Determinants of bank CDS spreads in Europe

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Abstract

This paper empirically analyzes the determinants of credit default swap (CDS) spreads from a sample of 45 listed European banks over the 2004-2010 period. We use variables related to accounting- and market-based data, an indicator of liquidity in the CDS market and several variables from the macroeconomic environment in which these financial institutions operate. These variables are analyzed during both the pre-crisis period (2004-2007) and the crisis period (2008-2010). The primary conclusion is that the market variables have the greatest explanatory power. Additionally, we find that the explanatory power of the model is considerably higher during the crisis period than it is during the pre-crisis period.

Keywords: credit default swaps; European banks; credit risk; bank risk; financial crisis

JEL classification: C52; G21; G33; M41

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1. Introduction

Among the various credit derivative instruments, credit default swaps (CDSs) are some of the best instruments that are currently available to assess the market's perception of the financial stability of institutions such as sovereigns, companies and banks (Annaert *et al.*, 2013). In fact, given the characteristics of the CDS, the literature concludes that CDSs are a better alternative than bonds in assessing credit risk (Das *et al.*, 2009). According to the Bank of International Settlements (BIS) (2015), CDSs have become increasingly popular over time. The outstanding gross national volumes have increased from less than USD 2 trillion in 2004 to nearly USD 60 trillion in 2007. However, in response to the financial crisis, the notional amounts of these CDSs have dropped to USD 16 trillion at the end of 2014. This decline in CDS activity is driven mainly by a contraction in inter-dealer activity.

The growing importance of the CDS market has resulted in the opening of different lines of research. For example, Hull *et al*. (2004) analyze both the relationship between CDS spreads and bond yields and the capacity of CDS spreads to anticipate rating changes. Blanco *et al*. (2005) study the theoretical equivalence of CDS prices and investment-grade bond credit spreads. Bao *et al.* (2012) and Dong and Wang (2014) study the credit value adjustment (CVA) of CDSs. Other important studies use CDS spreads as a proxy to analyze which type of model (accounting- or market-based) is more appropriate for measuring corporate credit risk (e.g., Das *et al.*, 2009; Trujillo-Ponce *et al.*, 2014).

There is also an extensive line of research that examines the relationship between equity markets and CDS spreads (Forte and Peña, 2009; Narayan *et al.*, 2014; Narayan, 2015; among others). Forte and Peña (2009) analyze market efficiency as a function of the relationships between changes in bond spreads, CDS spreads, and changes in credit spreads implied by the stock market. Narayan *et. al.* (2014) analyze the price discovery of CDS and equity returns by using panel data models. They conclude that in most sectors, the stock market contributes to price discovery. In sectors where both the stock and CDS markets contribute to price discovery, the stock market dominates this process. Narayan (2015) examines how the credit risks, which have increased significantly with the recent global financial crisis, as captured by CDS spreads, affect both the equity returns and return volatility. Their findings suggest that although CDS return shocks have a heterogeneous effect, they are more important in explaining sectorial equity returns than sectorial equity volatility is.

Our paper is closely related to studies investigating the determinants of CDS spreads. Fabozzi *et al.* (2007) test the influence of fundamental variables on the pricing of CDSs and conclude that interest rates, rating, industry and liquidity factors are the most significant predictors of CDS spreads. Ericsson *et al.* (2009) investigate the relationship between the theoretical determinants of default risk and CDS spreads. They find that firm leverage, equity volatility and risk-free interest rates are statistically significant, thus confirming that the theoretical determinants of default risk can explain a significant amount of variation in CDSs. Baum and Wan (2010) investigate the linkage between macroeconomic uncertainty and CDS spreads using both pooled ordinary least squares (OLS) and firm-fixed effects methodologies. Their findings suggest that macroeconomic uncertainty (i.e., the second moment in the levels of macroeconomic factors) is an important determinant of CDS spreads, even in the presence of traditional macroeconomic factors such as risk-free rates and Treasury term spreads. Batta (2011) examines the direct relevance of accounting information on CDS pricing. He concludes that the impact of accounting information on CDS prices must be taken with caution. Prices may appear to incorporate accounting information directly only because market participants are relying either on the information aggregation function of equity and debt markets or on the information processing function of rating agencies to value these instruments. Inspired by structural models, Galil *et al.* (2014) conclude that market variables have explanatory power after controlling for firm-specific variables. Three explanatory variables appear to outperform the other variables examined in this paper: the stock return, the change in stock return volatility and the change in the median CDS spread of the rating class. Pires *et al.* (2015) find that in addition to traditional variables, CDS spreads are determined by illiquidity costs. However, in contrast to stocks or bonds, CDS transaction costs should be measured by absolute, rather than relative, bid-ask spreads. Finally, Miyakawa and Watanabe (2014) introduce the notion of demand and supply, which has received little attention in the literature. By applying a limited dependent variable simultaneous equation system to a CDS index in the Japanese credit market, they conclude that including demand and supply factors is necessary to understanding fluctuations in CDS premiums because an increase in supply protection may result in a decrease in CDS premiums.

