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ARTICLE

Econometric Model to Estimate the Probability of Default and Loss Given Default in the EBA Stress Test in 2016

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ABSTRACT

In this research, an econometric with panel data using Ordinary least squares OLS model is constructed following the guidelines recommended by the EBA stress test methodology for 2016. The findings indicate that macroeconomic factors affecting defaults are the expected ones in the Spanish credit institutions. However, loan impairments do not follow the patterns that a priori would be normal. Divergent is outcomes in defaults and impairments: the Non-Performing Loans (NPL) is pro-cyclical and impairment losses are counter-cyclical.

1. Introduction

In recent years, there has been a generalized use and disclosure of the stress test. The aim is to provide security to financial markets, a sector that is significantly affected by rumors[1]. Stress tests provide transparency to the financial market and are an important tool for banking supervision [2]. However, their recent introduction and the complexity of the estimations have meant that some of their objectives are not being met. For example, Quijano [3] says that the publication of the results of the 2009 bank stress test taken by the Reserve had no impact on stock performance. However, the publication of the outcomes of the 2016 EU-wide stress test [4] conducted by the EBA caused a decrease of 5.1% in the European bank-

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ing sector and 7.1% in the Spanish banking sector, despite having good results.

This paper focuses on this latter stress test, specifically, on the estimation of defaults and on the losses expected from defaults in the credit portfolio of customers. The study is based on Spanish credit institutions. The methodology will be used to develop an econometric model to estimate the probability of default (PD) and the loss given default (LGD), following the 2016 EU-Wide Stress Test – Methodological Note [5]. For this purpose, data from the Spanish economy and Spanish credit institutions are used from 2004 to 2015.

The aim is to provide a new tool for stress tests in order to carefully estimate losses due to the non-payment of customer credit. These losses are usually the most significant, in terms of quantity, that credit institutions suffer.

The results may be used for supervision purposes by investors and, especially, by the credit institutions themselves in order to estimate future losses from defaults on loans, using the methodology recommended by the EBA for calculating the losses produced in the investment portfolios of credit institutions.

2. Background and Literature Review

The Stress testing were encouraged by the Basel Accords, whose first version was approved by the Bank for International Settlements (BIS) in 1988. Based on these rules, the stress tests are a common tool in the risks management to assess the potential impact of economic [6,7,8,9].

Agreeing to Til Schuermann and Nyoka[10,11], one of the consequences of the recent financial crisis is that the ordinary methods, such as regulatory capital ratios, are no longer consistent. This lack of confidence has made that in recent years, it has increased significantly use and disclosure of the stress test. The goal to offer security to financial markets, a sector that is which is very influenced affected by rumours [1].

Investors requirement reliable information to study the opportunity of investing in a credit entities, mainly when it may be subject to loans loss provisions [12].

The analysis of the impact to loan loss provisions on the Spanish financial system is not new and has been the object of interest in other periods. Freixas et al. [13] studied on the period of 1973-1992 using variables such as GDP and CPI. Fernandez de Lis et al. [14] analysed the determinants of Default in the dates of 1963-1999 and pointed to GDP as the most significant determinant. Delgado and Saurina [15] studied in the period 1982-2001 the GDP, interest, level of debt and asset prices in banks and savings banks. More recently, Foos et al. [16] study sixteen European countries including Spain, affirm that credit growth entails an increase in loss provisions. Climent and Pavia [17] study Spanish credit institutions in the period of 2004-2011. Among the most relevant variables that have had a significant impact on the increase of delinquency are, among variables, house prices, unemployment rates and property investment.

3. Material and Methods

3.1 Sample and Variables

The sample was chosen from just one country, Spain, because the peculiarities of what each country does with the data obtained from the credit institutions of one country are not optimal for the rest. Evidence of this is that the hypothetical situations (scenarios) are defined independently for each of the countries. In addition, if all countries are included, the heterogeneity of the data could offset opposing characteristics and distort the econometric models. However, the results can be used for other countries by replicating the model and adapting it to the peculiarities of each one of them.

