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Do CDS spread determinants affect the probability of default? A study on the EU banks

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Abstract

The paper is an investigation of the principal variables that have affected the EU banks' credit risk over the decade 2006–2016. In this context we adopt panel Tobit regressions in order to infer our object of analysis on the most significant CDS spread determinants illustrated by recent literature. In fact, the CDS spread should give a measure of credit risk, expressed by the probability of default. In accordance with the insertion of balance sheet, macroeconomic and market variables, we estimate the probability of default through a two-equation Merton model. Our results are analogous with the main trend of CDS spread determinants over time and contribute to continuing to consider the price of credit default swaps as a good indicator of banks' creditworthiness.

Keywords: probability of default, banks, structural models, CDS spread

JEL: G10, G21, G33

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1 Introduction

Over the last decade, European banking creditworthiness has been threatened by important events, such as financial crisis (Beyer, Cœuré, Mendicino 2017), the sovereign crisis (Gourinchas, Martin, Messer 2018; Roman, Bilan 2012) and the growth of non-performing loans (Baudino, Orlandi, Zamil 2018).

In this field, the analysis of banks' probability of default has become a non-trivial object of observation by financial regulators and academics (EBA 2017; Elizondo Flores et al. 2010).

The default probability of a bank is not just the likelihood of bankruptcy, but is also the deterioration of its creditworthiness. Consequently, it is the expression of credit risk defined as the possibility that an unexpected change in a counterparty's creditworthiness might generate a corresponding unexpected alteration in the market value of the associated credit exposure.

The probability of default of a bank depends on its specific factors on the one hand, and on market and macroeconomic factors on the other hand.

In this context, we intend to analyse the most significant variables affecting the probability of default, adopting CDS spread determinants. Specifically, a credit default swap is a credit derivative whose aim is to protect the buyer against an event of default dealing with the issuer of the underlying asset. Consequently, its price, called the spread, should disclose the market's credit risk perception and its determinants might explain the main variables causing the reference entity's credit risk. In particular the CDS spread has shown a leading role in price discovery, with reference to bond markets (e.g. Coudert, Gex 2010; Norden, Weber 2007; Blanco, Brennan, Marsh 2005) and rating announcements (Finnerty, Miller, Chen 2013; Hull, Predescu, White 2004).

In more detail, as a market indicator, CDS spread has been affected by high volatility, so we guess more accurate information might be given by the probability of default. Furthermore, the latter is implied in CDS spread and is an expression of credit risk. In accordance with the correlation between these two variables, we observe the influence of CDS spread determinants. Specifically, the related literature spans from accounting variables to market and general variables (Samaniego-Medina et al. 2016). In particular, contemporary research is developing in the study of systemic risk: general factors, indeed, seem to be more crucial than firm specific ones (Ejsing, Lemke 2011; Berndt, Obreja 2010).

In this paper, the EU banks' credit risk is analysed over the period 2006–2016. In particular, the study consists of a two-step analysis: in the first part, there is a calculation of the probability of default on a sample of 40 banks through a two-equation Merton model. This choice is consistent with the intention to estimate this variable under both firm specific and market perspectives. The second part deals with an investigation of the relationship between the estimated probability of default and the main CDS spread determinants: this inferential study is made by the implementation of Tobit regressions for panel data. Specifically, first we present a model for the whole period and then we distinctly analyse two sub-periods (namely 2009–2012 and 2013–2016) in order to focus our attention respectively on the sovereign debt crisis and on the NPL crisis.

Our contribution is twofold: an analysis the main variables affecting the EU banks' credit risk over time and a verification of analogies between the determinants causing the probability of default and CDS spread in order to assess if the latter is still a good indicator of banking credit risk.

2 Literature review

2.1 The estimation of the probability of default

There are various macro-categories of models to estimate the probability of default in order to measure credit risk.

In this paper we adopt a model belonging to the class of structural models. They are called in this way because they base the estimation of the probability of default of a company on the value of assets, on the value of debt and on the assets' volatility. Furthermore, structural models take inspiration from contingent claim analysis, and more specifically, from options theory (Black, Scholes 1973).

The two benchmarks are the Merton model (Merton 1974) and the KMV model (Kealhofer 1993; McQuown 1993; Vasicek 1984).

In particular, the Merton model is based on the intuition that the insolvency of a company takes place when the asset value is lower than the value of liabilities: if the investments made through the borrowed capital are lower than the expectations, there will be a loss in the equity.

The KMV model, benefiting from contingent claim analysis too, assumes that the value of shares is equivalent to the price of a call option on the value of an enterprise, with the same maturity of debt and with a strike price equal to the face value of debt repayment; in addition, the model obtains the probability of default starting from the calculus of the distance-to-default variable.

Structural models have been adopted and improved by a very large strand of literature, even recently. For example, Switzer, Tu and Wang (2018), in a study on the relation between corporate governance and default risk for 28 different countries outside North America during the post-financial crisis, measure the risk of default both through Merton-type five-year default probability and through CDS spread.

Blanc-Brude and Hasan (2016) develop a structural credit risk model that relies on cash flow data in order to derive credit risk metrics; the model, implemented through project finance debt, appears useful for illiquid assets, for which a time series of prices is not observable, and provides a clear link between an asset's fundamental characteristic and its risk profile.

Erlenmaier and Gersbach (2014), using a Merton model framework, study the relationship between default probabilities and default correlation among two firms, finding that correlation grows if the former rises.

Da and Gao (2010), criticizing Vassalou and Xing (2004), study the relationship between the stock market and default risk, measured through a default likelihood indicator derived from structural models. They find that the abnormal returns of risky stocks depend on short-term return reversals due to liquidity shock triggered by clientele change.

Other well-known categories of models are the scoring and the VaR models.

The scoring models assign a number, namely a score, that expresses the default probability of a firm. The most famous scoring model is Altman's Z-score (Altman 1968; 1993; 2013), which derives the score through financial ratios.

VaR (i.e. value at risk) models allow to measure the market risk associated with a financial asset. It represents the maximum possible loss arising from the detention of a financial asset over a given time horizon and with a specified level of confidence or probability (e.g. Changqing, Yanlin, Mengzhen 2015; Abad, Benito 2013).

2.2 CDS spread determinants

Below we illustrate the main recent contributions of literature on CDS spread determinants through the observation of balance sheet, market and macroeconomic variables.

Benbouzid, Leonida and Mallick (2018) suggest that CDS spread is driven by asset quality, liquidity and operations income ratio; they also check for bank size, finding a non-monotonic impact on CDS spread. Moreover, they estimate the level of bank size that minimizes the CDS spreads and find that financial institutions that grow beyond this threshold are subject to higher credit risk, implying that small and medium-sized banks are safer than large ones. In this context, they also highlight the "too--big-to-fail" phenomenon before the onset of the financial crisis.