Other works have focused their attention on the explanatory power of CDS determinants during the recent financial crisis. In this regard, Di Cesare and Guazzarotti (2010) report that since the onset of the crisis, CDS spreads have become much more sensitive to the level of leverage but that volatility has decreased in importance. They also report that since the beginning of the crisis, CDS spread changes have been increasingly driven by a common factor that cannot be explained by indicators of economic activity, uncertainty and risk aversion. Naifar (2012) investigates the dependence structure among default risk premium, equity return volatility and jump risk in the equity market both before and during the subprime crisis. His findings suggest that the heterogeneity of the markets, coupled with the diversity in risk exposure, causes the default risk premium and equity markets to exhibit different levels of sensitivity. Corò *et al.* (2013) find that regardless of the market conditions, liquidity risk is more important than firm-specific credit risk. Moreover, credit risk plays no role in explaining CDS price changes during the pre-crisis period. They conclude that multiple liquidity factors, including firm-specific and aggregate liquidity proxies and an asymmetric information measures, are critical determinants of CDS price variations. Pereira *et al*. (2014) examine the determinants of corporate CDS spreads in the US, the UK and the Eurozone. Their research reveals that the significance of the variables and their spread prediction power vary considerably over each period of analysis because accounting and market-based variables are more significant predictors of CDS spreads during periods of financial distress.

There are two basic reasons why corporations and banks should be analyzed in different ways. First, they have different financial structures, which require calculating different ratios for analysis (e.g., Raunig and Scheicher, 2009; Kato and Hagendorff, 2010). Second, it has been demonstrated that certain variables that affect credit spreads of corporations occasionally lose their explanatory power when they are applied to banks (e.g., Raunig and Scheicher, 2009; Grammatikos and Vermeulen, 2012). In this respect, the banking CDS has been analyzed from different approaches. Eichengree *et al*. (2012) use a principal components analysis to identify common factors in movement of the CDS spreads in banks. They find that even in stable times, the fortunes of international banks rise and fall with short-term global economic prospects. Benbouzid and Mallick (2013) relate CDS spreads in the UK banking sector to the performance of the housing sector. They find that housing price dynamics are a key driving factor behind the increase in CDS prices. Demirgüç-Kunt and Huizinga (2013) investigate the impact of bank size and government deficits on CDS spreads for an international sample of banks. Using sovereign bond and CDS holdings data for 65 major European banks, Vuillemey and Peltonen (2015) present a stress test model for the CDS market, with a focus on the interplay between banks' bond and CDS holdings. The model simulation shows that in the case of a sovereign credit event, direct and correlated bond exposures have a significantly greater impact on banks' losses than CDS exposures do.

To the best of our knowledge, the only two papers that have analyzed determinants of bank CDS spreads are those by Annaert *et al*. (2013) and Chiaramonte and Casu (2013). Chiaramonte and Casu (2013) use only accounting-based information to estimate the determinants of the CDS spreads of 57 international banks (43 of which are European). They find that over time, determinants of bank CDS spreads vary strongly with changes in economic and financial conditions. Annaert *et al.* (2013) analyze the CDS spread changes of 32 listed European banks. They conclude that individual CDS liquidity, along with other market and business variables, plays an important role in explaining credit spread changes.

This paper contributes to the literature by simultaneously analyzing accounting, market, liquidity and macroeconomic determinants of bank CDS spreads. To do this, we use a sample of 45 listed European banks because they belong to the same economic area and have similar financial standards. Moreover, the financial crisis has caused modifications in European regulation. Considering that policies of central banks about liquidity and quantitative requirements have changed, our second goal is to analyze whether the determinants of CDSs of European banks differ between the pre-crisis (2004-2007) and crisis (2008-2010) periods.

The remainder of the paper is structured as follows. After this introduction, Section 2 describes the data and methodology. Section 3 presents and discusses the results. Section 4 summarizes and presents the conclusions.

2. Data and empirical methodology

2.1. Sample

Our sample consists of European bank CDS spreads with 5-year maturities, which are available from the Datastream database during the period 2004-2010.[1] The banks are selected based on the availability of CDS spread data (from the CMA source).[2] The market and macroeconomic information has been collected from the Datastream database, whereas the accounting information is from the Bankscope database.[3] After the CDS data are matched with the information obtained from these two databases, the final sample consists of 270 observations from 45 commercial banks in 14 European countries. We use annual

1 For detailed information on the Datastream database, please see http://online.thomsonreuters.com/datastream

[2] This data is available in the database until September 2010.

[3] For detailed information on the Bankscope database, please see https://bankscope2.bvdep.com/version-2012116/home.serv?product=scope2006

data rather than quarterly balance sheet data because not all banks with CDS contracts report financial data on a quarterly basis. This has greatly reduced the number of observations. Tables 1 and 2 show the number of observations that constitute the sample, organized by country and year, respectively.

[INSERT TABLES 1 AND 2 ABOUT HERE]

As in similar studies, we use unconsolidated statements, which mitigates relevant differences in profit and loss statements and keeps the balance sheets of headquarters and subsidiaries from being negated.

2.2. Dependent variable

We consider the CDS spread (premium mid) with a 5-year maturity to be the dependent variable. Although there is broad-spectrum maturity, we focus exclusively on the 5-year contract, as it is generally considered to be the most liquid segment of the market (Völz and Wedow, 2011; Annaert *et al.*, 2013). We collect the CDS spreads at the end of each year (average for the last month) from 2004-2010.