Table one shows the variables used in the models and their description, And table two shows the correlation between them.

Table 1. Variables and Descripction

Dependent variables: Description	
PD	Probability ratio of default of the loan portfolio
LGD	Loan loss provisions for Probability of default
Explanatory variables: Description	
HICP-var	Harmonized index of consumer prices
Long-term interest	Ten year interest on public debt
Unemployment-var	Variation in the unemployment rate
Property prices	residential and commercial property prices
Real GDP	Real gross domestic product

3.2. Empirical Methods

The methodology used is that recommended in the 2016 EU-Wide Stress Test - EBA Methodological Note (2016). Note 29 says: "The EU-wide stress test is conducted on the assumption of a static balance sheet." Thus, the data from the credit institutions will be that which is included in their financial statements and management report. Note 33 says: "The approach of the exercise is a constrained bottom-up stress test – i.e. banks are required to project the impact of the defined scenarios but are subject to strict constraints, as well as to a thorough review by competent authorities." Therefore, the model will be built with the aim of allowing Spanish credit institutions to estimate im-

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Table 2. Correlation between the Variables

	LGD	PD	HICP	interest	Unemployment	Property prices	GDP
LGD	0.169						
PD	-0.008***	0.003					
HICP	0.206***	-0.020***	9.081***				
interest	-0.000	0.001**	-0.002**	0.001			
Unemployment	-0.027***	0.002***	-0.071**	0.001***	0.054		
Property prices	14.759***	-4.533***	-37.752***	0.271***	18.510***	42732.55	
GDP	0.004***	-0.001***	0.047***	-0.001***	-0.001***	2.435***	0.000619

Significance levels *,**,*** at the 1%, 5% and 10% respectively

pairment losses on loans to customers so that the authorities can supervise.

In the EBA methodological note 40 it states: "The estimation of impairments and translation to available capital requires the use of statistical methods and includes the following main steps: (i) estimating starting values of the risk parameters, (ii) estimating the impact of the scenarios on the risk parameters, and (iii) computing impairment flows as the basis for provisions that affect the P&L." Note 88 reads: "Likewise, for the estimation of projected parameters, as a general principle, banks should use models rather than resort to benchmarks to determine stressed PDpit and LGDpit parameters (under both the baseline and the adverse scenario). However, banks' models will be assessed by competent authorities against minimum standards in terms of econometric soundness and responsiveness of the risk parameters to ensure the model specification results in a prudent outcome." Accordingly, an econometric model is estimated to estimate the PDpit and LGDpit parameters. Other authors like Bertsatos and Sakellaris[18], also utilized dynamic and static econometric models for estimating the stress test.

The approach proposed in the 2016 EU-Wide Stress Test – Methodological Note EBA, (2016) to estimate the flow of impairments on new defaulted assets at time t+1 is given by:

Gross Imp Flow New(t+1) = Exp(t) x PDpit(t+1) x LGDpit^{NEW}(t+1) Equation 1

where Exp (t) is the exposure, in our case the loans granted to customers, PDpit(t + 1) are the NPLs caused by the exposure in year t + 1, and LGDpit^{NEW}(t+1) are the estimated impairment losses for the year t + 1.

Therefore, two models are estimated, one for the defaults (PD) and another for the loan impairments (LGD). The dependent variables are PD and LGD and the explanatory variables are those that are defined in the adverse macro-financial scenario for the EBA 2016 EU-wide bank stress testing exercise[19]: long-term interest rates, real GDP, HICP inflation, unemployment rate, and residential and commercial property prices.

The data sample includes the years 2004-2015. The dependent variables, PD and LGD, were obtained from the financial statements and management reports of practically all the Spanish credit institutions (banks, savings banks and credit unions), 75 different entities in the 12 periods. Thus, the models are estimated using unbalanced panel data, by ordinary least squares, since not all the entities cover the 12 periods. For the explanatory variables we have used data from Eurostat, the Bank of Spain, the Spanish National Institute of Statistics and the Ministry of Development of Spain.4

4. Empirical Results

Figure 1 shows the evolution of the two dependent variables during the study period.

