credit\ investment}$
Capital or funding structure	$cs1 = \frac{Equity}{Debt}$
	$cs2 = \frac{Credit\ investment + Securities\ portfolio}{Equity}$
Efficiency	$eff = \frac{Operating\ expenses}{Operating\ margin}$
Credit risk	$cr = \frac{Credit\ investments}{Assets}$
Liquidity risk	$lr = \frac{Cash}{Debt}$

[2]Unnim, BancaCívica, Banco Pastor, BBK Bank, Kutxa, Caja Vital and CAM.

Regarding the selection of explanatory variables (see table 2), both traditional ratios applied in economic and financial analysis and banking sector specific indicators are considered. The former include profitability and capital or funding structure ratios, and the latter refer to efficiency as well as credit and liquidity risk proxies. This procedure can be adapted to a CAMEL model to characterise banking failure, since this acronym stands for capitalisation (*cs*1), assets (*cs*2 and *cr*), management (*eff*), earnings (*roe*, *roa* and *r*3) and liquidity (*lr*). However, the use of data from public financial statements (balance sheets and income statements) imposes a first limitation to the analysis, even if it is an essential part of the paper's aim to evaluate the accuracy of this information in comparison with the data used in the stress tests. In addition, changes in the structure of the Spanish banking sector and the mergers and acquisitions that took place in 2011 prevent consideration of other possible indicators that would require calculating average figures.

3.3. Methods

3.3.1. Analysis #1: Predicting capital shortfall

Since the primary objective of the first analysis is to identify the set of independent variables that best predicts a binary dependent variable, logistic regression or logit analysis[3] will be used. This statistical technique models the probability of an event occurring (i.e. the probability of an observation being in the group coded 1) as a function of the predictors using a logistic function, according to this formula:

$$P(Y_i = 1) = \frac{e^{\beta_0 + \beta_1 X_{1i} + \ldots + \beta_k X_{ki}}}{1 + e^{\beta_0 + \beta_1 X_{1i} + \ldots + \beta_k X_{ki}}} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_{1i} + \ldots + \beta_k X_{ki})}} \qquad [1]$$

This technique has been used previously to predict bankruptcy in numerous contexts, such as the US (Kolari et al., 2002), the UK (Logan, 2001), Latin America and East Asia (Arena, 2008), OECD countries (Barrell et al., 2010), as well as in cross-country studies (Davis and Karim, 2008). Moreover, following the Demirgüç-Kunt and Detragiache (1998) model, it also has been used to develop early warning systems for banking crises.

Coefficients for the independent variables are usually estimated using the maximum likelihood method, but this procedure requires large samples–otherwise it may lead to unreliable results. Therefore, when using small samples, the use of *exact logistic regression*, which estimates those coefficients based on permutation distribution of appropriate statistical data without recourse to asymptotic

[3]According to Hair et al. (2010, p.339), 'discriminant analysis and logistic regression are the appropriate statistical techniques when the dependent variable is a categorical (nominal or nonmetric) variable and the independent variables are metric variables'. However, when the dependent variable has only two groups, logistic regression may be preferred to discriminant analysis because the former does not rely on strictly meeting the assumptions of multivariate normality and equal variance-covariance matrices across groups, and is much more robust when these assumptions are not met.

assumptions and results (Mehta and Patel, 1995), is more appropriate. Thus, owing to the small size of the sample considered in this analysis, the coefficients will be calculated using both estimation methods (standard and exact logistic regression) in each of the two considered scenarios (baseline and adverse).

3.3.2. Analysis #2: Predicting core tier 1 ratio

The aim of the second second analysis is to predict a quantitative variable, the core tier 1 ratio (*ct*1*r*) of each financial institution in each scenario, using a set of financial ratios as predictors. Therefore, two different regression models have been estimated:

Baseline Scenario (0): $$ct1r_{0,i} = \beta_{0,0} + \beta_{0,1}X_{1i} + \beta_{0,2}X_{2i} + \ldots + \beta_{0,k}X_{ki} + \varepsilon_{0,i} \qquad [2]$$

Adverse Scenario (1): $$ct1r_{1,i} = \beta_{1,0} + \beta_{1,1}X_{1i} + \beta_{1,2}X_{2i} + \ldots + \beta_{1,k}X_{ki} + \varepsilon_{1,i} \qquad [3]$$

The possibility of merging both data sets into a joint model including *scenario* as a dummy variable was rejected because it would violate the independence of error terms (one of the assumptions in multiple regression analysis) since each institution would have a pair of observations in the sample, each corresponding to a different scenario: $Cov(\varepsilon_{0,i}, \varepsilon_{1,i}) \neq 0$ with $i = 1, 2, \ldots, 23$.