2.3. Accounting-based CDS spread determinants

Our paper uses seven accounting variables as proxies for asset quality, capitalization, profitability, efficiency, liquidity and size. All of these variables have been widely used in previous studies (Das *et al.*, 2009; Chiaramonte and Casu, 2013).

To measure asset quality, we select the ratio of impaired loans to gross loans (IL/GL). This ratio indicates the total amount of doubtful loans. The smaller the ratio is, the greater the asset quality of the bank is. Therefore, we anticipate a positive relationship with CDS spreads.

We use the ratio of equity to total assets (Eq/TA) as a proxy for capitalization. This ratio reflects the inverse of the bank's leverage. That is, the higher the value of this ratio is, the lower the leverage is. Therefore, one would expect that as the proportion of debt with respect to the total assets reduces, it results in a smaller risk of default (i.e., lower CDS spreads). However, as some theoretical models state (e.g., Koehn and Santomero, 1980; Kim and Santomero, 1988), in incomplete market settings, reducing leverage may lead bankers to choose a riskier portfolio to compensate for the loss in utility caused by this reduction (Baselga-Pascual *et al.*, 2015). Similarly, Blum (1999), who relies on dynamic models, concludes that higher capital requirements may increase bank risk.

We select the return on assets (ROA) for profitability analysis. This ratio is an indicator of a bank's return on its investments. The relationship between this ratio and the CDS spread is unclear. According to Chiaramonte and Casu (2013), a bank that makes multiple investments with a low ROA may be perceived by the market as a high-risk entity. In this case, a low ROA can be positively correlated with high CDS spreads. However, if one assumes that higher levels of investment can result in greater future income, the market may react positively to such investments. In this case, moderate values of the ROA ratio can correlate positively with low CDS spreads.

As a measure of efficiency, we use the cost-to-income ratio (CIR). This ratio measures the bank's overhead costs as a percentage of income generated before provisions. The higher this ratio is, the lower the efficiency of the bank is. Thus, we expect a positive correlation between this ratio and the CDS spread.

We chose the following common ratios to measure bank liquidity: the interbank (Interbank) and the net loans to total assets (NL/TA) ratios. Interbank is defined as the money lent to other banks divided by the money borrowed from other banks. The greater this ratio is, the greater the liquidity of a bank is. Thus, this definition would imply an inverse correlation with CDS spreads. In contrast, the NL/TA ratio indicates the percentage of the bank's assets that are tied up in loans. The higher this ratio is, the less liquid the bank is. Therefore, a positive correlation with CDS spreads is expected.

Finally, Size captures the bank's absolute size measured as the natural logarithm of total assets. According to the moral hazard theory (e.g., De Jonghe, 2010; Uhde and Heimeshoff, 2009), larger banks may be more attracted to increasing risk taking, reducing market discipline and creating competitive distortions because they know that they will be bailed out of adverse situations. Conversely, larger banks may be less prone to risk because of their managerial capacities and efficiencies (Baselga-Pascual *et al.*, 2015).

2.4. Market-based CDS spread determinants

We use equity return (EqRet) and equity volatility (EqVol) as market-based CDS spread determinants. Both variables are commonly used in credit risk models that are based on market information (e.g., Das *et al.*, 2009; Ericsson *et al.*, 2009). Following Christie (1982) and Annaert *et al.* (2013), we have chosen the EqRet as a measure of financial leverage relative to market value.[4] We anticipate a negative correlation between this variable and CDS spread because the lower the stock returns are, the greater the leverage measured as a multiple of market value is and, consequently, the greater the anticipated CDS spreads are.

[4] These variables are included in the Merton (1974) model, which uses asset growth, asset volatility and leverage as the key economic drivers for bankruptcy (Annaert *et al.*, 2013).

With respect to EqVol, a higher equity volatility theoretically results in a higher credit spread because it increases the likelihood of reaching the default threshold (Annaert *et al.*, 2013). Therefore, we anticipate a positive correlation between this variable and the CDS spreads.

2.5. Liquidity

Most studies that have analyzed CDS spreads consider the liquidity of the contract to be an explanatory variable (e.g., Longstaff *et al.*, 2005). Although different metrics to proxy for liquidity of the CDS contract exist, we consider the absolute CDS bid-ask spread (Bid-Ask). A positive sign for the absolute bid-ask spread indicates that expected returns on CDSs increase when transaction costs increase (Bongaerts *et al.*, 2011). According to Pires *et al*. (2015), the absolute bid-ask spread is the appropriate measure to compare transaction costs in the CDS market as CDS premiums are expressed in a comparable way (i.e., in basis points per annum of the notional amount of the contract) and thus using the relative bid-ask spread can bias the comparison of liquidity between different CDSs. This distinction can help explain some apparently conflicting results in the literature: Chen *et al.* (2007) report a negative relationship of the relative liquidity proxy with the CDS spread, whereas Acharya and Johnson (2007) and Völz and Wedow (2011), among others, show a significant positive correlation of the absolute liquidity proxy with the CDS spread. Alternatively, assuming that the absolute spread is a good indicator of the amount of information asymmetry in the market, a higher bid-ask spread should be associated with a higher CDS level (Pires *et al*., 2015). We therefore anticipate a positive relationship between the absolute CDS bid-ask spread and the CDS spread in our equation.

