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The Determinants of CDS Spreads: The Case of Banks

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7.1 Introduction

Credit Default Swaps (CDS) are credit derivatives functioning as insurance contracts: in exchange for a fee paid to the seller, they provide protection to buyers from losses that may be incurred on sovereign or corporate debt resulting from a credit event that may include failure to pay (interest or principal on) and restructuring (of one or more obligations issued by the sovereign or the corporate) (IMF 2013). What makes the difference between a CDS and an insurance contract is that CDS contracts are freely tradable while insurance contracts are not.

CDS market became very significant in terms of volume during the last years, although its values dropped considerably during the financial crisis, mostly due to the investors' concerns about the fact that they are unregulated to a large extent as they are part of the over-the-counter

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(OTC) market. However, the CDS market remains sizeable, dominated by institutional investors (insurance companies and, more recently, hedge funds) and banks (Augustin et al. 2014).

The market evolution of CDS is intimately related to banks because they are the main originators of credit risk. Moreover, it seems that some trends in lending activity and in banks' risk-taking behaviour can influence the CDS market volume; for instance, it can be observed that as a consequence of the fact that large firms tend to gradually reduce the number of banking relationships, banks could tend to take on more risk that, in turn, they try to reduce by transferring it to third parties using credit derivatives.

The literature on CDS in banks has mainly focused on the potential effects of the use of CDS by banks—hedging versus speculative instruments (e.g. Minton et al. 2009). In this paper, the focus is on banks, but we use a perspective different than the one generally found in the previous literature. We are interested in studying CDS of banks as signals of their soundness and their risk of insolvency. In fact, CDS spreads should reflect market perceptions about the financial health of banks and can be used by regulators to extract warning signals regarding the financial stability (Annaert et al. 2013).

Studying CDS spreads determinants in banks is interesting for a number of reasons. First, because banks are important players on this market but have a special nature compared to other types of firms, due to the heavy regulation to which they are subjected, the high leverage, their special assets and trading activities that may create uncertainty and agency problems (Raunig and Scheicher 2009). As a consequence, the investors' perceptions and judgement of credit risk could be influenced by factors different than those typically considered to be important for other firms. Second, banks play an important role in financial systems. Since banks are strictly interconnected to each other, an increase in a bank's risk or the bank's default can produce important spillovers and, in crisis periods, contagion (e.g. European Commission 2014). Systemic risk caused by a default of a bank is so dangerous that the prudential authorities proceeded to further regulate the risk-taking behaviour of banks (Basel 3) by tightening the existing rules (such as those on capital requirements) and by introducing new prudential rules (such as liquidity ratios).

Since the 2007/2008 financial crisis mainly affected financial institutions, it is interesting to focus on them to better understand the mechanism by which the market assesses the risk of these special firms by pricing the CDS. Third, banks are important agents in every economic system and the insolvency of a bank has a very strong interconnection with the economy of a country. Even though a default of a bank can affect the economy through different channels, the main concern is related to the potentially dangerous effects on loans (volume and pricing) and on deposits. In some areas, such as Europe, this concern has recently been amplified by the new tightened rules on banks' recovery and resolution[1] (that implies the bail-in mechanism) that, among others, specify the sequence in which the power to write down or convert liabilities in resolution should be applied.

Despite the important role that financial intermediaries play on this market, little work exists regarding CDS spreads in the banking sector. One reason could be that the financial industry is considered to be an opaque industry where traditional credit risk models are likely to be less successful (Annaert et al. 2013). This could find confirmation in the fact that variables that proved to be significant determinants of credit spreads of non-financial companies tend to lose their explanatory power when applied to financial companies (Boss and Scheicher 2005; Raunig and Scheicher 2009). Another hypothesis is that for banks, other risk indicators are available and are considered important, such as the Basel capital ratios.

This study aims at offering several contributions to the literature. First, it enriches the literature focused on the banks' CDS spreads and it aims to increase the understanding of the determinants of CDS premium in this very special and relevant sector. Additionally, we want to investigate more deeply the credit spread puzzle issues that in the context of banks could be more pronounced and more challenging to address with respect to other types of firms (Hasan et al. 2015). Second, our research extends the previous studies both in terms of coverage of the sample and in terms of depth of analysis. Our sample is composed of international banks, while samples of other previous studies include banks that are active in more narrow geographical areas (Annaert et al. 2013, Kanagaretnam et al. 2016). Third, the debate on the role of CDS in the stability of financial systems is still ongoing (IMF 2013). CDS can be viewed as useful market-based risk indicators and valuable hedging instruments or as speculative tools suggesting that their prices do not reflect underlying fundamentals or actual risks, therefore unduly raising funding costs for governments (and corporations), threatening fiscal sustainability and exacerbating market tensions. The role of CDS for the financial stability is particularly important when banks are considered.

We study the determinants of CDS spreads using a regression analysis and focusing on a sample of 86 international banks from 2009 to 2012. We find the following main results. The explanatory power of the model increases when bank-specific and market/country variables are considered. Banks' capitalisation, size and rating are significant determinants of CDS spread. Among market factors, the market volatility and the slope of the yield curve prove to affect the CDS spread.

The remainder of the paper is organised as follows. In Sect. 7.2, we discuss the relevant literature. In Sect. 7.3, we describe the methodology and the data. In Sect. 7.4, we analyse the variables used in our models. In Sect. 7.5, we present and discuss the empirical analysis and its results. In Sect. 7.6, we discuss the results of the robustness tests. Finally, in Sect. 7.7, we summarise and conclude.

7.2 Literature

7.2.1 Studies on (Bonds and) CDS Spreads

Since CDS are relatively new products, literature about CDS spreads relies on the literature regarding credit spreads of corporate bonds. The theoretical literature on the determinants of credit spreads relies on Merton's seminal paper (1974). According to the credit risk theory deriving from Merton's model, the credit spreads depend on four (structural) factors: the risk-free interest rate, the level of the firm's debt (face value), the market value of the firm and the volatility of the firm's assets. Merton's theory is accepted by academics, but empirical studies following the theory generally do not confirm that structural default factors are able to sufficiently explain the credit spreads of bonds[2] (credit spread puzzle). As a consequence, the previous literature identifies several other factors, different than structural credit risk factors, helping to explain the credit spread changes (such as a non-diversifiable credit risk/systematic risk, a liquidity premium, several market-wide variables, different firm-specific factors) (Driessen 2005; Amato and Remolona 2003; Collin-Dufresne et al. 2001; Elton et al. 2001).

Only during the last decade, the literature started focusing directly on CDS spreads (rather than on bond spreads). Their relevance is due to the fact that they are representative of important structural developments in financial markets (Boss and Scheicher 2005). Furthermore, it is generally recognised that CDS allow studying credit spreads (O'Kane and Sen 2005) better than bonds for several reasons. First, CDS are directly observable, while bond spreads have to be derived by comparing corporate bonds to a risk-free asset that could imply problems when the choice has to be done (Annaert et al. 2013). Moreover, they can be considered fairly pure indicators of credit risk because the structure separates the credit risk component from other risks, such as interest rate and currency risk (FitchRatings 2007). Second, they are "light" instruments in that one does not need to fund an entire bond position, for example, to have essentially identical credit risk exposure (FitchRatings 2007). Third, bond spreads are more prone to be affected by several factors, such as market and institutional factors (liquidity, tax effects and market microstructure effects) (Annaert et al. 2013). Fourth, given their derivative nature, CDS spreads are more efficient and more rapid than bonds in signalling changes in the credit quality of the borrowers so that their power in price discovery process is more efficient (e.g. Carboni 2011; Coudert and Gex 2010; Ammer and Cai 2011; Blanco et al. 2005; Aktung et al. 2009). This last advantage of the CDS is confirmed by the importance which CDS assumed during the recent financial turmoil when regulators also started to focus on financial markets information and signals to take their policy actions.