4. Results

4.1. Analysis #1: Predicting capital shortfall

A first look at the correlation matrix (see table 3) reveals that *roa*, *cs2* and, particularly, *cs1* are strongly correlated with the indicator variable of capital shortfall in both the baseline and adverse scenarios. Moreover, there is also a strong linear correlation between *roa*, *roe*, *cs1* and *cs2*, on the one hand, and between *r3*, *rc* and *rl*, on the other. The only variable that seems to be non-correlated with the remaining ones is *eff*.

Table 3. Analysis #1 – Correlation matrix

corr. sig.	***Baseline scenario***	***Adverse scenario***	***roa***	***Roe***	***r3***	***cs1***	***cs2***	***eff***	***cr***	***lr***
roa	-.5858** .0033	-.451* .0308	1							
roe	-.4207* .0456	-.3226 .1332	.9176** .0000	1						
r3	-.0085 .9693	-.0935 .6713	.0912 .6790	.0570 .7961	1					
cs1	-.7161** .0001	-.6561** .0007	.6512** .0008	.5666** .0048	-.0948 .6671	1				
cs2	.5146* .0120	.4171* .0477	-.8452** .0000	-.944** .0000	-.0406 .8539	-.7456** .0000	1			
eff	-.3748 .0780	-.1058 .6308	.3891 .0665	.2719 .2095	.0539 .8071	.1164 .5968	-.2149 .3249	1		
cr	-.2204	-.0645	.0000	-.2019	-.6336**	.1184	.2376	.1049	1	

	.3121	.7701	.9999	.3555	.0012	.5905	.2749	.6338		
lr	-.2507 .2485	-.3774 .0759	.3033 .1595	.2293 .2926	.8517** .0000	.2060 .3456	-.2357 .2790	.0360 .8706	-.5428** .0074	1

**Correlation significant at 1% level; *Correlation significant at 5% level

All these strong correlations among the explanatory variables, as well as the small sample size, make it impossible to estimate a logistic regression model including the eight financial ratios as predictors. Thus, the explanatory variables have been included in the logit model using a stepwise procedure so that new predictors are successively added whenever they meet certain criteria of statistical significance[4].

Firstly, a model aimed to predict capital shortfall in the **baseline scenario** is estimated using both exact and standard logistic regression. In both cases, results indicate that just one variable (*cs*1) meets the criteria needed to be included in the model. Hence, *cs*1 (equity/debt), which is one of the two variables related to capital structure, is the best predictor for the probability of capital shortfall in the base scenario. The coefficients estimated using the two procedures are quite similar (see *baseline scenario models* in table 4) and the two corresponding p-values indicate that *cs*1 is a significant predictor at the 5% level. Moreover, the negative value of the coefficients indicates an inverse relationship between this financial ratio and the probability of capital shortfall.

Table 4. Analysis #1 – Model summary

Coefficient Significance	**Baseline scenario**		**Adverse scenario**	
	***Standard* logistic regression**	**Exact logistic regression**	***Standard* logistic regression**	**Exact logistic regression**
***cs*1**	-146.4081* .012	-134.7625** .0001	-98.5699* .017	-92.9769** .0008
intercept	-7.9560* .015		6.3025* .016	
LR $\chi^2(1)$	17.37** .00003		12.67** .00037	
Pseudo R^2	.5515		.4023	
Model score		11.28005** .0001		9.4715** .0007

**Significant at 1% level; *Significant at 5% level.

After using the model to predict the probability of capital shortfall and considering the usual cut-off value of 0.5, i.e. $\boldsymbol{Y}= 1$ if $\hat{P}(\boldsymbol{Y} = 1) \geq 0.5$, the estimated model correctly predicts the status of 20 out of the 23 banking institutions (86.96%): 8 out of 10 with capital shortfall and 12 out of 13 without it. The incorrectly classified banking institutions are: Caja3, Banco Pastor (false negatives: the model incorrectly predicts capital surplus) and Banca Cívica (false positive: the model incorrectly predicts capital shortfall).

