



J R C T E C H N I C A L R E P O R T S

European Deposit Guarantee Schemes: revision of risk based contributions using CDS spreads

Clara Galliani
Riccardo De Lisa
Stefano Zedda

2012

Report EUR 25510 EN

European Commission

Joint Research Centre

Institute for the Protection and Security of the Citizen

Contact information

Forename Surname

Address: Joint Research Centre, Via Enrico Fermi 2749, TP 361, 21027 Ispra (VA), Italy

E-mail: clara.galliani@jrc.ec.europa.eu

Tel.: +39 0332 78 6246

Fax: +39 0332 78 5733

<http://ipsc.jrc.ec.europa.eu/>

<http://www.jrc.ec.europa.eu/>

Legal Notice

Neither the European Commission nor any person acting on behalf of the Commission is responsible for the use which might be made of this publication.

Europe Direct is a service to help you find answers to your questions about the European Union
Freephone number (*): 00 800 6 7 8 9 10 11

(*): Certain mobile telephone operators do not allow access to 00 800 numbers or these calls may be billed.

A great deal of additional information on the European Union is available on the Internet.
It can be accessed through the Europa server <http://europa.eu/>.

JRC75345

EUR 25510 EN

ISBN 978-92-79-26414-6

ISSN 1831-9424

doi:10-2788/49174

Luxembourg: Publications Office of the European Union, 2012

© European Union, 2012

Reproduction is authorised provided the source is acknowledged.

Printed in Italy

Authors' affiliation

Clara Galliani

European Commission Joint Research Centre, IPSC, Scientific Support to Financial Analysis Unit

Riccardo De Lisa

University of Cagliari, DSEA and Fondo Interbancario di Tutela dei Depositi

Stefano Zedda

European Commission Joint Research Centre, IPSC, Scientific Support to Financial Analysis Unit and University of Cagliari, DSEA

Abstract

Deposit Guarantee Schemes (DGS) aim at protecting depositors of all credit institutions against bank failures. One of the most critical issues about DGS concerns the criteria to be used to assess the risk-based contribution that each member bank should pay to the Scheme. We propose an alternative model for risk-based contributions based on CDS spreads. We construct the same balance sheet ratios used in the Italian DGSs for a sample of EU banks issuing CDSs. Subsequently we perform panel regressions to explore the relationship between CDS spreads and balance sheet indicators. Results are used to construct an Aggregate Indicator of bank riskiness that is compared with the Aggregate Indicator currently used in the analyzed DGS.

Keywords: Deposit Guarantee Schemes, Credit Default Swaps, bank risk, balance sheet ratios.

TABLE of CONTENTS

1. Introduction	7
2. Literature review	8
3. Methodology	11
3.1 Bank CDS spreads.....	13
3.2 Balance sheet ratios	14
4. Results	16
4.1 Sensitivity analysis	16
4.2 Relationship between CDS spreads and balance sheet ratios used at the FITD in a sample composed of 48 European banks issuing CDSs	17
4.3 Correction of (Italian) bank riskiness indicator using regression coefficients found in the previous step. Comparison of the performance of the new indicators with the current indicator applied in the Italian DGS	19
5. Conclusions	21
References	22

1. Introduction

Deposit guarantee schemes (DGSs) are the part of the financial safety net designed to offer protection to depositors and consequently support the stability of the entire economy. DGSs ensure depositors that, in the event of a bank's failure, they will be able to recover at least a proportion of their deposits. They are not intended to deal by themselves with systemic crises generated by the failure of systemically important banks, but need to be part of a well-designed financial system safety net where all the participants work together and cooperate .

As explained in Diamond and Dybvig (1983), bank runs occur when depositors rush to withdraw their deposits because they expect a bank to fail. Bank runs are caused by a combination of two factors (see Ketcha, 2007): first the illiquidity of bank loans — the primary asset of banks —that means it is impossible to sell loans quickly without a loss in value. Second, the possibility for depositors to withdraw their deposits on demand or at short notice. Moreover, the 'first come, first served' nature of the process provides depositors with the incentive to run. A bank suffering a panic run will liquidate many of its assets at a loss and this will lead to its failure. DGSs are an instrument in the financial safety net implemented to avoid bank runs by maintaining a high level of public confidence in banks' ability to meet their obligations. For doing so DGSs need some funding or financial contributions from banks.