Alexandre, Guillemin and Refait-Alexandre (2016) study the impact of banks' disclosure on the evolution of the related CDS spreads during the Eurozone sovereign debt crisis. They show the importance of information in terms of reduction of risk premium, since specific disclosure about sovereign exposure has a negative impact on CASC (cumulative abnormal CDS spread change); in contrast, they demonstrate that broad information positively influences CASC.

De Vincentiis (2014) compares the riskiness of global systemically important banks (G-SIB) with the no-SIBs, studying their respective CDS spreads. During a crisis period she finds the significance of the bank-specific variables (dimensions, profitability and capital stability) on the one hand, and on the other hand, the significance of the country risk, measured by sovereign CDS spreads for both kinds of banks.

Li and Zinna (2014), observing sovereign and bank CDS term structures, distinguish between the influence of systemic and sovereign risk on the banking variables, finding the highest level of systemic risk for Spain and Italy in absolute value; in a relative sense, in contrast, the most important component of risk for the banks of these countries is their respective sovereign risk, since their assets are mostly related to their home countries.

Hewavitharana and Rahmqvist (2011) examine the determinants of CDS spreads through leverage, stock return, volatility and interest rate. In a volatile context, they find a positive relationship between interest rate and CDS spreads and a negative relationship between the latter and leverage. The first relationship could be explained by the fact that in a context of economic distress, a firm is unable to meet its short-term debt payments; the second, on the other hand, is unclear. Opposite findings are shown by Ericsson, Jacobs and Oviedo (2009) during a non-crisis period.

Demirguc-Kunt, Detragiache and Merrouche (2010) regress the changes of the active banks' 5Y CDS spreads on the changes of some market variables and banks' capital variables. Their results confirm the latter variables as not significant, with the exception of leverage ratio. The expected signs of risk--free interest rate and stock price volatility are confirmed, respectively, with significance and not significance.

Calice, Ioannidis and Williams (2011) focus their work on large complex financial institutions and, in a section of the paper, state the relevance of the volatility of assets with respect to the risk of default. Furthermore, they show the interconnection between the CDS market and the banking sector in a systemic risk perspective.

Alter and Schüler (2012) explain the phenomenon of "private-to-public" risk transfer in Europe: before government interventions, bank credit spreads disperse to the sovereign CDS market, but after the bailouts there is an increased influence of sovereign CDS spreads on the bank spreads.

Acharya, Drechsler and Schnabl (2011), observing the CDS market over the period 2007–2010, underline a "two-way" feedback between sovereign and financial credit risk in the Eurozone and show an association between the increase in the sovereign CDS and a decrease in banks' stock returns in the post-bailout period. Analogous conclusions dealt with by Caruana and Avdjiev (2012).

Specifically, on balance sheet indicators, Chiaramonte and Casu (2013) focus on a panel of international banks. They find that even if banks record very high levels of leverage, CDS spreads are not high as well until the outbreak of the crisis: this means that before this event, the market did not evaluate leverage as a significant factor of riskiness for banks, unlike the other sectors. Furthermore, in this study the significance of the indicator of asset portfolio quality as a predictor of default emerges.

The low explanatory power of leverage ratio for the banking sector is also shown by Düllmann and Sosinska (2007) and Kalemli-Ozcan, Soresen and Yesiltas (2011).

More recently Li and Fu (2017) carry out an analysis on CDS spread determinants and find that market value indicators (Tobin's Q, stock market returns and interest rate), appear to be more important than book value indicators (i.e. ROA, ROE). Their observations deal with two European countries (Germany and France) and two Asian countries (South Korea and Hong Kong).

3 Methodology

3.1 The sample

The sample is made up of 40 banks of the European Union both from the Eurozone (2 Austria, 2 Belgium, 4 Germany, 1 Finland, 4 France, 4 Greece, 2 Ireland, 6 Italy, 1 Netherlands, 2 Portugal, 1 Slovakia, 4 Spain) and outside the Eurozone (1 Czech Republic, 2 Denmark, 1 Poland, 3 Sweden)[1] (see Table 1). These observation units represent the main EU banks and are derived from a wider sample, after excluding banks that have failed during the period of analysis.

3.2 The estimation of the dependent variable: the probability of default

In this section we outline the method adopted to estimate the one-year probability of default of the banks in the sample.

This is a two-equation Merton model, so it belongs to the category of structural models for credit risk assessment.

More specifically, our model borrows from Merton's assumption of log-normal distribution of value of assets and the KMV's solution of a two-equation model. Even if value of banking assets generally isn't normally distributed in times of distress (like the period analysed), the estimation of the probability of default for banks is quite similar both under a log-normal and not log-normal distribution hypothesis, as demonstrated by Nagel and Purnanandam (2019).

[1] Sources of data: Datastream, Orbis Bank Focus, ECB, Eurostat.

The model is based on a system made by two unknowns: asset value and asset volatility.

$$\begin{cases} E_t = A_t\Phi(d_1) - L_t e^{-\mu(T-t)}\Phi(d_2) \\ \sigma_E = \sigma\Phi(d_1)\ At/Et \end{cases}$$

where:

E_t – current equity value,
A_t – asset value,
σ – asset volatility,
σ_E – equity volatility,
L_t – current liabilities book value,
$d_1 = \dfrac{\ln(At/L) + (\mu + \sigma^2/2)(T-t)}{\sigma\sqrt{T-t}}$,
$d_2 = d_1 - \sigma\sqrt{T-t}$,
μ = drift rate = $\ln(1+E[R_i])$[2],
$T = 1$,
$t = 0$.

The first equation derives from Black and Scholes formula; in the second formula, equity is like a call on the asset value and its volatility (namely its riskiness), depends on the volatility of the asset.

If the equity value E_t and an estimate of the equity volatility σ_E are known, there are two equations with two unknowns. This system of equations does not have a closed-form solution, but numerical routines can be used to solve it.

Now it is necessary to estimate the annual equity volatility σ_E. The estimation is based on the historical volatility measured over the preceding exchange days (conventionally 260), calculated on daily log returns.

Iorder to solve the system, the methodology adopted proceeds as follows.

First of all, the known variables at the current time t (namely: E_t, σ_E, L_t, μ and T) are inserted.

With reference to the unknown variables, i.e. the asset value (A_t) and the asset volatility (σ), we need to assign a feasible initial value.

These initial values are calculated with the following approximations:

$$At:\ Et + Lt$$
$$\sigma = \sigma_E Et/At\left(assuming\ \ \Phi(d_1) = 1\right)$$

After having also inserted the Black and Scholes formulas, the following target equation has to be solved in order to minimize the sum of squared percentage differences between model values and observed values of the equity and of assets, as shown below:

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2 According to CAPM (Sharpe 1963): $E[R_i] - R = \beta_i\left(E[R_M] - R_f\right)$,
so $E[R_i] = R_f + \beta_i * market\ risk\ premium$, where:
R_M – daily log-return of Stoxx Europe 600 Banks,
R_f – daily log Euribor.

$$\left(Model\ E_t\ /Observed\ E_t - 1\right)^2 + \left(Model\ \sigma_E\ /Observed\ \sigma_E - 1\right)^2$$

The aforementioned equation is solved if the difference between the estimated and the observed initial values of E_t and σ_E tends to zero.