[4]The significance of both the likelihood-ratio test and the Wald test have been considered, obtaining the same results.

Secondly, the probability of capital shortfall in the **adverse scenario** is modelled by means of both exact and standard logistic regression. Results are coincident with those in the baseline scenario: both estimation methods include just one predictor (again *cs*1). Therefore, this variable is also the best predictor for the probability of capital shortfall in the adverse scenario. The coefficients estimated using the two procedures are also very similar in this scenario and the two corresponding p-values indicate that *cs*1 is a significant predictor at the 5% level (see *adverse scenario models* in table 4). Likewise, the negative value of the coefficients also indicates that the lower the equity/debt ratio is, the higher the probability of capital shortfall.

In the adverse scenario, the model correctly predicts capital shortfall/surplus of 20 out of the 23 banking institutions (again 86.96%): 12 out of 13 with capital shortfall and 8 out of 10 without it. In this case, the incorrectly classified banking institutions are Banco Popular (false negative), and Bankinter and Banca Cívica (false positives).

The comparison of the corresponding results in the two scenarios reveals that Banca Cívica is the only institution incorrectly classified in both: a high probability of capital shortfall is predicted, although the stress test had classified this bank as having a capital surplus. A possible explanation may be that the actual classification of this bank is not based on the Spanish stress test results but on the EU-wide ones.

4.2. Analysis #2: Predicting core tier 1 ratio

Table 5 shows the linear correlation coefficients and their significances between the financial ratios proposed as explanatory variables and the dependent variable, core tier 1 ratio (*ct*1*r*), in each scenario. It seems clear that *cs1*, *cs2*,*roa* and *roe* are very significantly correlated with *ct*1*r* in both scenarios.

Table 5. Analysis #2 – Correlation matrix

corr. sig.	***Scenario***	***roa***	***roe***	***r3***	***cs1***	***cs2***	***efic***	***rc***	***rl***
ct1r	***base***	.6149** .0018	.5438** .0073	.0824 .7084	.7281** .0001	-.6631** .0006	.3421 .1101	.0156 .9436	.2840 .1891
	adverse	.6079** .0021	.5647** .0050	.149 .4974	.6996** .0002	-.6875** .0003	.3778 .0755	-.0781 .7230	.2773 .2002

** Correlation significant at 1% level; * Correlation significant at 5% level

On the other hand, it has been already mentioned that several explanatory variables are also highly correlated among themselves (see table 5). This fact, along with the small sample size, makes it inappropriate to develop a regression model including the eight financial ratios as predictors. Therefore, as in the previous case, explanatory variables have been included in the regression model using a stepwise procedure so that new predictors are successively added whenever they meet certain criteria of statistical significance.

The results of this analysis (see model #1 in table6) reveal that, in both scenarios, there is just one variable (again *cs*1: equity/debt) meeting the criteria necessary to be included in the corresponding models. The positive sign of the slope parameter indicates a direct relation between *cs*1 and *ct*1*r*, and the overall model fit, measured in terms of adjusted R^2, is close to 50% in both cases. The remaining variables are not included in the model because either they lack enough predictive power (*r3*, *eff*, *cr* and *lr)* or they are redundant due to their high correlations with *cs*1 (*roa*, *roe* and *cs*2).