The literature on CDS spreads can be virtually divided into studies focused on sovereign CDS (Fontana and Scheicher 2010; Heinz and Sun 2014; Drago and Gallo 2016) and those focused on (financial or non-financial) corporate CDS (e.g. Di Cesare and Guazzarotti 2010; Zhang et al. 2009). Given the objectives of the present work, we are interested in empirical studies focused on financial institutions' CDS. This literature includes a rather limited number of studies.

Düllmann and Sosinska (2007) consider three German banks during the period 2002–2005. They analyse CDS spreads focusing on the explanatory power of three risk sources: idiosyncratic credit risk, systematic credit risk and liquidity risk. They show that structural models based on equity prices and reduced-form models based on the prices of credit derivatives have their specific advantages and that together they can provide a more comprehensive assessment of the riskiness of the monitored banks.

Raunig and Scheicher (2009) compare 41 major banks to 162 non-banks during the period of 2003–2007. They investigate the determinants of CDS premium and, by means of regression analysis, they study how CDS investors discriminate between banks and non-banks and how their assessment has varied over time. They show that average CDS premium of banks is lower than non-banks' premium over the entire period and that the difference in the premium disappears during the turmoil. In their model, the empirical default probability (EDF is obtained from KMV database and represents an estimate of the probability of default based on the model of Merton), plus a vector of control variables (risk-free interest rate, slope of the yield curve, implied stock market volatility, idiosyncratic equity volatility, swap spread), is considered. They show that risk premium differs across time and across banks and non-banks and that the risk-free rate, implied stock market volatility and idiosyncratic volatility affect banks' CDS only to a small extent in the period from 10/2003 to 6/2007. During the turmoil (second semester of 2007), the significant determinants of banks' CDS tend to be the same for banks and non-banks with the exception of the slope of the yield curve that loses its explanatory power for banks. During the subprime turmoil, there exists a substantial repricing of banks' CDS relative to the CDS of other firms because banks have large exposures to securitisation instruments.

Annaert et al. (2013) study the determinants of (32) European listed banks CDS spreads during the period 2004–2010. They consider three sets of variables: credit risk variables (derived from the Merton's model), liquidity variables and market-wide factors. Their analysis confirms that the variables affecting CDS spreads vary across time (but not so much across rating classes). After the start of the crisis, structural factors gain significance, while bank-specific liquidity maintains its importance before and after the crisis. Some variables proxying the general economic conditions are important, but their significance and signs changed with the start of the crisis.

Hasan et al. (2015) study the determinants of (161) banks' CDS spreads from 23 countries during the period 2001–2011. They focus on three groups of variables: structural model variables, CAMELS factors,[3] and country-level, economic, governance and regulation factors. They show that some structural factors (leverage measures, equity return volatility and government bond yield) are significant determinants of banks' credit risk but that they have a limited explanation power (20%). CAMELS indicators provide incremental explanatory power (+10%). Asset quality (loan-loss provisions to total loans) is the most significant determinant of banks' CDS spreads (after controlling for time and bank fixed effects). Furthermore, they show that systematic risk and risk aversion (proxied by stock market return) are important determinants of CDS spreads. In addition, some country-level factors are significant because they influence the risk-taking behaviour of the banks: financial conglomerate restriction is negatively related to banks' CDS spreads (implying that competition helps to reduce the bank's credit risk), and deposit insurance is positively related to CDS spreads. Finally, since with time and bank fixed effects the model reaches 60–80%, they show that cross-bank variations in systematic risk and some unobserved time-varying factors have important explanatory power for banks' CDS spreads. During the crisis, the impacts of leverage and asset quality on CDS spreads become much stronger.

Kanagaretnam et al. (2016) analyse the determinants of 27 US Bank Holding Corporations (BHCs) for the 2001–2008 period and find that CDS spread is significantly associated with several CAMELS measures; their results indicate that BHCs with lower earnings and lower liquidity tend to have higher CDS spread. The study also demonstrates that risky ABS securities are an important driver of risk since 2006. In particular, their results indicate that BHCs with higher ABS balances are riskier and have a higher CDS spread. They also demonstrate that

CDS spread is positively and significantly associated with single-family (1–4 people) residential loans. Their results confirm that the real estate risk was a major risk for US BHCs during the financial crisis. Finally, they document that CDS spread is only significantly associated with equity market-based bank risk measures, but bears no association with other accounting-based bank risk measures, such as the standard deviation of historical return on asset, the standard deviation of historical net interest margin and Z-score. Consistent with Hasan et al. (2015), Liu et al. (2016) find that banks in countries with explicit deposit insurance systems have higher CDS spreads, supporting the "moral hazard" view. Explicit deposit insurance systems are positively and significantly related to bank CDS spreads for the 3-year, 5-year and 10-year periods, reflecting the "moral hazard" problem. Deposit insurance plays a stabilisation role when and where the market is volatile, as evidenced during the financial crisis and in countries with greater market volatility. This is consistent with the view that in the midst of a crisis, the immediate task is to restore confidence, and guarantees can be helpful.

Different from previous studies that fundamentally rely on the model of Merton (1974), Chiaramonte and Casu (2013) focus on balance-sheet indicators, suggesting that in the periods of financial stress, market data fluctuate wildly and changes in market data during a crisis period do not necessarily reflect the changes in credit risk. They investigate the determinants of CDS spreads and whether CDS spreads can be considered a good proxy of bank performance during the period 2005–2011. Their sample includes 57 international banks. They show that the determinants of CDS spreads vary across time. They demonstrate that banks' CDS spreads reflect the risk captured by the banks' balance-sheet ratios; the relationship between banks' CDS spreads and balance-sheet ratios becomes stronger during the crisis and post-crisis period; variables that a priori would be considered as determinants of CDS spreads, the Tier 1 ratio and the leverage, appear insignificant in all considered periods, and the liquidity indexes were not important before the crisis.

The studies by Chiaramonte and Casu (2013), Annaert et al. (2013) and Hasan et al. (2015) are those more closely related to our work. However, we differentiate from them for the following reasons. Annaert et al. (2013) limit the sample to European banks; they do not include the ratings in the regression analysis, but they distinguish different subsamples based on ratings; they do not consider balance-sheet variables as determinants of the CDS spreads but only market variables. Hasan et al. (2015) do not explicitly consider the effects of the ratings. Chiaramonte and Casu (2013) do not consider market and country-level factors nor the ratings. None of these studies consider the sovereign CDS.

7.2.2 Studies on CDS and Credit Ratings

The literature focused on CDS and ratings mainly uses event study methodology to test the presence of abnormal movements (in CDS spreads) in the presence of rating changes.