2.6. Macroeconomic CDS spread determinants

We use the following macroeconomic variables to capture market and economic conditions: the 10-year Treasury bond rate (T-Bond), Market Return (MarkRet) and Market Volatility (MarkVol). [5] These variables have been frequently used in studies that model credit risk (e.g., Das *et al.*, 2009).

The 10-year Treasury bond rate captures part of the sovereign default risk, and thus a positive correlation between this variable and CDS spreads of banks in the country may be expected. Nevertheless, a low-interest-rate environment generates an increase in risk-related bank assets and may alter the composition of bank portfolios toward a riskier position, suggesting a negative correlation between this variable and the bank CDS spread.

The MarkRet variable is used to capture the general business climate. When this variable improves, the probability of default decreases. Thus, a negative correlation with credit spreads is anticipated. As a proxy for this variable, we use the variation of the *Stoxx Europe 50 Index*. This index, which is also known as Europe's Leading Blue-chip Index, provides a representation of the super-sector leaders in Europe. This index covers 50 stocks from 18 European countries.

Finally, MarkVol captures the uncertainty that surrounds economic prospects, which is greater when there is greater market volatility. Therefore, we expect a positive correlation with CDS spreads. As a proxy, we use the *Vstoxx Volatility Index*, which captures the expected volatility for the *Dow Jones EuroStoxx 50 Index*.

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[5] We also included a measure of the overall bank industry return using the *Stoxx Europe 600 Bank Index*. Nevertheless, this indicator is eliminated because of its high collinearity with MarkRet.

2.7. Rating

We also control for the issuer's credit rating in our equation. The correlation between the credit rating and CDS spreads has been extensively studied. Most of the empirical studies conclude that the lower the issuer's credit rating is, the greater the CDS spreads are. A dramatic increase in these spreads occurs when the rating decreases from investment grade to speculative grade (Fabozzi *et al.*, 2007; Das *et al*., 2009; Annaert *et al*., 2013). In our study, we consider the rating of the bank at the end of the year, as provided by the Fitch Rating agency. Then, we include two dummy variables to account for the three credit rating categories contained in our sample (i.e., AAA, A and BBB).[6]

2.8. The empirical model

To investigate the relationship between the groups of studied variables (accounting, market, liquidity and macroeconomic variables) and the CDS spread, we estimate the following linear regression:

$$Y_{i,t} = \alpha + \beta_1 \cdot \text{IL/GL}_{i,t} + \beta_2 \cdot \text{Eq/TA}_{i,t} + \beta_3 \cdot \text{ROA}_{i,t} + \beta_4 \cdot \text{CIR}_{,t} + \beta_5 \cdot \text{Interbank}_{i,t} + \beta_6 \cdot \text{NL/TA}_{i,t} + \beta_7 \cdot \text{Size}_{i,t} + \beta_8 \cdot \text{EqRet}_{i,t} + \beta_9 \cdot \text{EqVol}_{i,t} + \beta_{10} \cdot \text{Bid-Ask}_{i,t} + \beta_{11} \cdot \text{T-Bond}_{i,t} + \beta_{12} \cdot \text{MarkRet}_{t} + \beta_{13} \cdot \text{MarkVol}_{t} + \beta_{14} \cdot \text{AAA (dummy)}_{i,t} + \beta_{15} \cdot \text{A (dummy)}_{i,t} + \varepsilon_{i,t} \quad (1)$$

For this regression, the subscripts *i* and *t* denote index banks and years, respectively, whereas *Y* denotes the dependent variable, which is the natural logarithm of the CDS spread at the end of the year. As previously stated, we consider seven firm-specific accounting variables, two market-based variables, one variable used as a proxy for the liquidity of the contract and three variables to account for the macroeconomic environment. Finally, we also control for the

[6] All of the banks in our sample are rated as investment grade (BBB or higher). We do not consider different subcategories or "notches".

credit rating of the bank. Similar to Chiaramonte and Casu (2013), we use levels, rather than differences, in our equation because we are more interested in explaining the spread than in making predictions. The notations of these explanatory variables are described in Table 3. In the regression above, $\varepsilon_{i,t}$ is the disturbance term.

Because panel data are used, we can estimate the model with either fixed or random effects. Hausman tests suggest that the fixed effects estimator is more appropriate in our case. Thus, we assume that the omitted variables may potentially correlate with the existing regressors.

[INSERT TABLE 3 ABOUT HERE]

3. Results

3.1. Results from the baseline model

Table 4 shows the mean and standard deviation of the CDS spreads and the different explanatory variables that form our equation for each of the years studied. It can be observed that the spreads increase considerably, nearly doubling during the years of the financial crisis (2008-2010). A similar effect is observed for the non-performing loans ratio (IL/GL), which increases from a mean value of 2% in the years prior to the crisis to more than 5% in 2009 and 2010. Additionally, there is a significant decline in bank profitability (from 0.660% in 2004 to 0.236% in 2010). Relative to other market variables, there is a distinct increase in the volatility of equity, particularly in 2008 and 2009.

[INSERT TABLE 4 ABOUT HERE]

Table 5 reports the regression results obtained in this study.[7] We observe the important roles that market variables (EqRet and EqVol) play as predictors of the CDS spread. Both variables exhibit strongly significant correlation (in all the considered models) in the anticipated direction. Consistent with previous studies (e.g., Annaert *et al*., 2012; Zhang *et al*., 2009), the CDS spread decreases as the equity return increases, suggesting that a higher growth in the firm value reduces the probability of default. Concerning equity volatility, our findings support the hypothesis that higher equity volatility often implies higher asset volatility, and thus the firm value is more likely to hit below the default boundary (Zhang *et al*., 2009).