Design of DGSs varies across countries. Differences are mainly driven by choices related to funding mechanisms: ex post and ex ante funding can be combined with risk-based or non risk-based contributions. Banks' risk-based contributions to DGSs are adjusted according to an evaluation of the riskiness of the financial institutions that have to contribute. The existence of DGSs give rise to moral hazard problems since guarantees push banks towards an increasing risk taking attitude. Nevertheless some recent papers highlight the important role risk-based contributions have in mitigating moral hazard problem by inducing a more prudent behaviour of banks and by improving their risk management (see European Commission Impact Assessment, 2010; Schich, 2008 and Ketcha, 2007).

Techniques used to compute risk-based contributions for DGSs mainly differ along three dimensions: the identification of banks' risk profiles, the selection of indicators able to represent those profiles and the aggregation methodologies used to combine them in a single index representing the overall banks' riskiness.

Once significant firms' profiles to be measures are identified, indicators that are able to summarize them can be recovered looking at three different sources: external credit ratings, accounting data and market prices.

In recent years, credit ratings have been widely criticized for their poor discriminatory power in the identification of insolvent financial institutions (recall for example the not prompt downgrade of Lehman Brothers, Freddie Mac and Enron).

In this paper we focus on CAMEL models based both on accounting variables and market values. The CAMEL model developed in 1980s by US supervisory authorities is the most known example of risk rating models based on accounting variables. In the CAMEL framework, each banking institution is evaluated on the basis of five basic balance sheet indicators revealing single banks' operations and performance, namely: Capital adequacy, Assets quality, Management, Earnings, Liquidity (see Sahajwala and Van den Bergh, 2000 for details). A composite rating is then constructed that represents a bank's current financial condition. Our analysis is developed taking into account the model currently adopted at the Italian DGS, that uses similar accounting variables. Market prices (stocks, bonds and CDS) can represent an additional source of information since they may efficiently summarize the state of health of those firms they are referred to.

CAMEL models that aim at assigning a risk score to financial institutions generally aggregate selected indicators in order to produce a single indicator of bank riskiness. The aggregation procedure of each ratios (by weighs) is mainly based on subjective choices that are not derived from empirical/statistical evidence.

Our contribution presents a new methodology to construct risk-based contributions, based on the relationship between balance sheet indicators and CDS spreads. In particular, we propose an indicator of banks' riskiness starting from accounting variables that are aggregated using their relative importance in explaining market variables (CDS spreads).

Banks CDSs are an assessment of the (credit) riskiness of issuers, so they can be employed as a benchmark for the calculation of any risk-based contribution to a general DGS. This paper uses CDS spreads data as a dependent variable in regressions having balance sheet indicators currently employed in the Italian DGS as independent variables. In this way the risk indicator is bechmarked to the market evaluation of riskiness in the banking system.

Literature on CDSs is relatively scarce since the CDS market enjoyed a significant increase in traded volumes only from 2004. Moreover, only a limited number of existing papers specifically examine CDS spreads in the banking sector and, among them, only one (Chiaramonte and Casu, 2010) investigates the relationship between CDS spreads and balance sheet indicators confirming that CDS spreads reflect the risk captured by bank balance sheet ratios.

The rest of the paper is organised as follows: the next section contains a brief revision of the literature about CDS and DGSs. Section 3 contains the description of the methodology used to construct the alternative model based on CDS spreads. Data and results are discussed in sections 4 and 5 whereas conclusions and further developments are presented in section 6.

2. Literature review

A CDS is a type of credit derivative designed to isolate the risk of default on credit obligations.

Credit derivatives are in general conceived to hedge, transfer, or manage credit risk and therefore they can be thought of as insurance against default. Two counterparties are involved, the protection buyer and the protection seller. The insured event is the loss arising from a default, the premium paid is the fee, and the maximum covered loss is called the notional amount (see Stulz, 2009). As explained in Cariboni et al. (2009), the idea is that credit risk is transferred without reallocating the ownership of the underlying asset.

CDSs take up a very large share of the credit derivatives market. They trade over the counter on a dealers' market where dealers trade with end-users as well as with other dealers. A CDS is a bilateral agreement whereby the protection buyer transfers the credit risk of a reference entity to the protection seller for a specified length of time. The buyer of the protection makes predetermined payments to the seller until either the maturity date is reached or the default event occurs. In the latter case, the protection buyer pays the protection seller a specified amount. The CDS spread is the yearly rate paid by the protection buyer to enter the contract against the default of the reference entity. Thus, it reflects the riskiness of the underlying credit.