Hull et al. (2004), after examining the relationship between CDS spreads and bond yields, test the relationship between CDS spreads and announcements, reviews and outlooks by rating agencies during the period 1998–2000. Their data set includes over 200,000 CDS spread bids and offers collected by a credit derivatives broker over a 5-year period. They analyse the relationship between the CDS market and rating announcements by carrying two tests. First, they condition on rating events and test whether credit spreads widen before and after rating events. They find that reviews for downgrade contain significant information, but downgrades and negative outlooks do not, and that there is an anticipation of all three types of ratings announcements by the CDS market. Successively, they condition on credit spread changes and test whether the probability of a rating event depends on credit spread level and changes. They find that credit spread changes or credit spread levels provide helpful information in estimating the probability of negative credit rating changes. In the case of positive rating events, the results are much less significant.

Norden and Weber (2004) study the informational efficiency of CDS and stock markets focusing on the impact of credit rating announcements during the period 2000–2002. Their sample includes CDS data provided by a large European bank. They employ event study methodology to test whether these markets respond to rating announcements in terms of abnormal returns and adjusted CDS spread changes. Both stock markets and CDS market demonstrate to be able to anticipate rating downgrades and reviews for downgrade. Furthermore, they show that the magnitude of abnormal returns is affected by the level of the old rating, previous rating events and, only in the CDS market, by the pre-event average rating level.

Di Cesare (2006) studies the ability of market-based indicators (CDS spreads, bond spreads and stock prices) to anticipate rating agencies. He considers a sample of the largest publicly listed international banks from 11 countries during the period 2001–2005. He verifies the presence of “abnormal movements” of the three market indicators before, in concomitance and after rating events (review for rating changes and actual rating changes). He shows that all indicators contain useful information to anticipate rating actions, especially for negative events and that, overall, CDS spreads are relatively more efficient in anticipating negative rating events—stock prices are better predictors in the case of positive rating events.

Burchi and Drago (2012) study the alignment between ratings and CDS focusing on a sample of US firms, in order to demonstrate the existence of a significant difference between the ratings and the CDS that could affect the lending policy of a bank.[4]

7.3 Methodology and Data

7.3.1 Methodology

We use a framework similar to that used in Annaert et al. (2013) and Hasan et al. (2015). We aim at empirically investigating the determinants of CDS spreads in banks considering three sets of regressors: (i) credit risk variables; (ii) bank-specific variables, including the ratings; and (iii) market and country-level variables, including the sovereign CDS spreads. Since we want to explain and not to predict CDS spreads, we do not lag the explanatory variables.

To test the determinants of CDS spreads in banks, we use the following model:

$$\text{CDS spread}_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Z_{it} + \beta_3 W_{jt} + \varepsilon_{it}$$

where CDS spread$_{it}$ is the natural log of CDS for bank i at year t, X_{it} are the credit risk variables for bank i at year t, Z_{it} are the bank-specific variables for bank i at year t, W_{jt} are the market and country-level variables for country/geographical area j at year t and ε_{it} is the idiosyncratic error.

To test whether variables are correlated, we use a Pearson correlation test.[5] We also check and exclude multicollinearity problems by analysing mean Variance inflation factor (VIF) of all the independent variables specified in the linear regression model (mean VIF < 3). In all regression models, we use country-clustered, heteroskedasticity-robust standard errors. We run a pooled OLS regression because the residuals are uncorrelated and OLS standard errors are not biased.[6]

We develop a stepwise analysis. Initially, we use the credit risk variables, and successively we add the bank-specific and the market/country-level variables. Finally, we test a GMM model when the sovereign CDS variable is included. Formally, this model is given by:

$$\text{CDS spread}_{it} = \beta_0 + \beta_1 \text{CDS spread}_{it-1} + \beta_2 X_{it} + \beta_3 Z_{it} + \beta_4 W_{jt} + \varepsilon_{it}$$

We argue that a GMM model is appropriate for several reasons. First, the estimators of Arellano-Bond method (Arellano and Bond 1991) are designed for sample with a small number of time periods (in our sample $T = 4$) and a large number of cross section units ($N = 86$ international banks) that may contain fixed effects and, separate from those fixed effects, idiosyncratic errors that are heteroskedastic and correlated within but not across individuals. Second, sovereign CDS spreads are endogenous to the banks CDS spreads and need to be instrumented accordingly. Third, as the use of the lagged dependent variable introduces autocorrelation in residuals, the dependent variable is instrumented with its lagged value.

7.3.2 Data

The empirical analysis focuses on a sample of 86 international banks from 25 countries[7] from 2009 to 2012. Initially, we considered all institutions classified as primary members according to the International Swaps and Derivatives Association (ISDA) guidelines. The initial number of banks was subsequently reduced due to the lack of data on Thomson Reuters Datastream. We ultimately obtained an unbalanced panel, and overall the study analyses 235 bank-year observations. The largest number of banks is from the USA (9), followed by Germany (8) and Italy (7). Even though the sample is geographically heterogeneous, it includes banks that are consistent in terms of transactions on international derivatives markets and all characterised by size and specific requirements to be admitted to ISDA.

Given the limited number of frequencies for some classes of rating and in order to run the regression analysis, we group the sample banks into five classes of ratings (Table 7.1). We can observe a heterogeneity in the distribution of the rating classes, if we consider the presence of five observations on the class B (following the methodology of Standard and Poor's), compared to 188 observations on the class A. The groups belonging to the range from AA+ to AA−(Rating AA) and from A+ to A−(Rating A) are the most consistent in terms of frequency (cumulatively 77.6%) compared to the entire sample.

As dependent variable we use the year-end CDS spreads, a choice strictly related to the type of explanatory variables considered, most with a balance-sheet nature. The data on banks CDS premium is from Thomson Reuters Datastream database over the period from 1 January 2009 to 31 December 2012. Datastream provides comprehensive coverage for firms and banks around the world and it is widely used for research on CDS.

We select the 5-year CDS quotes for senior debt issues since these contracts are generally considered to be the most liquid segments of the market (e.g. Meng and Gwilym 2008) and because they constitute the most important segment of the CDS market. As robustness, starting from the daily CDS spreads, we compute the average of CDS spreads over a year (average year-end CDS spreads) (Hasan et al. 2015).

We are aware that some authors distinguish among different restructuring credit events (and the contractual clauses attached to the restructuring)

Table 7.1 Sample distribution by ratings classes (number of banks in each rating class and the frequency)

Rating distribution	No of banks	Frequency (%)
Rating (AA)	79	22.97
Rating (A)	188	54.65
Rating (BBB)	61	17.73
Rating (BB)	11	3.20
Rating (B)	5	1.45

Period 2009–2012

(e.g. Hasan et al. 2015). Following other studies (e.g. Chiaramonte and Casu 2013; Annaert et al. 2013; Galil et al. 2014; Pires et al. 2015), in the present work we decide not to consider the different credit events because the data available on Datastream does not always permit to distinguish CDS spreads on the basis of contractual clauses (full, modified, modified, no restructure) and, in fact, many quotations appear as “no value”.