Now, according to Black and Scholes' formula, it is possible to calculate d_1 and d_2 in order to obtain the probability of default referred to the sample.

At this point there are all the elements necessary to calculate the distance to default (DD) through the following formula:

$$\mathrm{DD} = \frac{\left(\ln\left(\mathrm{At}\right) + \left(\mu - \sigma^2/2\right)\left(\mathrm{T} - \mathrm{t}\right) - \ln\left(L\right)\right)}{\sigma\sqrt{\mathrm{T} - \mathrm{t}}}$$

Now we can derive the one-year probability of default (*PD*) as:

$$PD = \Phi\left(-DD\right)$$

The estimated probabilities of default are shown below in Table 1 and Figure 1.

3.3 The regression model

In this section there is an inferential analysis based on panel generalized linear models, where the dependent variable is made by the probability of default before estimated.

Since the latter is a continuous variable delimited among the interval [0; 1], we adopt the Tobit model.

Random method is used since, as demonstrated by literature (Greene 2002; Baltagi 2000; Maddala 1987), random effects Tobit regressions for thin samples give more robust estimations than fixed effects regressions.

In particular, PD^* indicates the latent dependent variable in order to calculate the Tobit linear regression. Specifically:

$$PD^* = g\left(E\left[PD\right]\right)$$

where $g()$ represents the link function for a Tobit transformation.[3]

The independent variables, listed below, are balance sheet ratios, macroeconomic and market variables.

ROE – return on equity (profitability ratio),
LEV – leverage ratio (capital ratio),
*TIER*1 – Tier 1 ratio (capital ratio),
LOD – loans over deposits (liquidity ratio),

[3] The real dependent *PD* variable derives from the inverse of the link function g().

GDP – gross domestic product annual growth,
TENYR – ten year government bond yield.
Below, the equation for the overall period of analysis 2006–2016 is shown:

$$PD^*_{i,t} = \beta_0 + \beta_1 (ROE)_{i,t} + \beta_2 (LEV)_{i,t} + \beta_3 (TIER1)_{i,t} + \beta_4 (LOD)_{i,t} + \beta_5 (TENYR)_{i,t} + \beta_6 (GDP)_{i,t} + \varepsilon_{i,t}$$

(Model 1)

In order to analyse the impact of the Eurozone crisis on the probability of default of banks, we study the period 2009–2012, with a focus on macroeconomic and market variables. In this context, price volatility (PVOL) is introduced, while the impact of the debt crisis is controlled first through the ten year government bond yield and then with the insertion of a new variable: the sovereign CDS spread (SCDS)[4] of each country of the sample.[5]

Below the two related equations are shown:

$$PD^*_{i,t} = \beta_0 + \beta_1 (LEV)_{i,t} + \beta_2 (LOD)_{i,t} + \beta_3 (TENYR)_{i,t} + \beta_4 (GDP)_{i,t} + \beta_5 (PVOL)_{i,t} + \varepsilon_{i,t}$$

(Model 2a)

$$PD^*_{i,t} = \beta_0 + \beta_1 (LEV)_{i,t} + \beta_2 (LOD)_{i,t} + \beta_3 (SCDS)_{i,t} + \beta_4 (GDP)_{i,t} + \beta_5 (PVOL)_{i,t} + \varepsilon_{i,t}$$

(Model 2b)

Finally, a regression for the sub-period 2013–2016, the NPL crisis years, is implemented with deeper attention to the asset quality of banks. Consequently, GDP is replaced with a new balance sheet variable: non-performing loans over gross loans ratio (NPLGL).

The related equation is the following:

$$PD^*_{i,t} = \beta_0 + \beta_1 (ROE)_{i,t} + \beta_2 (LEV)_{i,t} + \beta_3 (TIER1)_{i,t} + \beta_4 (LOD)_{i,t} + \beta_5 (TENYR)_{i,t} + \beta_6 (NPLGL)_{i,t} + \varepsilon_{i,t}$$

(Model 3)

4 Results

4.1 The estimated probabilities of default

The estimated yearly probabilities of default are reported in Table 1 and shown graphically in Figure 1. The overall mean is 6.6% (Table 5a), but during the sub-periods, as could be expected, the mean values are higher, i.e. 7.6% and 8.2% respectively (Tables 6a and 7a). As concerns the variability of our results, we have shown the annual standard deviations (Table 1). In particular, we note the lowest values

[4] In order to have homogeneity for the unit of measurement, the original SCDS spreads, expressed in basis points, are converted into percentage points.

[5] The adoption of two distinct models is also statistically justified by the very high correlation between TENYR and SCDS covariates (+87%, see Table 9).

before the onset of the financial and sovereign crises, namely 2.4% and 3%, respectively, for 2006 and 2007. Starting from 2008, market volatility is reflected in the increase in the variability of our results. In particular, during the sub-period 2009–2012, the standard deviation reaches the values 17.4% and 17.8%, respectively, in 2009 and 2012: the lower values recorded in 2010 and 2011 could be explained by the government bailouts of banks; notwithstanding this, the successive regrowth of the standard deviation might be due to the “sovereign-bank risk nexus” (Fratzscher, Rieth 2019) of the European Union’s banking sector. Moreover, during the sub-period 2013–2016, the additional instability created by the NPL crisis emerges in the highest values of the variability of our estimations, with the greatest standard deviation equal to 21%, in 2015. The standard deviation of the estimated variable shows the variegated situation of credit risk in the EU: in fact, our results testify to higher values of default probability for peripheral European banks than core ones. Nevertheless, in our sample the maximum estimated probability of default (94.25%) concerns Dexia, a Belgian bank: we deem this observation unit an outlier.

4.2 The relation between the estimated probability of default and CDS determinants

In this section we illustrate the results of the regression analysis.

All the outputs are shown in tables reported. Both parameters for latent (PD^*) and real (*PD*) probability of default are shown.

Model 1 (Table 2) deals with the period as a whole.

The log-likelihood and the AIC are the best with respect to other experimented models (respectively 334.78 and -651.55, Table 11).[6] Each variable of the regression is significant, with the exception of *ROE*. All the signs are respected; even if the positive sign of Tier 1 ratio is questionable, this is consistent with the Pearson correlation sign (+10%, Table 8). Moreover, high levels of this ratio could mislead the observants from potential criticalities of banks, in terms of credit risk (Abou-El-Sood 2016).

In particular, there are reasonable positive signs for leverage, loans over deposits and ten year government bond yields, in fact, theoretically with respect to:

LEV – the higher the liabilities of the company, the higher the probability of default,

LOD – the higher the ratio, the lower the liquidity of bank, so the higher its credit risk,

TENYR – the higher the government bond yields, the higher the perception of sovereign risk, therefore the higher the growth of banks’ credit risk.