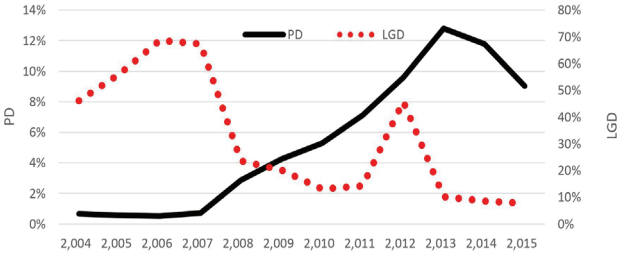

Figure 1. Evolution of the Dependent Variables

In the contrasts made to the data, the unit root hypothesis has been accepted in two explanatory variables, the HICP and the residential and commercial property prices. To avoid this problem, these variables have been included in the models in differences. Also, the dependent variables PD and LGD are cointegrated of order 1 C(1), so in the two models these variables will be included with a delay of one year, making the models dynamic. Furthermore, in 2012, a new financial regulation was implemented in

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Spain that greatly affected the impairment losses. [1] To take account of this circumstance, a dummy variable is included in the LGD model that takes value 1 in 2012 and 0 for all other periods.

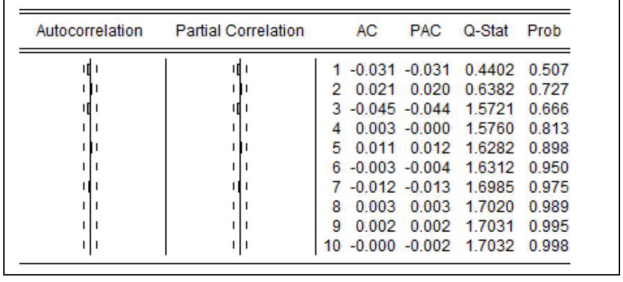
Thus, two models are proposed:

$$PD_{it} = \beta_1 + \beta_2 HICP_t + \beta_3 long - term\ interest_t + \beta_4 \text{Unemployment}_t + \beta_5 property\ prices_t + \beta_6 \text{Real GDP}_t + \beta_7 PD_{i,t-1} + \varepsilon_{it} \quad \text{Model 1}$$

$$LGD_{it} = \beta_1 + \beta_2 HICP_t + \beta_3 long - term\ interest_t + \beta_4 \text{Unemployment}_t + \beta_5 property\ prices_t + \beta_6 \text{Real GDP}_t + \beta_7 LGD_{i,t-1} + \varepsilon_{it} \quad \text{Model 2}$$

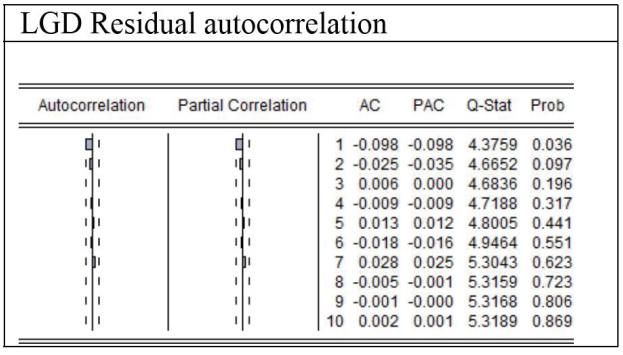
In neither of the models does residual autocorrelation exist (see Figure 2).