Figure 7.1 shows how the CDS premium of sample banks evolved over time. We can observe that the trend is different depending on the rating class. For AA-rated banks the CDS premium increased throughout the period considered. For A-rated and B-rated banks, CDS spreads achieved a peak in 2011 and then decreased in 2012. It seems that A-rated and B-rated banks are more vulnerable to the credit crisis while the AA-rated banks are less subject to the influence of turmoil. This result could be due to the sovereign debt crisis. We observe that CDS spreads of A and B-rated banks decrease with the intensifying of European sovereign debt crisis between 2011 and 2012. It seems that European sovereign debt crisis only affects the AA-rated banks whose CDS spreads continue to increase, while the A and B-rated banks, on average, show a contrary tendency. The composition of our

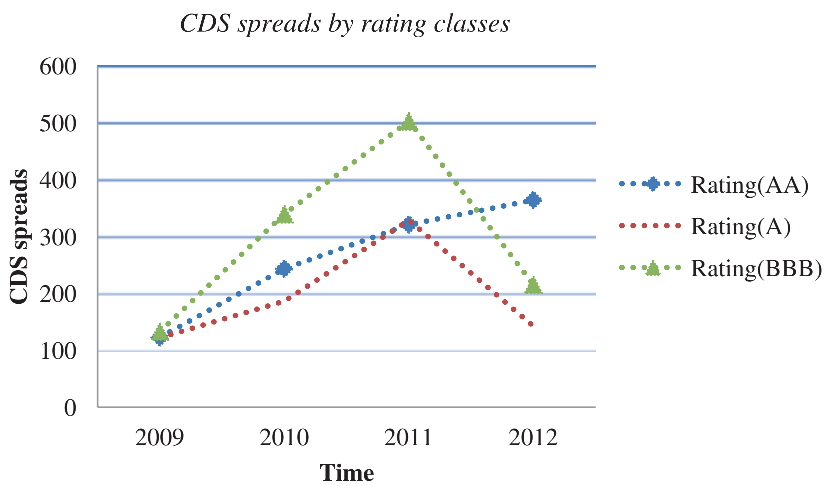

Fig. 7.1 Time-series plot of the average of year-end CDS spreads by rating classes

sample (the majority of banks is European) might affect the trend of the average CDS spreads between 2011 and 2012.

As independent variables, we consider credit risk factors, bank-specific factors, including the ratings, and market and country-level factors. All data on independent variables are obtained from Datastream. Data on ratings are obtained from Standard and Poor's Global Ratings. The implied volatility indexes data are obtained from different sources.[8]

7.4 Variables

7.4.1 Credit Risk Variables

Following the literature on credit spreads that relies on Merton's seminal paper (1974), we consider three types of credit risk variable: asset volatility, leverage and risk-free interest rate. Table 7.2 describes the variables and the predicted sign of their coefficients.

Asset volatility. Following the previous literature, we consider equity return volatility as a proxy for assets volatility (Ericsson et al. 2009; Annaert et al. 2013; Hasan et al. 2015). Starting from daily stock returns we construct volatility as the historical standard deviation in a particular year. An increase in volatility causes an increase in the default likelihood of the bank. As a consequence, the expected sign of the relationship between asset volatility and the banks CDS spreads is positive.

Leverage. Following the previous literature, as leverage measure we use the ratio between the book value of liabilities and the book value of liabilities plus the market value of equity (Galil et al. 2014; Hasan et al. 2015). The level of banks' leverage represents a variable which could positively or negatively influence the level of the CDS premium, depending on the level reached. A small increase in the leverage ratio could have a positive impact because it increases the profitability of a bank and reinforces its capability to repay bondholders and depositors. On the other hand, above a certain threshold, it produces an exponential growth of the risk. As highlighted by Hasan et al. (2015), in the case of banks it is controversial whether higher levels of leverage imply an increase in the bank's credit risk because banks have different asset

Table 7.2 Description of variables

Variable	Name	Description	Predicted sign
Credit risk variables			
Asset volatility	Asset vol	Equity return volatility. The historical standard deviation of bank's daily equity returns in a particular year	+
Leverage	Leverage	Book value of liabilities/book value of liabilities + market value of equity. Robustness: Bank stock returns	±
Risk-free rate 5Y	Risk-free rate (5-Y)	Risk-free interest rate. Proxied by the Datastream benchmark 5 year government redemption yield	±
Bank-specific variables			
Capitalisation	Tier1	Tier 1 capital ratio. Calculated according to the Basel Accord rules	–
Portfolio quality	Asset qual	Provision for loan losses/total loans	+
Profitability	ROE	ROE Robustness: Z-score	–
Size	Size	Log total assets	±
Liquidity	Liquidity	Net loans/demand deposits	–
Market and country-level variables			
Total return index	TRI	Datastream Total Return Index. The theoretical aggregate growth in value of the constituents of the index	–
Market volatility	Mkt vol	Implied volatility index (VIX, VSTOXX, S&P/ASX 200 VIX, HIS volatility index, India VIX, CBOEO EX implied volatility index, VXJ)	+
Slope of the yield curve	Slope	Difference between the 10-year and the 5-year treasury bond yields	–
GDP	GDP	Log of GDP	+
Sovereign CDS	Sov CDS (end)	Sovereign year-end CDS spread	+

and liability structures from other (non-financial) firms, due to the fact that their leverage ratios are considerably greater than those in other corporate sectors, and there is less variation among banks: the ability to draw on more deposits is a signal of greater growth potential but, at the same time, too much debt (to equity) can lead a bank to failure. In the robustness analysis, we use the bank stock returns as leverage measure (e.g. Annaert et al. 2013). We decided to not use an accounting measure of leverage to avoid the potential problem of multicollinearity when are used in the same regression as explanatory variables leverage and ROE.

Risk-free interest rate. We proxy the risk-free interest rate with the 5-year government bond yield using the Datastream benchmark 5-year government redemption yield. This choice appears consistent with the fact that we use the 5-year CDS spread as the dependent variable (Galil et al. 2014; Hasan et al. 2015). The expected relationship between CDS spreads and the risk-free interest is negative. This can be justified by the fact that interest rates are positively related to economic growth that should imply lower default risk. However, as emphasised by Hasan et al. (2015), the relationship could be positive across countries because banks have higher borrowing costs in countries with greater risk-free rates.

7.4.2 Bank-Specific Variables

This set of variables includes those suggested by the previous literature and by regulators (Basel Accords and EBA 2015). We use a set of variables aimed at capturing different indicators of the banks' soundness: capitalisation, portfolio quality, profitability, and liquidity. Finally, we control for banks' size.

Capitalisation. We consider the Tier 1 ratio as prescribed by Basel Accords (2 and 3) and also by EBA (2015) (that indicates CET1 rather than Tier1 as numerator). Tier 1 ratio represents a global riskiness indicator of the banks.[9] A higher value of this ratio should lower CDS spreads and therefore the expected sign for the coefficient is negative.

Also, the level of leverage (grouped in the credit risk variables) is a bank's capitalisation measure. It is worth noting that the new rules of Basel 3 explicitly include a financial leverage minimum coefficient, constructed as the ratio of Tier 1 capital to total risk exposure (denominator that can be proxied by the total assets). Basel 3 introduces a leverage ratio requirement equal to 3% that is intended to constrain leverage in the banking sector (thus helping to mitigate the risk of the destabilising deleveraging processes which can damage the financial system and the economy) and to introduce additional safeguards against model risk and measurement error by supplementing the risk-based measures (that is Tier 1 ratio and total capital ratio) with a simple, transparent, independent measure of risk.