Literature on CDSs started to grow from 2004, when the size of the CDS market became significantly large. It is divided into two strands: papers dedicated to the pricing characteristics of CDS spreads and papers focusing on the determinants of CDS spreads.

In the first group there are empirical analyses investigating the ability of CDS spreads to incorporate firm-specific information. Some empirical studies (see for example Blanco et al., 2005) prove the superiority of CDS spreads over corporate bond spreads in terms of price discovery: it has been shown that information mostly flows from CDS prices to bond prices.

Models for determinants of credit spread risk are usually classified into two categories: structural models and reduced form models.

Before the surge of the CDS market, empirical studies looking for the determinants of credit risk were based only on corporate spreads. Elton et al. (2001), Driessen (2005) and Amato and Remolona (2005) focus on the 'credit spread puzzle', trying to explain why historical default losses are not aligned with observed credit premia. A second group of empirical studies tries to identify determinants of credit spreads in a statistical way by regressing observed spreads on factors identified by theoretical models as explanatory variables (see for example Collin-Dufresne et al., 2001; Campbell and Taksler, 2003; Guazzarotti, 2004; Avramov et al., 2007; Cremers et al., 2004).

The first papers focusing on the determinants of CDS spreads suggest that, in addition to credit risk, CDS spreads reflect some other factors. For example, Aunon-Nerin et al. (2002) focus on contracts that were traded between January 1998 and February 2000 (with both sovereign and corporate underlying assets) to investigate the influence of some fundamental variables on a cross-section of credit default transaction data. They find that ratings, asset volatility, the size and direction of stock

price changes and leverage together with market information are able to explain up to 82 % of the variation in CDS pricing. More recent papers consider only bank CDS spreads in order to test whether those factors that determine CDS spread in non-financial institutions remain valid also for the banking sector. Almer et al. (2008) work on daily EUR-denominated CDS quotes relating to financial institutions during the period January 2001 – December 2007. Firstly, they show that short-term (six-month) and long-term (five-year) spreads have a high correlation during the whole period. Dividing the analysis into sub-periods, they find that in periods of turbulence spreads have the tendency to co-move; in calm markets they seem independent. They also seek to identify factors that drive short- and/or long-term CDS spreads. Annaert et al. (2009) perform an empirical analysis of the determinants of CDS spread changes for 31 listed Euro-area banks over the period January 2004 – October 2008. They find three main results: first, the determinants of changes in bank CDS spreads exhibit significant time variation. Second, variables suggested by structural credit risk models (risk-free interest rate, leverage and asset volatility) are not significant in explaining bank CDS spread changes, both in the period prior to the crisis and in the crisis period itself. However, some of the variables proxying for business conditions, market conditions and uncertainty are significant, but both the magnitude and the sign of coefficients have changed over time. Third, CDS market liquidity became a significant factor in explaining bank CDS spread changes when the crisis broke out in the summer of 2007.

Chiaramonte and Casu (2010) investigate the relationship between balance sheet ratios and CDS spreads in three periods: pre-crisis (January 2005 – June 2007), crisis (July 2007 – March 2009) and during-and-post-crisis (April 2009 – March 2010). This is the first paper that uses specifically balance sheet information to explain variations in CDS spreads. More particularly, they analyse the following explanatory variables: Asset quality; Capital; Profitability; Liquidity. Their sample is composed of 57 international banks (43 of which are European). They find that both in the pre-crisis and — in particular — in the crisis periods bank CDS spreads reflect the risk captured by balance sheet ratios. But significant explanatory variables are different in the three sub-periods considered. In particular, the ratio of loan loss reserve to gross loans is the only significant variable in all three periods. Both leverage and the Tier 1 ratio are never among the determinants of CDS spreads and, finally, liquidity does not explain CDS spreads in the pre-crisis period.

Some other papers focusing on the banking sector analyze CDS spreads in order to explain details of the current financial crisis. Eichengreen et al. (2009) investigate common components driving the variance of CDS spreads before and during the crisis. Calice and Ioannidis (2009) focus on the group of large complex financial institutions (LCFIs) as defined by the Bank of England (2001). They find that CDS indices in Europe and the US are important in explaining the movement in LCFIs' equity prices, as are credit fundamentals. Additionally, they find robust short-run evidence of an overall increase in correlations across these two markets since the middle of 2007. Huang et al. (2008) propose

a framework for measuring and stress-testing the systemic risk of a group of major financial institutions. CDS spreads are used together with equity prices of individual banks in order to construct an indicator of systemic risk in the banking sector. Hart and Zingales (2009) use CDS spreads to design a new capital requirement for large financial institutions (LFIs) that are too big to fail.