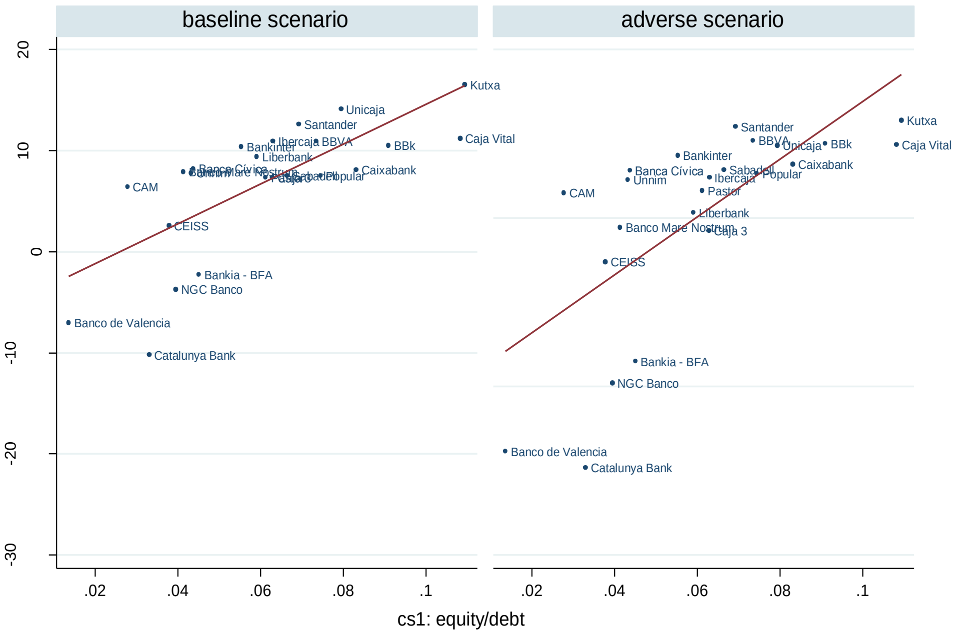
Since each regression model includes just one predictor, it is possible to plot the corresponding line of fit in a scatterplot (see figure 1).

Table 6. Analysis #2 – Model summary

Coefficient	Model #1		Model #2		Model #3	
Standard error	Baseline scenario	Adverse scenario	Baseline scenario	Adverse scenario	Baseline scenario	Adverse scenario
cs1	197.251** 40.523	343.052** 76.462	98.854** 24.65	146.14** 37.117	96.248** 25.951	134.707** 37.733
Fobr			-11.858** 1.555	-23.73** 2.341	-13.395** 4.038	-30.474** 5.871
fobr×cs1					44.324 107.019	194.425 155.609
Intercept	-5.147 2.618	-20.476** 4.94	2.82 1.712	-4.531 2.579	2.992 1.797	-3.779 2.613
s^2	4.646	8.767	2.408	3.626	2.46	3.576
Adjusted R^2	.508	.465	.868	.908	.862	.911

$^{**}p < .01$; $^{*}p < .05$

Figure 1. Analysis #2 – Fitted regression (first model)



The plots in figure 1 reveal the presence of four outlying observations that bias the regression coefficients and distort the overall model fit since they counteract the general pattern of all the remaining observations. Furthermore, a box-plot of the dependent variable *ct*1*r* (see figure 2) reveals that these four banking institutions should be considered as outliers in both scenarios since they display extremely low levels of core tier 1 ratio when compared to the remaining observations. In fact, they (Catalunya Bank, Banco de Valencia, NGC Banco and Bankia-BFA) are those institutions in which FOBR has a majority holding (the so-called ‘group 1’).