The expected negative sign dealing with *GDP* is respected: it is intuitive that better economic conditions represent a good framework to lessen banking sector credit risk caused by the shortage of customers’ loans repayment (Ghyasi 2016).

We also note that the highest correlation between the probability of default and the adopted covariates concern macroeconomic variables (+ 35% for *TENYR* and -24% for *GDP*, Table 8): the result confirms the relevance of these factors for banking credit risk assessment over the period analysed, as stated by recent research (Jabra, Mighri, Mansouri 2017).

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[6] Even if Model 1a reports a slightly better margin for the Akaike test (-1.9), the best log-lik concerns Model 1; furthermore, Model 1a has shown important criticalities in terms of multicollinearity. Moreover, we wanted to test the significance of a non-trivial ratio, like ROE.

As concerns the analysis of the period 2009–2012, we observe the results referred to by Model 2a and Model 2b (Tables 3a and 3b).

These models provide the best results in terms of log-likelihood and Akaike test compared to other ones (Table 12). In particular, Model 2b seems to be even better than Model 2a (the referred values are respectively 131.65 and -247.30).

As already mentioned, in this period of observation there is more focus on the covariates most representative of the systemic risk, such as *TENYR, SCDS* spread and *PVOL* (Tamakoshi, Hamori 2013). These variables are the most correlated with the probability of default (respectively 44%, 42% and 50%, Table 9).

The results of the two regressions confirm the expected signs. In particular the positive sign for the government bonds, already discussed, is interesting as well as for:

– *PVOL*: the higher the stock volatility, the higher the credit risk transmitted by the market to banks;

– *SCDS*: the higher the spread, the higher the market perception of sovereign risk, so the higher the transfer of riskiness to the banking sector.

In particular, the sovereign CDS spread variable is the most significant in the analysis for this sub--period: as demonstrated (Avino, Cotter 2014) during the Eurozone debt crisis, the *SCDS* spread has a leading role in the discovery of banking credit risk.

Finally, as concerns Model 3 (Table 4), we focus our attention on the specific conditions of banks, with more regard to the balance sheet ratios and on the issue of NPLs.

In particular, *GDP* is replaced with the non-performing loans on gross loans ratio. This choice is justified by the fact that during the period analysed there is greater attention on the asset quality of banks. Meanwhile, the observation of sovereign risk and of the general level of liquidity is still relevant; in this sense we believe that it is important to also insert the *TENYR* variable. Consequently, this model shows better results in terms of log-lik and AIC (respectively 126.33 and -234.65) compared to Model 3a (Table 13).[7]

All the signs presented in the correlation matrix (Table 10) are confirmed. In particular, the new covariate is positively correlated with the probability of default by 38%: obviously the higher the percentage of NPL, the higher the riskiness of the bank. Specifically, the regression has shown a significant output for this variable.

We also note the very high significance of the leverage ratio.

These results confirm the negative relation between the latter and the NPL ratio (Kashif et al. 2016); furthermore, we show the necessity to consider the quality of loans assets under a systemic point of view, as the variable is correlated with macroeconomic variables (Gila-Gourgoura, Nikolaidou 2017; Serwa 2016), like interest rates (Table 10).

5 Conclusions

This paper has investigated credit risk in the EU banking sector. To this purpose, we have inferred probability of banks' default on CDS spread determinants through a two-step analysis: we have first estimated the dependent variable and then implemented Tobit panel regressions.

[7] Even if Model 1 shows better results in terms of log-likelihood and Akaike test in relation to Model 3, it is not consistent with the object of research for the period 2013–2016 and it is also biased by multicollinearity among the covariates.

The probabilities of default have been estimated through a structural model: this choice appears consistent with the aim of studying credit risk both from the perspectives of firms and the market.

In the regression analysis we intended to understand both the main variables affecting the probability of default over time and whether they are the same that influence the CDS spread: in this way, we wanted to see if the latter can still be considered a good indicator of banking credit risk.

Specifically, the estimation of the probability of default has shown growing values over the years, with a particular increase during the periods of crisis.

Overall, as concerns the inferential analysis, we observed the influence of some variables related to CAMELS factors (Chodnicka-Jaworska, Jaworski 2017) and, analogously to recent CDS spread literature, we found a growing impact of macroeconomic and market variables during times of distress (e.g. Annaert et al. 2013).

In particular, during periods of crises, in terms of sovereign debt and NPLs respectively, the influence of country credit risk and asset quality problems appears significant.

The attention to these two aspects has been highlighted by the analysis of the referred periods (2009–2012 and 2013–2016 respectively), through the insertion of two explanatory variables: sovereign CDS spread variable (*SCDS*) and non-performing loans over equity (*NPLGL*).

The choice of the *SCDS* variable is due to the linkage of macroeconomic and policy uncertainty to the banking sector: as stated by academics, this is especially true for countries affected by the sovereign debt crisis (Drago, Di Tommaso, Thornton 2017; Yu 2017).

As concerns the study of the period 2013–2016, the adoption of *NPLGL* allows to observe the impact of the relation between asset quality and the capital structure of banks. This fact is particularly interesting since, as demonstrated (Bonaccorsi di Patti et al. 2014), in time of distress a high level of leverage ratio reduces banks' resilience: the worsening of assets due to macroeconomic factors becomes more destabilising if the level of equity is too low with respect to debt. This issue is also pivotal from an economic point of view, as credit risk due to NPLs, could reduce the lending activity of banks (Cucinelli 2015).

Definitively, we deem that the credit default swap price can still be considered a good indicator of banks' credit risk, despite the volatility caused by the speculative use of this derivative. As shown throughout the paper, its determinants have had an analogous impact on the default probability.

As concerns the perspectives for new research, the insight into banking probability of default could be proceeded by analysing credit risk from a systemic perspective (Giglio, Kelly, Pruitt 2016; Black et al. 2016), with a special focus on asset quality (Bottazzi, De Sanctis, Vanni 2016). In this context we believe it would be interesting to put more attention on the study of NPLs, finding out their main determinants and the possible strategies to reduce banking credit risk (Bruno, Iacoviello, Lazzini 2015). Moreover, as the European banking sector is characterized by linkages in terms of both sovereign and financial exposures, the research may be improved with other methodologies, such as network analysis (Westphal 2015).