[INSERT TABLE 5 ABOUT HERE]

Regarding the accounting variables, they all exhibit the anticipated direction in correlation with the CDS spread. We report a significant positive relationship between the IL/GL ratio and the CDS spread, indicating that banks with higher non-performing loans have higher CDS premiums. We also find that the higher the capitalization (Eq/TA) is, the higher the CDS spread is. As some theoretical models state, this result reflects that capital requirements force banks to reduce leverage, which may lead bankers to choose a riskier portfolio to compensate for the loss in utility caused by this reduction. Finally, as expected, the banks with the best liquidity ratios (Interbank and NL/TA ratio) have lower CDS spreads.

We observe a significant positive correlation between the variable used to approximate the liquidity of the contract (Bid-Ask) and the CDS spread. That is,

[7] We consider different alternatives to our baseline equation, in which some of the dependent variables are excluded because of potential collinearity. Although we have contemplated collinearity when choosing our variables, this is a problem, specifically when MarkRet and MarkVol are both included in the equation. Following to Graham (2003), we also create two new purged explanatory variables, MarkVol (residual) and A (dummy) (residual), by regressing MarkVol and A (dummy) against MarkRet and AAA (dummy), respectively. We then use those residuals instead of the original variables in our baseline equation (model in column 8).

the greater the illiquidity of the contract is, the higher the spreads demanded by investors are. Corò *et al.* (2013) consider that liquidity risk is more important than firm-specific credit risk in explaining CDS price changes. Moreover, they find that credit risk plays no role in the period prior to the financial crisis. In the same line, Pires *et al.* (2015) conclude that a large component of the variation of CDS spreads is due to illiquidity costs.

Although all of the macroeconomic variables show the anticipated direction of correlation with CDS spreads, only the market return (MarkRet) and the market volatility (MarkVol) coefficients are statistically significant (though not in all of the models). The significant negative impact of MarkRet on CDS spread is consistent with a business cycle effect, given that higher market returns suggest an improved economic environment (Zhang *et al.*, 2009). Similarly, a high market volatility may capture the uncertainty that surrounds economic prospects, increasing the probability of default (Corò *et al.*, 2013).

Finally, we find a significant relationship between the credit rating and the CDS spread, as found in previous studies (e.g. Das *et al.*, 2009; Pires *et al.*, 2015).

3.2. A comparative analysis between the pre-crisis period (2004-2007) and the crisis period (2008-2010)

We now divide the sample into two periods: a pre-crisis period (2004 to 2007) and a crisis period (2008 to 2010). We use this approach to examine possible differences in our regression because of the impact of the financial/economic crisis on the European banking sector. Although the results obtained using this approach resemble those of our baseline model, we observe certain differences between the periods (before and during the crisis) with respect to the explanatory power of the model and the statistical significance of certain explanatory variables (see Table 6). As suggested by Alexander and Kaech (2008), the association between CDS spreads and their determinants depends very much on the market circumstances prevailing at the time. In particular, we find that the model's explanatory power is considerably higher during the crisis period (with an adjusted R^2 value of 66% during the crisis period versus 48% during the pre-crisis period). This finding is consistent with that reported for the banking industry by other authors, such as Annaert *et al*. (2013) and Chiaramonte and Casu (2013).

[INSERT TABLE 6 ABOUT HERE]

Regarding the accounting variables, the IL/GL and CIR ratios become significant predictors of the CDS spread only during the crisis period. This finding suggests that banks with both higher impaired loans and operating costs have been hit particularly hard during the crisis period (i.e., higher CDS spreads). We also observe that the Eq/TA ratio changes its sign during the crisis period. This result seems to indicate that greater capitalization specifically reduces the banks' CDS spreads during a period of economic and financial instability. This finding supports the view that a stronger capital position is an important benefit during a crisis period and suggests that the current emphasis on strengthening capital requirements is broadly appropriate. Finally, when we divide the sample into two periods, Size becomes significant, which suggests that larger banks have higher CDS spreads, according to the hypothesis that larger banks tend to be riskier due to a moral hazard problem (De Jonghe, 2010).

Concerning the market variables, although the variable used to measure equity volatility continues to be strongly significant in our regression, the equity return variable now loses statistical significance (during the crisis period) while maintaining the anticipated sign in its relationship to CDS spreads. Our results are in line with the empirical evidence provided by Alexander and Kaech (2008), who find that, in ordinary market circumstances, CDS spreads are more sensitive to stock returns than they are to stock volatility. They also report that CDS spreads are extremely sensitive to stock volatility during periods of CDS market turbulences.

The macroeconomic variables retain their anticipated signs and their statistical significance, which seems to confirm the importance of macroeconomic conditions in both periods, pre-crisis and crisis. Finally, although the rating variable retains its anticipated sign, it is only statistically significant during the crisis period, which seem to corroborate a solid relationship between ratings and CDS spreads in periods of economic instability, where the credit quality, measured by the rating variable, may affect the magnitude of the CDS spread.