PD Residual autocorrelation



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.031	-0.031	0.4402	0.507
		2	0.021	0.020	0.6382	0.727
		3	-0.045	-0.044	1.5721	0.666
		4	0.003	-0.000	1.5760	0.813
		5	0.011	0.012	1.6282	0.898
		6	-0.003	-0.004	1.6312	0.950
		7	-0.012	-0.013	1.6985	0.975
		8	0.003	0.003	1.7020	0.989
		9	0.002	0.002	1.7031	0.995
		10	-0.000	-0.002	1.7032	0.998

LGD Residual autocorrelation



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.098	-0.098	4.3759	0.036
		2	-0.025	-0.035	4.6652	0.097
		3	0.006	0.000	4.6836	0.196
		4	-0.009	-0.009	4.7188	0.317
		5	0.013	0.012	4.8005	0.441
		6	-0.018	-0.016	4.9464	0.551
		7	0.028	0.025	5.3043	0.623
		8	-0.005	-0.001	5.3159	0.723
		9	-0.001	-0.000	5.3168	0.806
		10	0.002	0.001	5.3189	0.869

Figure 2. Residual autocorrelation

For heteroscedasticity models, they were estimated using the robust method of White and cross-section weights. Table 3 shows the descriptive statistics for all variables used:

Table 4 shows the Vector Autoregressive, and the table 5 shows impulse response functions

Table 4. Vector autoregression

	PD	LGD
PD(-1)	0.936	0.185988
	(0.060)	(0.053)
	[15.519]	[3.475]
PD(-2)	0.055	0.030
	(0.068)	(0.054)
	[0.813]	[0.555]
HICP-var	0.001	-0.019
	(0.001)	(0.009)
	[0.120]	[-2.165]
Long-term interest	1.005	10.101
	(0.157)	(2.741)
	[6.387]	[3.684]
Unemployment-var	0.0320	-0.510
	(0.004)	(0.090)
	[6.515]	[-5.635]
Property prices	-0.001	-0.001
	(0.000)	(0.000)
	[-3.639]	[-1.286]
Real GDP	-0.006	6.667
	(0.112)	(1.335)
	[-0.056]	[4.993]
Adj. R-squared	0.866921	0.257688
F-statistic	413.5758	22.98568
Standard errors in ( ) & t-statistics in [ ]		

Table 3. Descriptive statistics of the variables

	PD	LGD	HICP-var	Long-term interest	Unemployment-var	Property prices	Real GDP
Mean	4.39%	40.20%	-87.0%	4.09%	9.07%	1,805.52 €	1.76%
Median	2.47%	29.79%	-3.23%	4.10%	-2.60%	1,843.00 €	3.17%
Maximum	37.35%	551.46%	200.0%	5.85%	58.76%	2,071.00 €	4.17%
Minimum	0.07%	-12.43%	-1150.0%	1.74%	-16.51%	1,459.00 €	-3.57%
Std. Dev.	5.26%	41.16%	301.63%	0.80%	23.31%	206.91 €	2.49%
Observations	531	531	531	531	531	531	531

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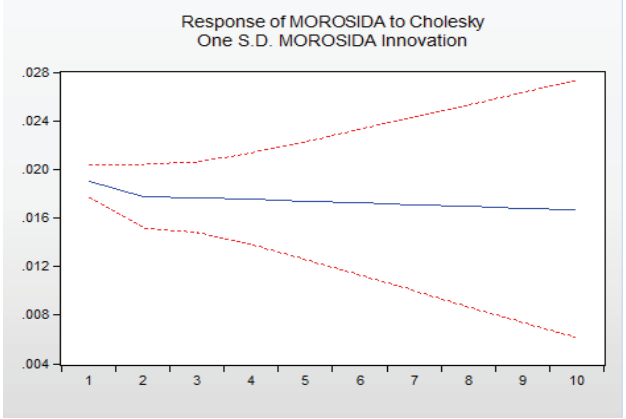
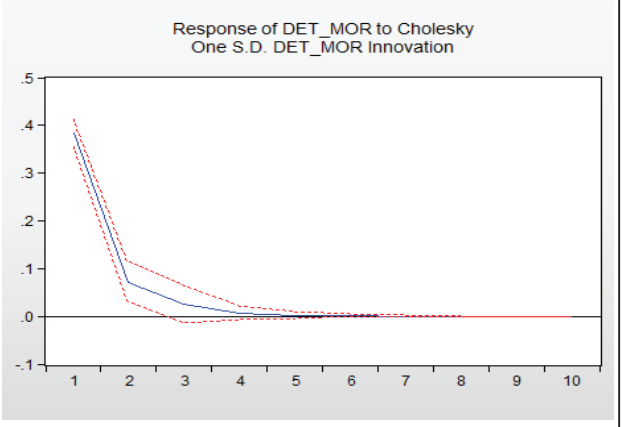
Table 5. Impulse response functions