Portfolio quality. Following the previous literature (EBA 2015; Chiaramonte and Casu 2013; Hasan et al. 2015), we expect that asset quality is negatively related to CDS spreads. We consider the provision for loan losses ratio to proxy the asset quality of the banks. A higher ratio indicates that the bank has more bad loans and, therefore, the expected sign of the coefficient is positive.

Profitability. Following the previous literature (EBA 2015; Chiaramonte and Casu 2013; Hasan et al. 2015), we use return on equity (ROE), also considered a bank's efficiency indicator. We expect a negative sign of the coefficients of the ROE. Additionally, to take into account the overall banks performance, that is profitability and risk (ECB 2010), in the robustness, we use the Z-score, a measure of riskiness of the bank that combines profitability, leverage, and return volatility in a single indicator, that increases with higher profitability and capitalisation levels, and decreases with unstable earnings (Berger et al. 2009).

Liquidity. As a measure of banks' liquidity, we use the net loans/demand deposits ratio.[10] The expected sign of the relationship between liquidity and CDS spreads is negative. The higher the liquidity, the lower should be the probability for banks in incurring in liquidity crisis, the lower should the overall risk of the bank. However, the sign of relationship could be controversial because the liquidity risk has a different nature than the credit risk, that captured by the CDS premium. As the financial crisis demonstrated, the consequences of the liquidity shocks cannot be neglected because, when not adequately managed, they could easily transform the liquidity crisis of the bank in an insolvency problem. The concern about the liquidity risk is confirmed by the attention of regulators towards liquidity and funding position after the financial crisis. Apart from what Basel 3 prescribes in terms of liquidity ratios, this attention is confirmed in Europe by the recent guidelines of European Banking Authority (EBA) about SREP (EBA 2014) where, in order to assess the bank's economic viability, authorities have to review and evaluate the liquidity of the bank, taking into account the liquidity and funding risks.

Size. Finally, we control for bank's size proxied by the total assets. The expected sign of the relationship between bank's size and CDS spreads is controversial (De Nicolò 2000; Stever 2007). On one hand, it is expected to be positive because a larger bank may have a greater capacity to absorb risk (Berger et al. 2009). On the other hand, due to the size-related diversification benefits and the economies of scale, the larger banks should be less risky. However, the managers of larger banks could take advantage of the benefits of risk diversification to push the risk profile of the bank further (Hughes et al. 2001). It follows that we have no specific expectations about the sign of this relation.

Ratings. Since both ratings and CDS spreads should capture the credit risk of a bank, we expect a positive relationship.

7.4.3 Market and Country-Level Variables

Following the previous literature, we consider some market-wide and country-level variables. This empirical strategy is due to several reasons. First, many studies demonstrated that credit risk variables have a limited explanatory power. Second, given the heterogeneity of our sample, that includes banks from very different geographical areas and countries, it seems appropriate to control for these differences. Moreover, banks' performance, risk and regulations are often correlated to economic development (La Porta et al. 1998; Demirgüç-Kunt et al. 2004; Hasan et al. 2015). Third, as several studies have shown, default probabilities and recovery rates are influenced by the business cycle (e.g. Altman et al. 2005). Fourth, the importance of macroeconomic factors in assessing the risk of a bank is recognised by regulators (EBA 2015). As a consequence, in our empirical analysis we consider some market-wide indicators (total return index, market volatility, slope of the term structure) and some country-level indicators (GDP and sovereign CDS spreads).

The total return index. Following the previous literature (e.g., Annaert et al. 2013), we include a market-wide stock index return as control variable. We use Datastream Total Return Index with reference to the region of the world in which the company is domiciled.[11] When the general business climate improves, the defaults probabilities should decrease (an increase in recovery rates is also expected). Therefore, the expected relationship with CDS spreads is negative.

Market volatility. Following the previous literature (Collin-Dufresne et al. 2001; Annaert et al. 2013; Galil et al. 2014), we include the implied volatility indexes as control variable. We use different indexes taking into account the region of the world in which the company is listed. Given the heterogeneity of some countries which are located on the same geographic area, in some cases, when available, we use country-specific implied volatility indexes. Specifically, we use VIX for the USA, VSTOXX for Europe, S&P/ASX 200 VIX for Australia, HIS volatility index for China, India VIX for India, CBOEO EX implied volatility index for emerging markets, VXJ for Japan. A higher volatility implies a higher economic uncertainty, an increase in investors' risk aversion (Annaert et al. 2013) and, therefore, a higher risk. As a consequence, a positive relationship with the CDS premium is expected.

Slope of the term structure. Following the previous literature (Ericsson et al. 2009; Annaert et al. 2013; Galil et al. 2014), we include the slope of the term structure as control variable, defined as the difference between the 10-year and the 2-year treasury bond yields obtained from Datastream of the benchmark series. Also, the slope of the term structure is considered an important signal of the future business cycle. A higher slope predicts an improvement in business cycle and indicates that interest rates tend to increase. Both arguments should be related to a decrease in credit risk and, therefore, a negative sign of the coefficient is predicted.

GDP. We control for GDP of each country in which the sample bank is listed. An expected positive relationship with CDS spreads is expected.

Sovereign CDS spreads. The previous literature did not explicitly consider this variable. However, given the special nature of the companies included in our sample and taking into account that banks typically own a significant volume of sovereign bonds in their portfolio,[12] we decided to include this variable. Taking into account the very special period of analysis that we are interested in, during which several countries experienced a sovereign debt crisis, this choice seems appropriate. The importance of sovereign CDS spreads in assessing the risk of a bank is also recognised by regulators. For instance, in its recent guidelines on the minimum list of qualitative and quantitative recovery plan indicators, EBA (2015) explicitly includes the sovereign CDS. We are aware of the possible analysis limitations arising from the potential endogeneity between banks' CDS and sovereign risk (captured by sovereign CDS). To solve this problem, when the sovereign CDS variable is included in the regression model we use a GMM model. Notwithstanding this econometric strategy, we argue that the results of the estimates should be discussed with caution given the very complex and debated relationship between bank and sovereign risk.

7.4.4 Descriptive Statistics

Table 7.3 outlines the descriptive statistics of independent and dependent variables. The mean of year-end CDS spreads is 235.48 basis points with a standard deviation of 32.188 basis points. The mean of average year-end CDS spreads is 233.04 with a standard deviation of 25.526. Both CDS spreads record very similar mean values. However, the lower standard deviation of the average year-end CDS spreads, due to the construction of this variable, implies that the average year-end CDS spread is more stable than the year-end CDS spread. The year-end CDS spreads range from 100 to 2646.39 basis points whereas the average year-end CDS range from 100 to 1955.43 basis points.

Panel A describes the variables divided into three groups: credit risk variables, bank-specific variables and market and country-level variables.