3.3. An analysis of the explicative power of the explanatory variables

To measure the relative importance of each group of explanatory variables (accounting, market, liquidity and macroeconomic), we divide our initial regression (Table 7). We find that the market variables (EqRet and EqVol) have the greatest explanatory power, with an adjusted R^2 value of 58%. The accounting variables have an adjusted R^2 value of 41%, whereas the variable that measures the liquidity of the contract has an adjusted R^2 value of 29%. Finally, the variables that measure the effect of macroeconomic factors on the CDS spread only have an adjusted R^2 value of 18%.[8]

[INSERT TABLE 7 ABOUT HERE]

[8] Because macroeconomic variables cannot explain the cross-section variation, caution should be used when determining their explanatory power.

4. Summary and conclusions

This paper empirically analyzes the determinants of CDS spreads in a sample of 45 European banks over the 2004-2010 period. We use variables related to accounting- and market-based data, an indicator of liquidity in the CDS market and several proxy variables for the macroeconomic environment in which these financial institutions operate. We demonstrate the important role of the market variables (EqRet and EqVol) as predictors of the CDS spread. Regarding accounting variables, the non-performing loan ratio (IL/GL), the capitalization ratio (Eq/TA) and the liquidity proxies (Interbank and NL/TA ratio) are statistically significant among all models. We also report a significant positive correlation between the variable used to approximate the liquidity of the contract (Bid-Ask) and the CDS spread. Finally, although only the market return and market volatility coefficients are statistically significant (not in all models), all of the macroeconomic variables exhibit the anticipated direction of correlation with CDS spreads. Therefore, CDS premiums appear to be driven not only by credit risk determinants, but also by illiquidity costs and business cycle factors.

When we divide the sample into two periods, i.e., a pre-crisis period (2004 to 2007) and a crisis period (2008 to 2010), we obtain similar results to those of the baseline model, although a few differences are observed with respect to the explanatory power of the model and the statistical significance of certain explanatory variables. Similar to Chiaramonte and Casu (2013) and Annaert *et al*. (2013) for the banking industry and to Trujillo-Ponce *et al.* (2014) for a sample of European firms, we conclude that the explanatory power of the model is considerably higher during the crisis period than it is before the crisis period. This finding may be explained by a lower sensitivity of CDS spreads to the studied financial indicators during periods of economic stability.

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Table 1. Commercial banks in the sample by country

Country	Banks	Observations	Percentage
Austria	2	13	4.81
Belgium	2	13	4.81
Denmark	1	7	2.59
France	4	27	10.00
Germany	4	24	8.89
Ireland	2	14	5.19
Italy	8	42	15.56
Netherlands	3	14	5.19
Norway	1	3	1.10
Portugal	2	14	5.19
Spain	4	24	8.89
Sweden	3	20	7.41
Switzerland	2	13	4.81
United Kingdom	7	42	15.56
Total sample	45	270	100%

Table 2. Number of observations in the sample by year

Year	Observations	Percentage
2004	31	11.48
2005	39	14.44
2006	41	15.19
2007	39	14.44
2008	41	15.19
2009	40	14.82
2010	39	14.44
Total	270	100

Table 3. Explanatory variables

Explanatory variables	Notation	Expected sign	Source
Accounting-based			
Impaired Loan / Gross Loans (in %)	IL/GL	+	Bankscope
Equity / Total Asset (in %)	Eq/TA	-/+	Bankscope
Net Income / Average Total Assets (in %)	ROA	+/-	Bankscope
Cost / Income Ratio (in %)	CIR	+	Bankscope
Interbank Ratio (in %)	Interbank	-	Bankscope
Net Loans / Total Asset (in %)	NL/TA	+	Bankscope
Natural Log of Total Assets	Size	+/-	Bankscope
Market-based			
Equity Return	EqRet	-	Datastream
Equity Volatility	EqVol	+	Datastream
Liquidity			
Absolute CDS Bid-Ask Spread (in basis points)	Bid-Ask	+	Datastream
Macroeconomic			
10-year Treasury Bond (in %)	T-Bond	+/-	Datastream
Market Return (Stoxx Europe 50)	MarkRet	-	Datastream
Market Volatility (Vstoxx Volatility Index)	MarkVol	+	Datastream
Credit rating			
1, if rating assigned by Fitch Rating = AAA (0, otherwise)	AAA (dummy)		Bankscope
1, if rating assigned by Fitch Rating = A (0, otherwise)	A (dummy)		Bankscope