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Appendix

Table 1
Estimated 1-year probabilities of default (%)

Bank	Country	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Erste Bank	AT	0.0013	0.0214	11.3802	12.5521	0.6499	2.5887	1.2421	0.1496	0.3369	0.0571	1.2100
Raiffeisein	AT	0.1388	0.1378	19.9823	8.7844	1.6466	3.8253	1.7096	0.0254	1.2341	1.8268	0.3414
Dexia	BE	0.0000	0.0359	22.8580	17.8459	1.0382	19.6051	81.8931	92.1384	94.2523	82.6617	78.5243
Kbc	BE	0.0001	0.0005	17.8605	42.9350	1.7806	9.2255	5.4217	0.0832	0.0194	0.0020	1.4266
Komercni	CZ	0.0010	0.0002	4.6179	1.5108	0.0190	0.0827	0.0014	0.0006	0.0000	0.0001	0.0035
Deutsche Bank	DE	0.0000	0.0008	10.9768	8.1137	0.1130	2.5760	0.4595	0.0031	0.0017	0.0609	5.0432
Commerzbank	DE	0.0201	0.0505	16.9895	15.3462	0.0484	7.0341	3.0058	1.4104	0.0687	0.0117	2.6059
Oldenburgische	DE	0.0004	0.0000	0.9107	0.0000	0.0000	0.2789	5.2301	1.2911	0.5066	0.3310	4.1039
Umweltbank	DE	0.3074	0.0099	0.5247	0.2185	0.0067	0.4536	0.0863	0.0167	0.6941	0.0408	1.1443
Danske Bank	DK	0.0000	0.0001	4.3222	2.9154	0.1920	1.0602	0.0799	0.0029	0.0000	0.0007	0.4136
Jyske Bank	DK	0.0013	0.0038	4.3558	3.8345	0.2671	5.6768	0.0412	0.0002	0.0009	0.0001	0.5589
Alandsbanken	FI	0.1281	1.7088	1.2778	0.9125	0.6126	2.3333	2.8642	2.8256	0.7601	0.7533	0.4897
Bnp Paribas	FR	0.0001	0.0063	7.0703	6.8205	0.8275	6.0508	0.8893	0.0111	0.0011	0.0181	1.7191
Natixis	FR	0.0938	0.6078	21.0389	19.0177	1.0917	4.1189	1.8163	0.0883	0.0224	0.0780	2.8843
Credit Agricole	FR	0.0016	0.0025	13.6560	5.0653	1.5305	6.3699	3.0810	0.1030	0.0300	0.0814	2.0650
Societe Generale	FR	0.0002	0.0213	11.8453	5.6002	2.3322	10.5916	3.1705	0.1846	0.0241	0.0415	3.5456
Alpha Bank	GR	0.0032	0.0026	3.8666	5.5396	8.2749	27.4157	44.2052	16.5831	1.4238	57.9601	19.7663
Eurobank Ergasias	GR	0.0019	0.0019	2.9150	6.8875	10.9372	29.1574	52.1272	67.2399	8.0791	63.6779	34.6116
National Bank of Greece	GR	0.0476	0.0012	9.9012	6.2688	5.7469	20.3922	29.4034	31.1368	5.5515	69.0042	30.3454
Piraeus Bank	GR	0.0005	0.0035	0.0445	5.3925	5.3566	6.1934	39.9120	32.1413	32.7963	24.6892	77.5244
Allied Irish Bank	IE	0.0003	0.0907	23.3827	76.5610	29.9724	35.5197	10.1566	7.1893	5.9234	10.5089	12.2838
Bank of Ireland	IE	0.0000	0.1237	43.5979	76.4810	25.7042	23.2742	3.6090	0.6083	0.7127	0.1255	7.0524
Unicredit	IT	0.0000	0.0043	9.7546	6.7776	0.9536	7.8806	7.6572	0.2479	0.1997	0.1787	10.4555
Intesa Sanpaolo	IT	0.0001	0.0000	4.7223	2.5188	0.8273	8.2518	2.4263	0.1779	0.1300	0.0826	5.0267
Mps	IT	0.0000	0.0000	0.8089	0.3142	0.1174	3.4115	9.5726	2.7722	16.0134	4.7379	24.9590
Bpm	IT	0.0001	0.0111	4.9237	8.1553	0.4828	3.7701	5.8116	1.3121	3.0206	0.4914	17.5933
Mediobanca	IT	0.0000	0.0000	0.0382	0.2749	0.1107	0.5897	1.5797	0.4650	0.1073	0.0301	4.5596
Ubi	IT	0.0000	0.0000	0.3674	1.1081	0.0681	3.2483	2.4953	0.4623	0.7346	0.2657	6.8629

Bank	Country	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Van Lanschot Kempen	NL	0.0116	0.0000	0.0077	0.0057	0.0013	0.0035	0.0128	0.1146	0.0036	0.0179	0.5353
Bank Pekao	PL	0.0330	0.0129	2.5547	3.1983	0.0011	0.1538	0.0016	0.0001	0.0002	0.0006	0.0045
Banco Comercial Portugues	PT	0.0000	0.0714	1.2391	0.2799	0.3616	3.1291	4.7774	2.2977	6.9877	3.3889	10.7004
Banco Bpi	PT	0.0033	0.0001	2.4482	0.1603	0.3258	1.9702	1.2842	0.7268	1.1137	3.3594	1.1133
Vseobecna Uverova Banca	SK	0.0000	0.0000	0.0523	1.9835	4.4289	0.6791	1.9801	1.6934	5.2014	1.5411	3.7892
Swedbank	SE	0.0013	0.0875	12.0110	14.6453	0.1128	0.8142	0.0015	0.0012	0.0000	0.0002	0.3509
Nordea	SE	0.0010	0.0001	3.2560	5.0227	0.0207	0.3209	0.0024	0.0000	0.0000	0.0049	0.4994
Halendsbanken	SE	0.0007	0.0002	2.6635	3.0017	0.0005	0.0302	0.0002	0.0000	0.0000	0.0016	0.4760
Banco Sabadell	SP	15.2395	19.1470	34.9278	29.7639	30.0656	31.2084	42.7197	36.7448	33.1377	34.2728	52.2021
Banco Santander	SP	0.0000	0.0000	3.4814	1.2493	1.1721	0.4316	0.3900	0.0037	0.0002	0.1130	3.0060
Bankinter	SP	0.0002	0.0910	2.5758	0.3707	0.8126	0.7238	1.5614	0.3040	0.0293	0.0041	0.4297
Bbv Argentaria	SP	0.0000	0.0000	2.4481	0.8780	0.9079	0.9231	0.5487	0.0034	0.0017	0.0049	2.0035
Std. dev.		2.4	3	10	17.4	7.5	9.6	17.8	19	16	21	19

Table 2
Regression results: 2006–2016

Variables	PD* (Tobit)	t-value	PD	Pr(>|t|)
Intercept	-1.769e-01 (3.099e-02)	-5.708	-1.831869e-01	1.14e-08 ***
ROE	-7.779e-06 (2.499e-05)	-0.311	-3.348211e-05	0.755614
LEV	1.535e-05 (5.490e-06)	2.797	2.708538e-05	0.005158 **
TIER1	1.002e-02 (1.561e-03)	6.416	9.304568e-03	1.39e-10 ***
LOD	3.299e-04 (7.927e-05)	4.162	2.587386e-04	3.16e-05 ***
TENYR	1.735e-02 (2.623e-03)	6.616	2.165324e-02	3.68e-11 ***
GDP	-5.767e-03 (1.738e-03)	-3.318	-3.366672e-03	0.000906 ***
LogLik 334.775 AIC -651.5499				