Panel B reports the summary statistics of CDS spreads based on the rating classes. It is interesting to note that the ratings and CDS spreads are not always aligned. This is observable both when we take into account the mean values and when we consider the maximum values. In particular, A-rated banks show a CDS average spread less than that

Table 7.3 Summary statistics of full sample and divided by rating classes

Variables	No of obs	Mean	STD	Min	Max	Units
Dependent variable						
Year-end CDS	235	235.48	32.188	100.00	2646.39	Basis points
Average year-end CDS	235	233.04	25.526	100.00	1955.43	Basis points
Panel A: Independent variables						
Credit risk variables						
Asset vol	235	2.44	1.669	0.00	10.21	%
Leverage	235	89.74	0.051	78.13	98.96	%
Risk-free rate (5Y)	235	2.77	1.162	0.49	7.23	%
Bank-specific variables						
Tier1	235	11.24	6.177	0.01	23.27	%
Asset qual	235	1.03	1.073	0.00	7.62	%
ROE	235	8.69	8.765	0.00	50.93	%
Z-score	235	7.32	10.508	0.14	75.64	%
Size	235	19.82	1.216	16.98	21.80	Logs
Liquidity	235	5.98	7.292	0.46	44.31	%
Market and country-level variables						
TRI	235	8.30	0.904	3.83	8.95	Logs
Mkt vol	235	23.21	4.605	14.70	32.15	%
Slope	235	1.49	0.56	0.51	3.55	%
GDP	235	12.75	2.276	7.81	18.58	Logs
Sov CDS (end)	235	262.36	1389.61	10.79	14909.36	Basis points
Panel B: CDS spreads by rating classes						
Rating (AA)						
Year-end CDS	57	251.11	326.66	1.00	1490.38	Basis points
Average year-end CDS	57	255.17	313.53	1.00	1955.43	Basis points
Rating (A)						
Year-end CDS	137	187.78	235.427	38.00	2646.39	Basis points
Average year-end CDS	137	189.93	147.929	47.04	1572.27	Basis points
Rating (BBB)						
Year end CDS	33	324.34	343.844	47.23	1941.50	Basis points
Average year-end CDS	33	326.16	269.226	50.00	1199.07	Basis points
Rating (BB)						
Year-end CDS	7	917.99	800.255	108.47	2576.55	Basis points
Average year-end CDS	7	806.58	597.334	192.32	1938.56	Basis points
Rating (B)						
Year-end CDS	1	446.04	186.100	81.94	446.04	Basis points
Average year-end CDS	1	601.69	263.722	133.57	601.69	Basis points

of AA-rated banks. This evidence is in contrast with the fact that ratings and CDS spreads are both aimed at capturing the same phenomenon (the credit risk). As evidenced by Burchi and Drago (2012), while the misalignment between ratings and market credit spreads is known in the literature, the reasons that explain the valuation differences are still relatively little explored. In recent years, a number of studies suggest that these differences are due to a different assessment of certain systematic risk and market-wide factors, such as liquidity (Perraudin and Taylor 2004; Becker and Ivashina 2015; Elton et al. 2001), not reflected by the ratings and, instead, captured by CDS spreads.

7.5 Results

In this section, we study the explanatory power of the different factors considered in our model. As dependent variable we consider CDS spreads at the end of each year. We develop a stepwise analysis (Table 7.4).

Initially, we estimate the coefficients of the credit risk variables (column 1, Model I). Successively, we add the bank-specific variables (column 2, Model II) and the rating (column 3, Model III). Afterwards, we test the model by also using the market/country-level variables (column 4, Model IV). Finally, we add the sovereign CDS variable (column 5, GMM Model).

When only the credit risk variables are considered, the results show that none of the regressors is statistically significant. This result is not surprising given the very special sector and period that we consider. As emphasised by the previous literature (e.g. Hasan et al. 2015), the credit spread puzzle is more pronounced in the case of banks. Furthermore, as demonstrated by previous studies, the determinants of the CDS spread vary across time (Annaert et al. 2013), and this effect could be more pronounced during a crisis period (financial crisis and sovereign debt crisis). These preliminary findings indicate that other factors have to be considered to explain the CDS spreads.

When also the bank-specific variables are considered, the explanatory power of the model increases. Model II and III present an adjusted

Table 7.4 Results of OLS regression.

Dependent variable: year-end CDS spreads					
log (CDS end)	Model I	Model II	Model III	Model IV	GMM
$log(CDSend)_{t-1}$					0.4735**
					(0.202)
Asset vol	−0.0996	−0.1453	0.1810*	0.2267**	0.6702**
	(0.078)	(0.107)	(0.101)	(0.089)	(0.299)
Leverage	−0.3912	−0.2813	−0.4931	0.6319	0.6498
	(0.628)	(0.919)	(0.962)	(0.833)	(0.718)
Risk-free rate (5Y)	0.1396	0.0426	0.0600	−0.0319	0.0902
	(0.088)	(0.053)	(0.059)	(0.056)	(0.091)
Tier1		−0.0777***	−0.0817***	−0.0918***	−0.1366**
		(0.013)	(0.014)	(0.022)	(0.067)
Asset qual		0.1364	0.0392	0.1791**	0.1068*
		(0.096)	(0.078)	(0.089)	(0.062)
ROE		0.0124	0.0199	0.0162	−0.0065
		(0.011)	(0.015)	(0.012)	(0.025)
Size		−0.2573***	-0.3050**	−0.2092**	−0.1301***
		(0.094)	(0.124)	(0.105)	(0.029)
Liquidity		−0.0121**	−0.0094	0.0001	0.0069
		(0.005)	(0.006)	(0.008)	(0.034)
Rating (AA)					
Rating (A)			0.0751	−0.0928	1.7143*
			(0.156)	(0.154)	(0.974)
Rating (BBB)			0.3071	0.2558	0.3267
			(0.356)	(0.328)	(0.240)
Rating (BB)			1.2751***	0.8533**	0.8940***
			(0.372)	(0.336)	(0.309)
Rating (B)			0.4854	0.4212	1.1707
			(0.582)	(0.537)	(1.766)
TRI				−0.0460	0.6568
				(0.124)	(0.425)
Mkt vol				0.0625***	0.0962**
				(0.013)	(0.047)
Slope				−0.1924**	-0.1264**
				(0.077)	(0.062)
GDP				0.0482	0.1971
				(0.056)	(0.152)
Sov CDS (end)					0.3507***
					(0.038)

(continued)

Table 7.4 (continued)

Dependent variable: year-end CDS spreads					
log (CDS end)	Model I	Model II	Model III	Model IV	GMM
$log(CDSend)_{t-1}$					0.4735**
Constant	5.2534***	7.9008***	6.5640***	5.6725**	−16.0593**
	(0.619)	(1.550)	(2.299)	(2.300)	(6.915)
No. of observations	235	235	235	235	235
R^2	0.0439	0.1415	0.2157	0.3485	
Country clustering	Y	Y	Y	Y	
VIF[1]	1.02	1.3	1.58	1.74	
Sargan test					0.006
Hansen test					0.004