Table 4. Summary statistics by year

Year	CDS spread	IL/GL	Eq/TA	ROA	CIR	Interbank	NL/TA	Size	EqRet	EqVol	Bid-Ask	T-Bond	MarkRet	MarkVol
2004	1.105	2.232	5.068	0.660	62.381	91.817	45.988	8.642	0.125	0.187	3.195	3.748	0.043	-0.335
	(0.127)	(1.727)	(2.238)	(0.473)	(14.947)	(78.686)	(16.965)	(0.459)	(0.142)	(0.039)	(1.156)	(0.519)	(0.000)	(0.000)
2005	1.143	2.146	4.958	0.637	59.722	89.873	47.111	8.364	0.239	0.173	3.127	3.416	0.201	0.001
	(0.225)	(1.820)	(2.104)	(0.495)	(14.867)	(77.669)	(17.577)	(0.487)	(0.146)	(0.045)	(1.268)	(0.470)	(0.000)	(0.000)
2006	0.990	2.048	5.118	0.864	56.614	86.730	49.069	8.416	0.223	0.220	4.221	4.045	0.100	0.033
	(0.237)	(1.827)	(2.587)	(0.844)	(11.213)	(75.516)	(19.594)	(0.495)	(0.177)	(0.046)	(9.945)	(0.452)	(0.000)	(0.000)
2007	1.578	1.851	4.963	0.743	58.957	85.945	51.289	8.486	-0.152	0.276	4.415	4.385	-0.004	0.218
	(0.323)	(1.479)	(2.530)	(0.401)	(13.857)	(66.768)	(21.020)	(0.487)	(0.157)	(0.086)	(2.932)	(0.345)	(0.000)	(0.000)
2008	2.140	3.023	4.460	0.097	75.951	65.418	54.669	8.456	-0.632	0.652	11.521	3.643	-0.434	1.429
	(0.330)	(3.102)	(2.375)	(0.932)	(50.639)	(55.283)	(21.607)	(0.507)	(0.184)	(0.210)	(10.268)	(0.595)	(0.000)	(0.000)
2009	1.990	5.049	5.614	0.016	61.192	83.441	51.795	8.471	0.422	0.716	15.598	3.769	0.241	-0.452
	(0.203)	(5.031)	(2.580)	(0.731)	(19.417)	(82.620)	(19.942)	(0.507)	(0.492)	(0.335)	(16.117)	(0.587)	(0.000)	(0.000)
2010	2.183	5.568	5.805	0.236	66.509	80.872	52.080	8.481	-0.140	0.401	10.401	4.150	0.000	-0.006
	(0.254)	(4.479)	(2.662)	(1.152)	(25.563)	(67.965)	(19.910)	(0.533)	(0.253)	(0.157)	(7.219)	(1.555)	(0.000)	(0.000)
Total	1.605	3.156	5.140	0.458	63.107	83.085	50.442	8.468	0.007	0.383	7.713	3.882	0.018	0.147
	(0.543)	(3.406)	(2.463)	(0.828)	(25.850)	(72.000)	(19.647)	(0.498)	(0.417)	(0.269)	(9.997)	(0.805)	(0.211)	(0.583)

Note: This table reports means and SD (in parentheses) for the entire sample by year. The sample consists of 45 European commercial banks (270 observations). See Table 3 for a description of the variables.

Table 5. Determinants of CDS spreads in European banks

Variables	(1) CDS spread	(2) CDS spread	(3) CDS spread	(4) CDS spread	(5) CDS spread	(6) CDS spread	(7) CDS spread	(8) CDS spread
IL/GL	0.125*	0.144**	0.141**	0.143**	0.174**	0.184***	0.132*	0.141**
	(0.068)	(0.065)	(0.065)	(0.060)	(0.067)	(0.068)	(0.067)	(0.065)
Eq/TA	0.186***	0.200***	0.197***	0.195***	0.237***	0.247***	0.178**	0.176***
	(0.061)	(0.066)	(0.062)	(0.060)	(0.066)	(0.069)	(0.068)	(0.061)
ROA	-0.128	-0.161	-0.166	-0.191	-0.323***	-0.316**	-0.147	-0.141
	(0.121)	(0.127)	(0.128)	(0.114)	(0.120)	(0.120)	(0.130)	(0.124)
CIR	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)
Interbank	-0.001*	-0.001**	-0.001***	-0.001**	-0.001**	-0.001**	-0.001**	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NL/TA	0.045***	0.047***	0.045***	0.046***	0.046***	0.049***	0.047***	0.045***
	(0.013)	(0.014)	(0.013)	(0.013)	(0.016)	(0.017)	(0.014)	(0.013)
Size	0.400	0.587**	0.406	0.364	0.378	0.703**	0.532**	0.359
	(0.395)	(0.258)	(0.249)	(0.259)	(0.300)	(0.316)	(0.246)	(0.405)
EqRet	-0.540***	-0.611***	-0.522**		-0.419**	-0.472**	-0.860***	-0.533**
	(0.195)	(0.196)	(0.206)		(0.206)	(0.206)	(0.117)	(0.203)
EqVol	1.667***	1.605***	1.603***	1.532***			1.765***	1.611***
	(0.322)	(0.338)	(0.319)	(0.311)			(0.313)	(0.337)
Bid-Ask	0.020**	0.021**	0.020*	0.022**	0.046***	0.047***	0.020*	0.020**
	(0.009)	(0.010)	(0.011)	(0.010)	(0.018)	(0.018)	(0.011)	(0.009)
T-Bond	-0.011	0.053	0.049	0.099	0.009	0.034		0.042
	(0.107)	(0.114)	(0.110)	(0.102)	(0.114)	(0.118)		(0.114)
MarkRet	-1.205		-0.882**	-1.720***	-1.489***			-0.734*
	(0.929)		(0.413)	(0.220)	(0.394)			(0.401)
MarkVol	0.174*	0.249*				0.513***		0.476
	(0.087)	(0.144)				(0.140)		(0.983)