Impulse response functions PD



Impulse response functions LGD

The results of the model econometric are shown in Table 6.

Table 6. Econometric models

	Model 1. PD	Model 2. LGD
C	-0.034**	1.600
	(0.014)	(0.360)
HICP	0.001**	-2.025**
	(0.000)	(0.010)
Long-term interest	0.656***	1.999
	(0.136)	(2.002)
Unemployment	0.023***	-0.380***
	(0.004)	(0.079)
Property prices	0.000	0.000
	(0.000)	(0.000)
Real GDP	-0.219	6.114***
	(0.143)	(2.130)
PD(-1) LGD(-1)	0.960***	0.331***
	(0.027)	(0.030)
Dummy 2012		0.394***
		(0.028)
Adjusted R-squared	0.938	0.784
Durbin-Watson statistic	2.084	2.206
F-statistic	1144.231	236.105

Significance levels *,**,*** at the 1%, 5% and 10% respectively. Robust standard errors between parentheses.

The impact on PD and LGD of the variables indicated by the EBA in stress test scenarios are:

Regarding the probability of default (PD), there exists considerable inertia of the dependent variable over the next year. With regard to other variables, the increase in the long-term interest rates produces an increase in PD; the same happens with unemployment and to a much lesser extent with the HICP. The only variable that causes a decrease in PD is the increase in real GDP, although its significance level is 0.12. And finally, the residential and commercial property prices variable is not statistically significant and, in addition, its coefficient is 0.

Turning to the LGD, the results are not the same, or similar. While there is also dependent variable inertia, it is much less, the coefficient being 0.33 compared to 0.96 for the PD. The increase in the HICP and the Unemployment decreases the LGD. The dummy variable has been significant with a coefficient of 0.39. The only variable that reduces the LGD with its increase is the Real GDP. The price of housing continues with the same coefficient, 0, and is not statistically significant, with the long-term interest not being statistically significant either.

6. Discussion

The results obtained for the PD are expected because it is logical that both the increase in unemployment and rising interest rates would involve an increase in the PD. The same happens with the Real GDP; if this parameter is increased it is logical that the PD would decrease. However, the results obtained for the LGD are not as logical. This circumstance can be seen in Figure 1. The graph shows that when the PD increases, the LGP decreases, and there is no reason for it to be that way. In the econometric model it is found that when the economy is growing (increase in Real GDP and lower unemployment), the LGD grows, just the opposite of the results obtained in the model of the probability of defaults. In this case, a smoothing effect of the results occurs, agreeing with other studies [20]. It is also

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significant that the level of inertia of the dependent variable (LGD) is three times lower than in the model of the PD. For all this we can say that the effects of the macroeconomic variables are not the same in the LGD as in the PD, and they are also not the expected ones. In addition, one must take into account the possible legislative changes, or other events that may affect the dependent variables studied, as was demonstrated with the legislative changes of 2012.

7. Direction for Future Work

The investigation should be deepened in three areas: Firstly, in the smoothing that has been detected and its possible causes. Secondly, the effects of the internal variables on the PD and LGD should be investigated, as they are likely to have a significant effect. The PD and LGD may not be the same in solvent credit institutions with high profits as in entities in economic difficulties. Finally, it is not logical that the significant change in the price of housing does not affect the study variables, so this aspect should also be looked into more closely.