The dependent variable is the natural logarithm of the year-end CDS spreads
Period 2009–2012
This table reports the results of OLS regression. Robust standard errors (clustered at the country level) are in parenthesis below the estimated coefficients. ***, ** and * indicate statistical significance at the 1–5% and 10% level, respectively. VIF is the variation inflation factor;[1] mean VIF values greater than 10 may warrant further examination
Asset volatility (Asset vol) is the historical standard deviation of bank's daily equity returns in a particular year. Leverage is the ratio between book value of liabilities and the sum of book value of liabilities and market value of equity . The risk-free interest rate with 5-year maturity (Risk-free rate (5-Y)) is proxied by the Datastream benchmark 5-year government redemption yield. Tier 1 ratio (Tier1) ratio is calculated according to the Basel Accord rules. Asset quality (Asset qual) is the ratio between provision for loan losses and total loans. ROE is return on assets. Size is the natural logarithm of total asset. Liquidity is the ratio between net loans and demand deposits. Total return index (TRI) is the theoretical aggregate growth in value of the constituents of the index. Market volatility (Mkt vol) is the implied volatility index. Slope of the yield curve (Slope) is the difference between the 10-year and the 5-year treasury bond yields. GDP is natural logarithm of GDP of each country. Sovereign CDS spreads (Sov CDS (end)) are the sovereign CDS spreads of each country. Rating AA is the reference rating of our regression

R–squared of 14.15 and 21.57%, respectively. In Model II we use the bank-specific variables while in Model III we also consider the rating. It seems that Model III is better able to capture the determinants of CDS spreads. If we focus on the bank-specific variables, results reported in column 2 show that banks' capitalisation (measured by the Tier 1 capital ratio) has a significant explanatory power with the expected negative sign. This result is confirmed by all the estimates that we run in the present work. We argue that one of the main indicators that market participants consider when assessing the banks' risk is the level of capitalisation. This result is in line with the previous studies (Chiaramonte and Casu 2013; Hasan et al. 2015) and also with the regulators indications that consider the capital buffers as the most important defence against the potential bankruptcy. Capitalisation is important also to protect deposits and to survive during a crisis or to external shocks. This result confirms that markets and regulators are aligned when assessing the banks' risk.

The banks' liquidity proves to be significant with the expected negative sign (Kanagaretnam et al. 2016) only in Model II while it loses its importance in the other estimates. This can be due to the fact that liquidity risk and credit risk (captured by CDS spreads) have a different nature. Findings on the importance of liquidity in determining the banks' (credit) risk are only partially consistent with concerns and expectations of regulators (EBA 2015) that, especially after the turmoil, started to consider liquidity as an important source of risk.

The size variable presents a significant coefficient (at 1%) with negative sign, signalling that larger banks are perceived by the market participants as less risky. As emphasised in previous sections, the relationship between bank's size and CDS spreads is controversial. In our case, the negative effect of the size can be due to the potential ability of larger banks to achieve diversification benefits and economies of scale. Furthermore, this result seems to confirm the too-big-to-fail paradigm since larger banks are perceived as less risky. Also this result is confirmed by all the estimates carried out in the present work.

In Model III, we test the model including the credit risk variables and the bank-specific variables, plus the ratings. The results confirm the significance of capitalisation and size and show that ratings affect the CDS premium. The ratings variables are significant when we pass from investment to non-investment grade banks. The coefficient of the rating BB variable is strongly significant (at 1%) and the sign of the coefficient is positive. For the interpretation of the sign of the coefficient, we have to consider that the control group in our estimates is the AA-rating group of banks. The sign and the values of the coefficients of the rating classes are consistent with our expectations. When the rating decreases, the CDS premium increases and this increase is significant when switching from investment to non-investment grade banks. This result is always confirmed.

In Model IV, we test the complete model, adding the market and country-level variables. As expected, the explanatory power of the model increases (adjusted R–squared equal to 34.85%). Overall, findings show that market and country-level variables are important in explaining CDS spreads. With reference to the credit risk and the bank-specific variables, these findings substantially confirm the results previously obtained. When the market and country-level variables are included, the asset volatility tends to gain significance with the expected positive sign. Also, the asset quality variable is significant at 5% with the expected positive sign. A higher ratio of bad loans positively affects the bank's credit risk. This result is consistent with the previous literature (Chiaramonte and Casu 2013; Hasan et al. 2015; Kanagaretnam et al. 2016) and indicates that market participants and regulators tend to be aligned (EBA 2015). Since the most important assets of the banks' portfolio are represented by loans, this result highlights the CDS capacity to capture the credit risk of a bank. Among market and country-level factors, the variables market volatility and slope of the yield curve are significant (at 1 and 5%, respectively) with the expected sign of the coefficients. Findings indicate that, in the case of banks, the market variables affect their credit risk. However, this conclusion has to be contextualised taking into account the specialness of the period considered; in fact, the years from 2009 to 2012 were characterised by the crisis in many countries and geographical area, such as Europe.

The findings obtained so far seem to indicate the importance of market and country-level factors in determining the banks' CDS spread. Because since 2011 some countries have experienced the sovereign debt crisis, we decided to further investigate this issue by explicitly considering the sovereign CDS spread as determinants of the banks CDS spread. In column 5, we report the results of the estimates obtained using the GMM model. The findings demonstrate that sovereign CDS spreads strongly affect the banks' CDS while the results of the other variables tend to be stable in term of significance with respect to those obtained from previous estimates. The results of the sovereign CDS variable are probably due to the high percentage of sovereign bonds present in the asset portfolios of the most important international banks. However, as previously emphasised, these results should be considered

Table 7.5 Results of the normalised beta of the OLS regression

Normalised beta				
	Model I	Model II	Model III	Model IV
Asset vol	−0.1237	−0.1863	0.2320	0.2963
Leverage	−0.0506	−0.0386	−0.0677	0.0873
Risk-free rate (5Y)	0.1838	0.0598	0.0841	−0.0462
Tier1		−0.0559	−0.0588	−0.1237
Asset qual		0.1328	0.0382	0.1787
ROE		0.2643	0.2231	0.1841
Size		−0.1932	−0.0764	−0.1390
Liquidity		−0.1206	−0.0944	0.0012
Rating (AA)				
Rating (A)			0.0466	−0.0576
Rating (BBB)			0.1447	0.1084
Rating (BB)			0.3165	0.2189
Rating (B)			0.0501	0.0449
TRI				−0.0422
Mkt vol				0.3638
Slope				−0.1654
GDP				0.1143

The dependent variable is the natural logarithm of the year-end CDS spreads
Period 2009–2012
This table reports the results of the normalised beta of the OLS regressions
Asset volatility (Asset vol) is the historical standard deviation of bank's daily equity returns in a particular year. Leverage is the ratio between book value of liabilities and the sum of book value of liabilities and market value of equity. The risk-free interest rate with 5-year maturity (Risk-free rate (5-Y)) is proxied by the Datastream benchmark 5-year government redemption yield. Tier 1 ratio (Tier1) ratio is calculated according to the Basel Accord rules. Asset quality (Asset qual) is the ratio between provision for loan losses and total loans. ROE is return on assets. Size is the natural logarithm of total asset. Liquidity is the ratio between net loans and demand deposits. Total return index (TRI) is the theoretical aggregate growth in value of the constituents of the index. Market volatility (Mkt vol) is the implied volatility index. Slope of the yield curve (Slope) is the difference between the 10-year and the 5-year treasury bond yields. GDP is natural logarithm of GDP of each country. Rating AA is the reference rating of our regression

with caution given the very complex and debated relationship between bank and sovereign risk.