Notes:
Standard errors are reported between parentheses. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Table 3a
Regression results: 2009–2012

Variables	PD* (Tobit)	t-value	PD	Pr(>|t|)
Intercept	-1.763e-01 (5.002e-02)	-3.525	-1.778909e-01	0.000424 ***
LEV	9.942e-06 (6.057e-06)	1.641	7.825915e-06	0.100710
LOD	3.729e-04 (1.707e-04)	2.185	2.106018e-04	0.028915 *
TENYR	1.146e-02 (3.596e-03)	3.187	8.660292e-03	0.001438 **
GDP	-7.088e-03 (2.652e-03)	-2.673	-4.873829e-03	0.007518 **
PVOL	3.828e-03 (1.726e-03)	2.218	5.307751e-03	0.026566 *
LogLik 126.62 AIC -237.24				

Notes:
Standard errors are reported between parentheses. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Table 3b
Regression results: 2009–2012

Variables	PD*(Tobit)	t-value	PD	Pr(>|t|)
Intercept	-1.330e-01 (5.219e-02)	-2.549	-1.498391e-01	0.0108 *
LEV	1.400e-05 (5.870e-06)	2.385	1.108484e-05	0.0171 *
LOD	3.886e-04 (1.718e-04)	2.262	1.974230e-04	0.0237 *
SOVCDS	8.289e-04 (1.763e-04)	4.703	6.327701e-04	2.57e-06 ***
GDP	-7.784e-03 (2.467e-03)	-3.156	-5.325199e-03	0.0016 **
PVOL	3.717e-03 (1.620e-03)	2.295	5.503724e-03	0.0217 *
LogLik 131.65 AIC -247.30				

Notes:
Standard errors are reported between parentheses. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Table 4
Regression results: 2013–2016

Variables	PD*(Tobit)	t-value	PD	Pr(>|t|)
Intercept	-1.894e-01 (6.046e-02)	-3.132	-0.1727660220	0.001735 **
ROE	-9.980e-04 (3.370e-04)	-2.962	-0.0006404325	0.003061 **
LEV	1.138e-04 (3.264e-05)	3.487	0.0002077859	0.000488 ***
TIER1	7.213e-03 (3.656e-03)	1.973	0.0041359406	0.048508 *
LOD	1.844e-04 (2.088e-04)	0.883	-0.0001716661	0.377120
TENYR	1.147e-02 (6.315e-03)	1.816	0.0270416300	0.069365.
NPLGL	4.113e-03 (1.416e-03)	2.906	0.0031506336	0.003666 **
LogLik 126.33 AIC -234.65				

Notes:
Standard errors are reported between parentheses. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Table 5a
Descriptive statistics of probability of default 2006–2016

Min.	Q1	Median	Mean	Q3	Max.
0.0000	0.01578	0.70337	6.60025	5.03084	94.25233

Table 5b
Descriptive statistics of the covariates 2006–2016

	Q1	1st.	Median	Mean	Q3	Max.
ROE	-4298.470	2.335	7.490	-11.479	14.133	120.810
LEV	-9357.70	404.7	634.2	699.6	884.2	9973.7
TIER1	-7.300	8.575	11.175	11.308	13.158	28.700
LOD	46.32	117.98	145.29	169.26	191.93	1002.19
TENYR	0.090	2.121	3.797	3.877	4.430	22.498
GDP	-9.1000	-0.3000	1.2000	0.9216	2.6000	25.1000

Table 6a
Descriptive statistics of probability of default 2009–2012

Min.	Q1	Median	Mean	Q3	Max.
0.00000	0.3852	2.1579	7.5739	6.7883	81.8931

Table 6b
Descriptive statistics of the covariates 2009–2012

	Min.	Q1	Median	Mean	Q3	Max.
LEV	-9357.7	460.1	666.1	604.7	903.1	6103.5
LOD	79.69	122.62	145.53	169.40	198.50	524.69
PVOL	12.10	25.67	30.73	31.25	36.89	54.97
TENYR	1.403	3.004	3.979	4.968	5.424	22.498
GDP	-9.1000	-3.7250	0.2000	-0.8869	1.9000	6.0000
SOVCDS	0.0249	0.1430	0.4147	13.7617	1.1993	359.3228

Table 7a
Descriptive statistics of probability of default 2013–2016

Min.	Q1	Median	Mean	Q3	Max.
0.00000	0.02169	0.49053	8.20211	4.21784	94.25233

Table 7b
Descriptive statistics of the covariates 2013–2016

	Min.	Q1	Median	Mean	Q3	Max.
ROE	-225.700	1.137	5.680	1.879	10.393	98.140
LEV	35.8	301.2	461.5	610.2	768.5	5166.9
TIER1	7.47	11.85	12.90	14.06	16.20	28.70
LOD	76.14	111.13	132.81	162.30	188.90	598.18
TENYR	0.0900	0.8425	1.7142	2.5155	2.8925	10.0542
NPLGL	0.200	3.765	5.925	11.222	13.355	58.040

Table 8
Correlation matrix 2006–2016

	PD	ROE	LEV	TIER1	LOD	TENYR	GDP
PD	1	-0.11	0.12	0.10	0.21	0.35	-0.24
ROE	-0.11	1	0.20	0.21	-0.05	-0.30	0.20
LEV	0.12	0.20	1	0.01	0.25	-0.24	0.05
TIER1	0.10	0.21	0.01	1	0.06	-0.30	0.15
LOD	0.21	-0.04	0.25	0.02	1	-0.03	-0.06
TENYR	0.35	-0.30	-0.24	-0.30	-0.03	1	-0.45
GDP	-0.24	0.20	0.05	0.15	-0.06	-0.44	1

Table 9
Correlation matrix 2009–2012

	PD	LEV	LOD	TENYR	GDP	PVOL	SCDS
PD	1	-0.07	0.15	0.44	-0.30	0.49	0.42
LEV	-0.07	1	0.07	-0.37	0.12	-0.16	-0.42
LOD	0.15	0.07	1	-0.05	0.01	0.14	-0.02
TENYR	0.44	-0.36	-0.05	1	-0.51	0.52	0.87
GDP	-0.30	0.12	0.01	-0.51	1	-0.22	-0.41
PVOL	0.50	-0.16	0.14	0.52	-0.22	1	0.42
SCDS	0.42	-0.42	-0.03	0.87	-0.41	0.42	1