Figure 2. Analysis #2 – Box-plot

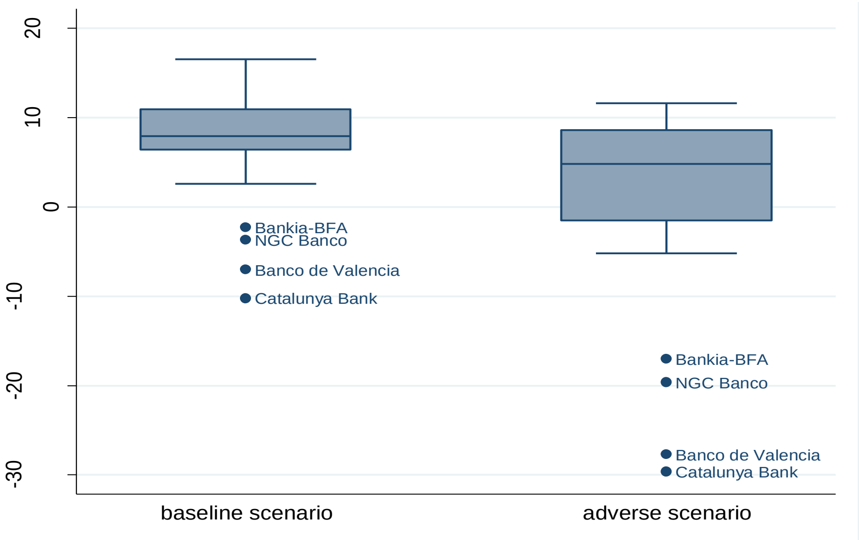
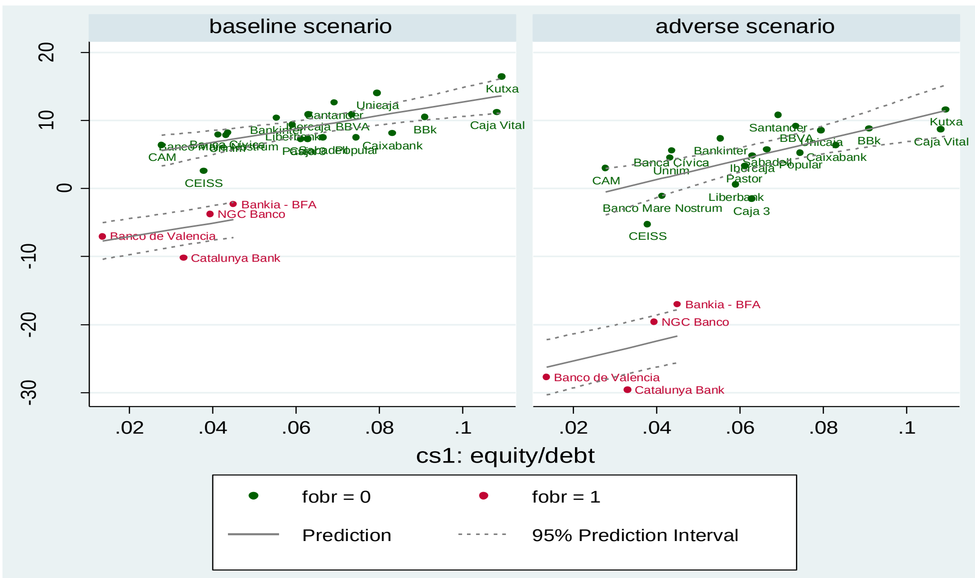


Figure 3. Analysis #2 – Fitted regression (final model) and prediction interval



Hence, in order to deal with these observations, a dummy variable, called *fobr*, is included among the potential predictors of the model (*fobr* has a value of 1 for these four banking institutions and a value of 0 otherwise).As might be expected, *fobr* turns out to be significant in both scenarios and, together with *cs*1, is included in the models, increasing the overall fit up to 86.8% and 90.8% in the baseline and adverse scenarios respectively (see model #2 in table 6). Figure 3 displays the line of fit in each scenario together with the corresponding 95% prediction intervals.

Model #2 does not specify an interaction effect between $cs1$ and *fobr*. Therefore, in each scenario, the slope parameter is the same for all institutions (whether they belong to the 'FOBR group' or not). In order to test this specification, an interaction effect between $cs1$ and *fobr* is included in a new regression model (see model #3 in table 6). Its results indicate that, in both scenarios, this interaction term is not statistically significant, i.e. one slope over the two categories of *fobr* suffices to express the effect of *cs1* on $ct1r$. Thus, it seems clear that model #2 is the most appropriate; consequently, the two final estimated models are the following:

$$\text{Baseline scenario: } \overline{ct1r_{0,i}} = 2.82 + 98.854cs1_i - 11.858\,fobr_i \quad [4]$$

$$\text{Adverse scenario: } \overline{ct1r_{1,i}} = -4.531 + 146.14cs1_i - 23.73\,fobr_i \quad [5]$$

Next, a series of statistical tests are used in order to determine if the data meet the assumptions underlying ordinary linear regression (all these results are summarised in table 7):

Table 7. Analysis #2 – Final model: regression diagnostics

Assumptions	**Tests**	**Results**	
		Baseline scenario	**Adverse scenario**
Linearity	Ramsey *RESET* Test	$F(3, 17) = 1.07$ $p = 0.3887$	$F(3, 17) = 0.71$ $p = 0.5608$
Normality	Shapiro-Wilks Test	$Z = 1.065$ $p = 0.1434$	$Z = 0.843$ $p = 0.1996$
	Jarque-Bera Test	$\chi^2(2) = 2.77$ $p = 0.2503$	$\chi^2(2) = 1.44$ $p = 0.4858$
Homoscedasticity	White Test	$\chi^2(4) = 1.8431$ $p = 0.7646$	$\chi^2(4) = 5.0916$ $p = 0.2780$
	Breusch-Pagan/Godfrey Test	$\chi^2(1) = 0.08$ $p = 0.7789$	$\chi^2(1) = 1.20$ $p = 0.2737$
	Levene Test (*fobr*)	$F(18, 3) = 0.5402$ $p = 0.3482$	$F(18, 3) = 0.4568$ $p = 0.2491$
Lack of multicollinearity	Condition number	6.76	6.76
	Variance inflation factor	1.38	1.38