The coefficients in Table 7.4 can be misleading if one omits the standard deviations from the analysis. In Table 7.5 we report the normalised betas of the regressions that allow us to compare the impact of the independent variables on the banks' CDS spreads. If we focus on the complete model (column 4, Model IV of Table 7.4), we can observe that the variable that has the greatest effect on the CDS spread is the market volatility. A one standard deviation increase in market volatility from its trend is associated with an increase of more than 1/3 of a standard deviation of CDS spreads relative to its own trend. It is worth to note that also Tier 1, asset volatility, asset quality, size and BB rating variables have a strong impact on the CDS spreads of banks.

7.6 Robustness Tests

In this section, to further verify our results, we implement some robustness checks concerning the model specification and the estimation method.[13]

First, we use an alternative measure of CDS spreads to check whether our results are sensitive to our choice of the year-end CDS spreads. As dependent variable, we use the average of year-end CDS spreads. The results are qualitatively similar to those obtained previously and reported in Table 7.4.

Our main results are confirmed by this robustness test: (i) by adding the bank-specific and the market/country variables to the model, its explanatory power tends to increase; (ii) when the bank-specific variables are considered, their relative importance in determining CDS spreads is higher than the importance of the credit risk variables; (iii) the BB-rating variable is always strongly significant; (iv) when the market and country-level variables are included, almost all the variables aimed at capturing the general business climate prove to be significant.

Second, given the importance that leverage typically assumes in explaining CDS spreads, we perform tests by using another measure of leverage. As suggested by the previous literature, we employ the bank stock returns (Annaert et al. 2013). The results confirm the previous findings with the leverage variable not showing statistical significance. This indicates that CDS spreads are not sensitive to the definition of leverage.

Third, given the insignificance of the ROE, we use an alternative measure of the profitability of the bank. We perform a test employing the Z-score that does not prove to be significant and therefore confirming previous results.

Finally, we re-estimate all regressions by using a Panel data model with bank fixed effects to account for unobserved time-invariant bank characteristics.[14] The findings generally confirm our main results reported in Table 7.4.

7.7 Conclusions

This study examines the determinants of CDS spreads in banks during 2009–2012. Consistent with the previous literature, empirical findings generally show that banks-specific and market and country-level variables affect CDS spreads. One of the main indicators that market participants consider when assessing the banks' risk is the level of capitalisation; this result is in line with regulators indications that consider the capital buffers as the most important defence against the potential bankruptcy. Also the size of the bank proves to be a significant determinant of the CDS spreads, signalling that larger banks are perceived by the market participants as less risky. The ratings of the banks are significant when switching from investment to non-investment grade banks. The sovereign CDS spreads affect the banks' CDS.

Our findings demonstrate that market participants attribute great importance to market and country factors. A hypothesis that can explain these results relates to the period under investigation during which the banks have been affected by the financial turmoil and the sovereign debt crisis in several European countries. It is plausible to expect that when there is no financial panic and a lower level of speculative activity, therefore when markets tend to be more stable, the importance of each of the possible determinants of CDS spreads changes. Given the changed scenario—with the crisis that have been overcome, at least in some countries—, given the new rules in several banking sectors (Basel 3, European Banking Union, and so on), and given the sovereign debt relief, future research could focus on the issues investigated in the present work to study whether and how the determinants of banks CDS spreads vary across time.

Our findings could provide insight for regulators. Results of the empirical analysis could indicate that CDS could function as a catalyst, increasing the speed with which a crisis may spread. This insight is confirmed by the importance of sovereign CDS as determinant of the bank's CDS spreads. Since banks have demonstrated to be transmitters of financial stress, with dangerous effects on the financial stability, regulators should pay more specific attention to the CDS market in banking systems, also to mitigate the procyclical effect frightened by critics of the Basel Accords. Furthermore, our findings corroborate the efforts made by policy makers in increasing the requirements and transparency of credit rating agencies and in searching new strategies to face the too-big-to-fail paradigm. Finally, the results seem to indicate that regulators and market participants are aligned when considering the importance of capitalisation in determining the banks' risk.

Notes

1. See "Bank Recovery and Resolution Directive" n. 2014/59/EU.
2. Another problem highlighted by empirical studies is related to the fact that the impact of structural default factors is time-varying.
3. The acronym CAMELS is derived from the components of a bank's condition that supervisors assess using a mix of publicly available and private information to assign a composite overall rating. These components are as follows: C (Capital Adequacy), A (Asset Quality), M (Management), E (Earnings), L (Liquidity) and S (Sensitivity to Market Risk).
4. Drago and Gallo (2016) study the relationship between ratings announcement and CDS premium with reference to sovereign. Using event study methodology, they test the impact of rating changes announcements (given by Standard & Poor's) on the euro-area sovereign CDS market during the period 2004–2013. They show that when downgrades are considered, there is a significant effect on the CDS market, especially for speculative grade countries. When upgrades are considered they demonstrate the existence of a more limited impact: only on the announcement day and on the following day. Furthermore, they find that outlooks are not significant while negative reviews have an impact only on the days following the announcement.

5. Pearson correlation matrix does not show problems of correlation among independent variables because all correlation coefficients are lower than 50%. Additionally, the correlation coefficients between CDS spreads and each of the independent variables have the expected sign. Asset quality, ROE, slope of the yield curve and market volatility are the variables with the strongest and statistically significant correlation with CDS spreads. For the sake of brevity, we decide to not show the correlation matrix, available upon request.
6. We test the autocorrelation of the error term by using a Durbin–Watson statistics. In all regressions, the observed statistics is greater than the upper value in Durbin–Watson table. Therefore, we do not reject the null hypothesis of non-autocorrelated errors.
7. The countries are as follows: Abu Dhabi, Australia, Austria, Belgium, China, Denmark, France, Germany, Japan, Greece, India, Ireland, Italy, Malaysia, Norway, the Netherlands, Portugal, Singapore, South Korea, Spain, Sweden, Switzerland, Turkey, the UK, the USA.
8. VSTOXX data are obtained from The Wall Street Journal (www.wsj.com); VIX data from CBOE (www.cboe.com); S&P/ASX 200 VIX and HIS volatility index from www.investing.com; India VIX from the National Stock Exchange of India (www.nseindia.com); CBOEO EX implied volatility index from https://sg.finance.yahoo.com; VXJ Japan from the Center for Mathematical Modeling and Data Science (Osaka University) (www-mmds.sigmath.es.osaka-u.ac.jp/en/).
9. Some authors emphasised that Tier 1 ratio suffers several limitations such as the calculation of risk-weighted assets (RWA) (Vallascas and Hagendorff 2013), the different definitions across jurisdictions and the lack of information to enable operators to fully evaluate and compare the quality of capital among institutions (BIS 2011).
10. The lower the loans, the greater the reserves of the front line that banks can use to bridge the liquidity imbalances (government bonds).
11. Given their specialness and given the data availability, for China and India we employed the country total return index. The return index represents the theoretical aggregate growth in value of the constituents of the index. The index constituents are deemed to return an aggregate daily dividend which is included as an incremental amount to the daily change in price index.
12. The economic policies of the European Central Bank (long-term refinancing operation, LTRO, and quantitative easing) have recently

allowed banks to buy many government bonds and take advantage of the carry trade mechanism.

13. For the sake of brevity, we decide to not show the results, available upon request.
14. We estimate the Panel data with random and fixed effects. The Hausman test indicates that fixed effect is more appropriate.

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