Table 10
Correlation matrix 2013–2016

	PD	ROE	LEV	TIER1	LOD	TENYR	NPLGL
PD	1	-0.34	0.53	0.14	0.39	0.44	0.38
ROE	-0.34	1	-0.16	0.06	-0.04	-0.24	-0.32
LEV	0.53	-0.16	1	0.16	0.77	-0.13	-0.15
TIER1	0.14	0.06	0.16	1	0.19	0.02	-0.08
LOD	0.39	-0.04	0.78	0.19	1	-0.10	-0.08
TENYR	0.44	-0.23	-0.13	0.02	-0.10	1	0.72
NPLGL	0.38	-0.32	-0.15	-0.08	-0.08	0.72	1

Table 11
Log-likelihood and Akaike test 2006–2016

	ROE	LEV	TIER 1	LOD	TENYR	GDP	Log-lik	AIC
Model 1	×	×	×	×	×	×	334.78	-651.55
Model 1a		×	×	×	×	×	334.73	-653.45
Model 1b	×		×	×	×	×	330.85	-645.71
Model 1c	×	×		×	×	×	315.16	-614.32
Model 1d	×	×	×		×	×	326.13	-636.26
Model 1e	×	×	×	×		×	305.52	-595.03
Model 1f	×	×	×	×	×		329.35	-642.70

Table 12
Log-likelihood and Akaike test 2009–2012

	ROE	**LEV**	**TIER 1**	**LOD**	**TENYR**	**GDP**	**PVOL**	**SCDS**	**Log-lik**	**AIC**
Model 2a		×		×	×	×	×		126.62	-237.24
Model 2b		×		×		×	×	×	131.65	-247.30
Model 2c	×	×	×	×	×	×	×		126.99	-233.99
Model 1	×	×	×	×	×	×			125.20	-232.40

Table 13
Log-likelihood and Akaike test 2013–2016

	ROE	**LEV**	**TIER 1**	**LOD**	**TENYR**	**GDP**	**NPLGL**	**Log-lik**	**AIC**
Model 3	×	×	×	×	×		×	126.33	-234.65
Model 3a	×	×	×	×		×	×	124.80	-231.60
Model 1	×	×	×	×	×	×		131.02	-244.05

Figure 1
Estimated probabilities of default 2006–2016

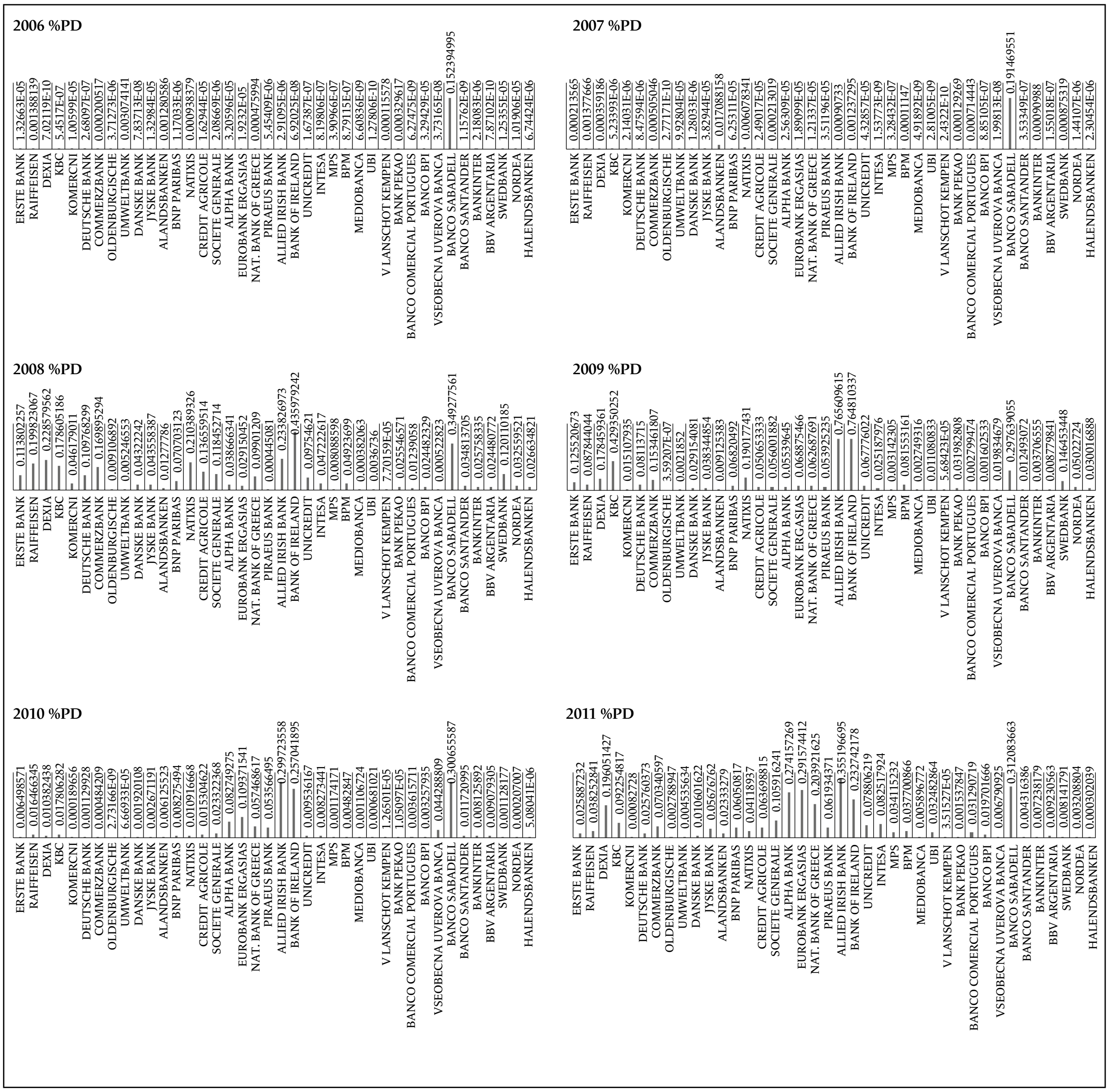
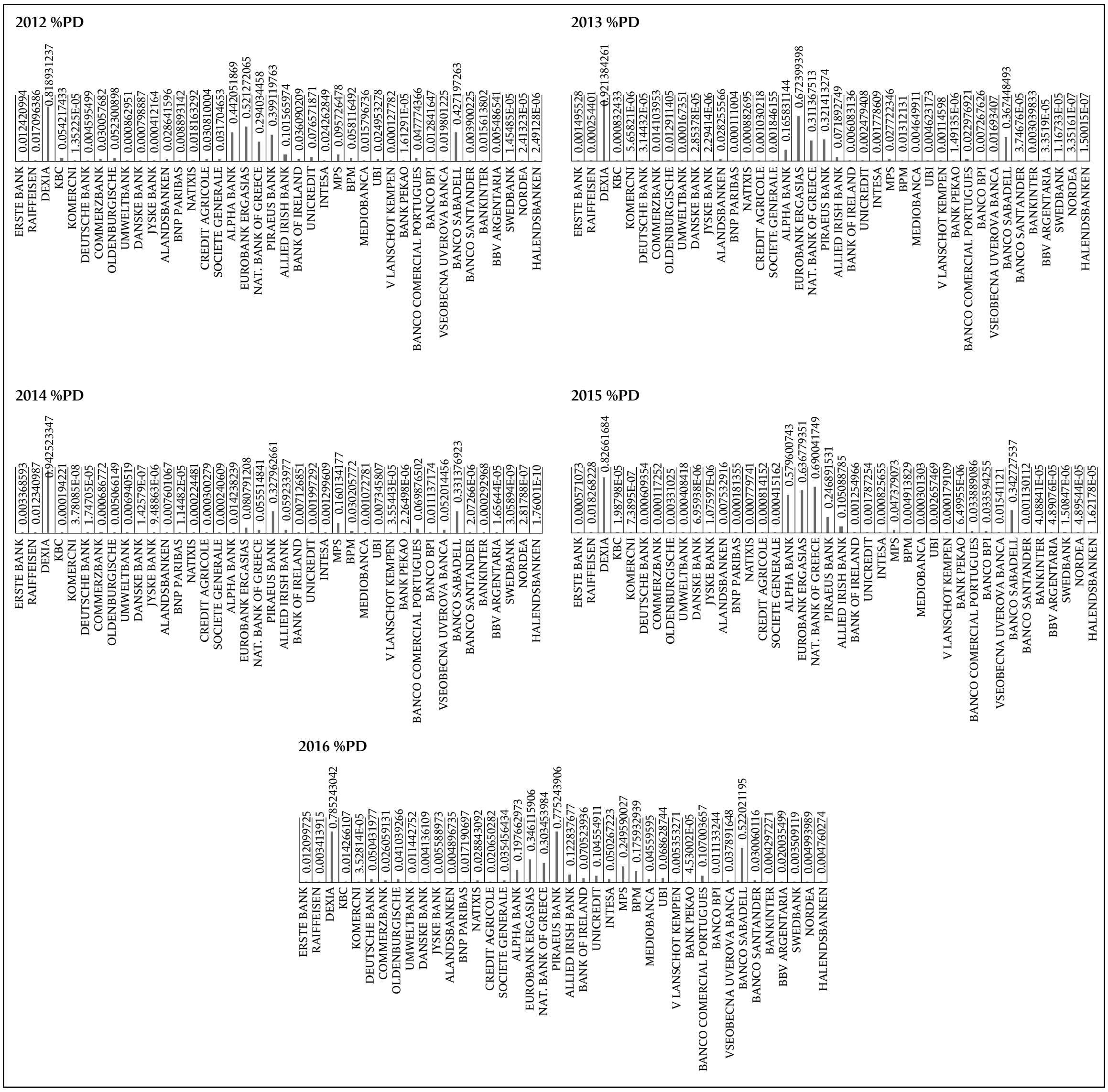