Annotation

① This is an example of the uniqueness that each country can have.

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References

[1] Climent-Serrano, S. Stress test based on Oliver Wyman in Bank of Spain: an evaluation. Banks and Bank Systems, 2016a,11 (3), 64-72.

[2] Sahin, C., & de Haan, J. Market reactions to the ECB's Comprehensive Assessment. Economics Letters. http://dx.doi.org/10.2139/ssrn.2572985.

[3] Quijano, M. Information asymmetry in US banks and the 2009 bank stress test. Economics Letters. http://dx.doi.org/10.1016/j.econlet.2014.02.014.

[4] EBA (2016) EBA publishes 2016 EU-wide stress test results. http://www.eba.europa.eu/-/eba-publishes-2016-eu-wide-stress-test-results.

[5] EBA 2016 EU-Wide Stress Test – Methodological Note. http://www.eba.europa.eu/documents/10180/1259315/2016+EU-wide+stress+test-Methodological+note.pdf

[6] Huang, X., Zhou, H., & Zhu, H. A framework for assessing the systemic risk of major financial institutions. Journal of Banking and Finance. doi:10.1016/j.jbankfin.2009.05.017.

[7] Coffinet, J., Pop, A., & Tiesset, M. Monitoring financial distress in a high-stress financial world: The role of option prices as bank risk metrics. Journal of Financial Services Research. DOI: 10.1007/s10693-012-0150-2.

[8] Bellini, T. Integrated bank risk modeling: A bottom-up statistical framework. European Journal of Operational Research. doi:10.1016/j.ejor.2013.04.031.

[9] Cerutti E. & Schmieder C. Ring fencing and consolidated banks' stress tests. Journal of Financial Stability. doi:10.1016/j.jfs.2013.10.003.

[10] Schuermann, T. Stress testing banks. International Journal of Forecasting. doi:10.1016/j.ijforecast.2013.10.003

[11] Nyoka, C. Banks and the fallacy of supervision: the case for Zimbabwe. Banks and Bank Systems,2015, 10(3).

[12] Beltratti, A. and Stulz, R.M. The credit crisis around the globe: why did some banksperform better? Journal of Financial Economics. doi:10.1016/j.jfineco.2011.12.005

[13] Freixas Dargallo, X., De Hevia Payá, J. and Inurrieta Beruete, A. Determinantes macroeconómicos de la morosidad bancaria: un modelo empírico para el caso español', Moneda y Crédito, 1994, 199, 125-156.

[14] Fernández de Lis, S. Martínez, J. and Saurina, J. Crédito bancario, morosidad y dotación de provisiones para insolvencias en España, Boletín Económico Banco de España, Noviembre, 2000, 1-10.

[15] Delgado, J. and Saurina, J. Riesgo de crédito y dotaciones a insolvencias. Un análisis con variables macroeconómicas, Moneda y Crédito, 2004, 219, 11-42.

[16] Foos, D. Norden, L. and Weber, M. Loan growth and riskiness of Banks, Journal of Banking & Finance, 2010, 34, 2929-2940

[17] Climent-Serrano, S. an Pavia, JM. An analysis of loan default determinants: the Spanish case. Banks and Bank Systems, 2014, 9, (4) 116- 123.

[18] Bertsatos, G., & Sakellaris, P. A dynamic model of bank valuation. Economics Letters, http://dx.doi.org/10.1016/j.econlet.2016.05.014

[19] EBA Adverse macro-financial scenario for the EBA 2016 EU-wide bank stress testing exercise. http://www.eba.europa.eu/documents/10180/1383302/2016+EU-wide+stress+test-Adverse+macro-financial+scenario.pdf .

[20] Climent Serrano, S., Dotaciones para los deterioros de los créditos. Un estudio por ciclos económicos. Cuadernos de Economía (2016b), http://dx.doi.org/10.1016/j.cesjef.2016.01.001.

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