AAA (dummy)	0.501	0.111	0.112	0.127	0.149	0.156	0.081	0.104
	(0.330)	(0.202)	(0.200)	(0.190)	(0.206)	(0.205)	(0.116)	(0.199)
A (dummy)	-0.774***	-0.702**	-0.688**	-0.743**	-0.649*	-0.722*	-0.578*	-0.614*
	(0.253)	(0.342)	(0.323)	(0.297)	(0.355)	(0.374)	(0.324)	(0.325)
Intercept	-7.929	-12.600**	-8.877*	-8.257	-8.125	-14.912**	-11.145**	-7.959
	(7.947)	(5.170)	(4.826)	(4.967)	(5.761)	(6.285)	(4.815)	(8.124)
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Year dummies	No	No	No	No	No	No	Yes	No
Country dummies	No	No	No	No	No	No	Yes	No
N	270	270	270	270	270	270	270	270
Adjusted R^2	69.61%	69.11%	69.42%	68.41%	68.40%	64.20%	68.95%	69.28%

Note: This table reports alternative fixed-effects regressions of the log of CDS spreads. The model in column (2) excludes *MarkRet*. The model in column (3) excludes *MarkVol*. The model in column (4) excludes *EqRet* and *MarkVol*. The model in column (5) excludes *EqVol* and *MarkVol*. The model in column (6) excludes *EqVol* and *MarkRet*. The model in column (7) includes year and country dummies instead of macroeconomic variables. Finally, the model in column (8) is a robust estimation of model in column (1) where the values of *MarkVol* and *A (dummy)* are replaced by their residuals, which are generated in previous regressions against *MarkRet* and *AAA (dummy)*, respectively. See Table 3 for a description of the variables. Robust standard errors, which are clustered by banks, are reported in parentheses. Significance levels are indicated as follows: *** = significant at the 1% level, ** = significant at the 5% level, and * = significant at the 10% level.

Table 6. Comparative analysis between the pre-crisis period (2004-2007) and the crisis period (2008-2010)

Variables	*Pre-crisis period (2004-2007)* **CDS spread**	*Crisis period (2008-2010)* **CDS spread**
IL/GL	0.125	0.074**
	(0.139)	(0.035)
Eq/TA	0.099*	-0.139*
	(0.053)	(0.071)
ROA	-0.093	-0.057
	(0.106)	(0.068)
CIR	0.004	0.001*
	(0.003)	(0.001)
Interbank	-0.001*	-0.001*
	(0.000)	(0.000)
NL/TA	0.016*	0.025*
	(0.009)	(0.013)
Size	0.338*	0.420*
	(0.192)	(0.238)
EqRet	-0.814*	-0.081
	(0.484)	(0.126)
EqVol	2.420**	0.748**
	(0.431)	(0.329)
Bid-Ask	0.017**	0.017**
	(0.008)	(0.008)
T-Bond	0.896	0.139*
	(0.661)	(0.081)
MarkRet	-1.002**	-0.640*
	(0.425)	(0.321)
MarkVol	0.528***	0.686***
	(0.164)	(0.129)
AAA (dummy)	0.319	-0.500
	(0.258)	(0.376)
A (dummy)	-0.385	-0.711*
	(0.708)	(0.368)
Intercept	3.787	-5.387
	(13.254)	(6.070)
Clustering level	Bank	Bank
N	150	120
Adjusted R^2	48.26%	66.01%

Note: This table reports fixed-effects regressions of the log of CDS spreads for the pre-crisis period (2004-2007) and the crisis period (2008-2010). See Table 3 for a description of the variables. The values of *MarkVol* and *A (dummy)* are replaced by their residuals, which are generated in previous regressions against *MarkRet* and *AAA (dummy)*, respectively. Robust standard errors, which are clustered by banks, are reported in parentheses. Significance levels are indicated as follows: *** = significant at the 1% level, ** = significant at the 5% level, and * = significant at the 10% level.

Table 7. Regressions by group of explanatory variables

Variables	**(1) CDS spread**	**(2) CDS spread**	**(3) CDS spread**	**(4) CDS spread**
IL/GL	0.237***	-	-	-
	(0.059)			
Eq/TA	0.040*	-	-	-
	(0.021)			
ROA	-0.406***	-	-	-
	(0.118)			
CIR	0.008***	-	-	-
	(0.003)			
Interbank	-0.002	-	-	-
	(0.002)			
NL/TA	0.067***	-	-	-
	(0.016)			
Size	1.374***		-	-
	(0.448)			
EqRet	-	-0.812***		
		(0.139)		
EqVol	-	3.014***	-	-
		(0.261)		
Bid-Ask	-	-	0.084***	-
			(0.022)	
T-Bond	-	-	-	0.199
				(0.170)
MarkRet	-	-	-	-1.972***
				(0.165)
MarkVol	-	-	-	2.252***
				(0.527)
Intercept	-27.596***	2.549***	3.018***	2.934***
	(8.713)	(0.100)	(0.166)	(0.663)
Clustering level	Bank	Bank	Bank	Bank
N	270	270	270	270
Adjusted R^2	41.14%	58.10%	28.94%	18.09%

Note: This table reports fixed-effects regressions of the log of CDS spread for accounting-based variables (column 1), market-based variables (column 2), liquidity variable (column 3) and macroeconomic variables (column 4). See Table 3 for a description of the variables. Robust standard errors, which are clustered by banks, are reported in parentheses. Significance levels are indicated as follows: *** = significant at the 1% level, ** = significant at the 5% level, and * = significant at the 10% level.