Figure 1, cont'd



Do CDS spread determinants affect the probability of default? A study on the EU banks

Extended summary

The paper is an investigation of the principal variables that have affected the EU banks' credit risk over the decade 2006–2016. More specifically, we intend to analyse the most significant variables affecting the probability of default, adopting CDS spread determinants. In fact, the default probability of a bank is the expression of credit risk, defined as the possibility that an unexpected change in a counterparty's creditworthiness might generate a corresponding unexpected alteration in the market value of the associated credit exposure. The probability of default of a bank depends on its specific factors on the one hand, and on market and macroeconomic factors on the other hand. In this context, we intend to analyse the most significant variables affecting the probability of default, adopting CDS spread determinants. Specifically, a credit default swap is a credit derivative whose aim is to protect the buyer against an event of default dealing with the issuer of the underlying asset. Consequently, its price, called the spread, should disclose the market's credit risk perception and its determinants might explain the main variables causing the reference entity's credit risk. In particular the CDS spread has shown a leading role in price discovery, with reference to bond markets (e.g. Coudert, Gex 2010; Norden, Weber 2007; Blanco, Brennan, Marsh 2005) and rating announcements (Finnerty, Miller, Chen 2013; Hull, Predescu, White 2004). In more detail, as a market indicator, CDS spread has been affected by high volatility, so we guess more accurate information might be given by the probability of default. Furthermore, the latter is implied in CDS spread and is an expression of credit risk. In accordance with the correlation between these two variables, we observe the influence of CDS spread determinants. Specifically, the related literature spans from accounting variables to market and general variables (Samaniego-Medina et al. 2016). In particular, contemporary research is developing in the study of systemic risk: general factors, indeed, seem to be more crucial than firm specific ones (Ejsing, Lemke 2011; Berndt, Obreja 2010).

In this context our study consists of a two-step analysis: in the first part, there is a calculation of the probability of default on a sample of 40 banks through a two-equation Merton model. This choice is consistent with the intention to estimate this variable under both firm specific and market perspectives. The second part deals with an investigation of the relationship between the estimated probability of default and the main CDS spread determinants: this inferential study is made by the implementation of Tobit regressions for panel data. Specifically, first we present a model for the whole period and then we distinctly analyse two sub-periods (namely 2009–2012 and 2013–2016), in order to focus our attention respectively on the sovereign debt crisis and on the NPL crisis.

Our contribution is twofold: an analysis of the main variables affecting the EU banks' credit risk over time and a verification of analogies between the determinants causing the probability of default and CDS spread, in order to assess if the latter is still a good indicator of banking credit risk.

Specifically, the estimation of the probability of default shows growing values over the years, with a particular increase during the periods of crisis.

Overall, as concerns the inferential analysis, we observe the influence of some variables related to CAMELS factors (Chodnicka-Jaworska, Jaworski 2017) and, analogously to recent CDS spread literature, we find a growing impact of macroeconomic and market variables during times of distress (e.g. Annaert

et al. 2013). In particular, during periods of crises, in terms of sovereign debt and NPLs respectively, the influence of country credit risk and asset quality problems appears significant.

Definitively, we deem that the credit default swap price can still be considered a good indicator of banks' credit risk, despite the volatility caused by the speculative use of this derivative. As shown throughout the paper, its determinants have an analogous impact on the default probability.

As concerns the perspectives for new research, the insight into banking probability of default could be proceeded by analysing credit risk from a systemic perspective (Giglio, Kelly, Pruitt 2016; Black et al. 2016), with a special focus on asset quality (Bottazzi, De Sanctis, Vanni 2016). In this context we believe it would be interesting to put more attention on the study of NPLs, finding out their main determinants and the possible strategies to reduce banking credit risk (Bruno, Iacoviello, Lazzini 2015). Moreover, as the European banking sector is characterized by linkages in terms of both sovereign and financial exposures, the research may be improved with other methodologies, such as network analysis (Westphal 2015).