- *Linearity:* according to the Ramsey RESET test, there is no functional misspecification in either scenario.
- *Normality:* The Shapiro-Wilks and Jarque-Bera tests indicate that the residuals do not significantly depart from normality in either scenario.
- *Homoscedasticity:* The White and Breusch-Pagan/Godfrey tests do not indicate the presence of heteroscedasticity related to scale in either scenario. Moreover, in order to test between-group heteroscedasticity (*fobr* being the group membership variable), the Levene test has been used, revealing no significant differences between the residual variances of the two groups in either scenario.
- *Lack of multicollinearity:* The condition number and the variance inflation factor are very small in comparison to the common cut-off thresholds (20 and 10, respectively) so there is no evidence of the two predictors being collinear.
- *Absence of outliers:* a look at the standardised residuals does not reveal the presence of outliers in either scenario (the most extreme value is -2.12).

5. Conclusion

One of the outstanding issues of the financial crisis has been the question of the solvency of the credit institutions. These institutions have also been at the centre of most of the restructuring and recapitalisation measures taken in the European and Spanish context. In fact, the difficulties of recent years have underlined the need to strengthen capital and liquidity levels, in an attempt to avoid credit crunches.

While capital accords were being amended, different stress tests were conducted to analyse both individual and global financial resilience in the banking sector. Three EU-wide stress tests have been carried out since 2010. In fact, prior to the ECB assuming single supervision in 2014, a new stress test exercise will be conducted. In the Spanish case, the banking sector was subjected to a stress test in the summer of 2012, assessing the core tier 1 ratio over a two-year time frame under two different macroeconomic scenarios. The results not only showed that half of the banking groups had a capital shortfall, but also influenced the merger process, while defining four different groups of entities according to their capital requirements and their needs to cover them.

Considering the 23 credit institutions under analysis, the objective of this study has been to determine the degree to which the solvency status of each institution as given by the stress tests could have been predicted on the basis of data obtained from financial statements.

In order to do this, the stress test results are used to define the dependent variable, firstly in terms of capital shortfall or surplus, and, secondly, in terms of the core tier 1 ratio. The statistical tools used are, respectively, logit and regression models, using in each case financial ratios as predictors. The results show that the models based on the equity-to-debt ratio as the explanatory variable provide a good fit in both scenarios considered by the stress tests.

In the first analysis, more than 85% of the institutions are correctly classified, while those that are not may have been so classified owing to data being taken from the EU-wide stress test instead of the Spanish one. In the second analysis, the model is also based on the same ratio as predictor, although a dummy variable has to be included to deal with the four outliers corresponding to the entities where the FOBR has a majority holding. After doing this, the overall fit rises to almost 90%.

However, some limitations of the analysis presented by this paper should be pointed out.

- Only the credit institutions that underwent the stress tests could be analysed. This determines the small number of institutions considered in the sample and conditions the statistical methods that can be applied.
- The selection of explanatory variables depends on data contained in financial statements in 2011,i.e.,for those institutions involved in restructuring processes it has been impossible to obtain data for previous periods, and ratios requiring average figures.
- The value for the dependent variable has generally been defined according to the Spanish stress test results. However, when a company is part of a group, the value is derived from the 2011 EU-wide stress test, even though different time frames are involved.
- In order to check the validity of a predictive logistic model, it is usual (and advisable) to split the sample into two subgroups, the first being used to estimate the model and the second to check its validity. In this case, the small number of institutions under investigation (just those submitted to a stress test) makes it impossible to follow this validation procedure.

To conclude, the stress test results have provided extensive information on the solvency status of Spanish banking institutions. However, a close approximation of these results in terms of either capital shortfall/surplus or core tier 1 ratio could have been correspondingly derived from a logit or a regression model where the main predictor is the equity-to-debt ratio.

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