The present contribution starts from the paper by Chiaramonte and Casu (2010), which provides evidence of the close relationship between CDS spreads and information contained in banks' balance sheets. Their work, together with preceding contributions focusing on determinants of CDS spreads, highlights the fact that CDS spreads represent not only credit risk, but the more general state of health of the financial institutions concerned.

3. Methodology

As a first step, the explanatory power of the Italian model is investigated by using sensitivity analysis (SA) tools.

The first-order sensitivity index (also known in literature as Pearson's correlation ratio or main effect), S_i , is an appealing measure of importance of a variable for several reasons (Paruolo et al., 2011):

- it offers a precise definition of importance, namely 'the expected reduction in variance of the composite indicator that would be obtained if a variable could be fixed';
- it is always positive, which makes it interpretable in all cases;
- it can be used regardless of the degree of correlation between variables;
- it is 'model-free', which means that it can be applied in principle also in non-linear aggregations, unlike the effective weights or the Pearson correlation coefficient that are constrained by the linear assumption; and finally
- it is not invasive, which means that no changes are made to the composite indicator or to the correlation structure of the indicators. This is contrasted with the technique of eliminating one indicator at a time in order to assess its impact on the final ranking.

Here SA is employed to test the importance of the variables by a commonly used variance-based measure S_i (see Saltelli and Tarantola, 2002) also known in literature as Pearson's correlation ratio or first-order sensitivity index.

S_i is defined as follows:

$$S_i = \frac{V_{X_i}(E_{X_{-i}}(Y|X_i))}{V(Y)} \quad (1)$$

the ratio between $V_{X_i}(E_{X_i}(Y|X_i))$, the expected reduction in variance of the composite indicator by fixing a variable, and the unconditional variance, $V(Y)$.

In order to compute S_i we can transform the problem by the following:

$$V_{X_i}(E_{X_i}(Y|X_i)) = V(f_i(X_i))$$

As to say, $V_{X_i}(E_{X_i}(Y|X_i))$ can be estimated by an appropriate interpolation and smoothing algorithm applied to a simple scatter plot of the composite indicator Y 's scores *versus* any variable X_i .

In the simple case where $f(i)$ is a linear function, S_i reduces to R_i^2 the square of Pearson's correlation between Y and X_i .

Note that this smoothing approach is but one of many possible strategies to estimate the values of S_i .

In Paruolo et al. (2011), kernel regression is used, while other modelling applications are based on design points (see Saltelli et al., 2010 for a review). Our estimations are based on the non-parametric multivariate smoothing approach in Ratto and Pagano (2010), called state-dependent regression, that is equivalent to smoothing splines and kernel regression but is performed using a recursive algorithm to identify relevant ANOVA terms².

As a second step, we investigated if basic accounting ratios statistically explain the CDS variance. For doing so, we estimated the relationship between five-year CDS spreads for 48 European banks and FITD balance sheet ratios constructed for the same sample of banks is investigated. The regression is performed on the following model:

$$CDS_{jt} = \beta x_{jt} + \varepsilon_{jt}$$

where j represents the individual bank, and t indicates the time periods. The explanatory variables involved are the four bank balance sheet ratios used by the Italian DGS: $A1$, $B1$, $D1$, $D2$.

More specifically,

- $A1$ represents the risk profile. It is constructed as the ratio between bad loans and supervisory capital;
- $B1$ investigates the solvency profile, represented by the ratio between the supervisory capital (including Tier 3) and supervisory capital requirements;
- $D1$ and $D2$ represent the profitability profile. $D1$ is the cost to income ratio and $D2$ is the ratio between loan losses (net of recoveries) and profit before tax.

¹ See Paruolo et al. (2011).

² See Ratto and Pagano (2010).

Regressions are firstly conducted over the period 2006-2010, and then over the core (European) crisis period 2008-2010. Bank CDS spreads do not react in advance to the crisis and require less than a three-month lag to incorporate the balance sheet information. Thus, we run regressions with both bank CDS spreads and balance sheet variables at time t , as in Chiaramonte and Casu (2010).

As a second step, if the regressors of CDs model are statistically significant, the beta coefficients found in the regressions performed in the previous step are kept and an indicator of bank riskiness is constructed that represents an alternative to the one used in the Italian framework.

The last step consists in comparing the performance of the current Italian model with the performance associated with the new indicator constructed using CDS spreads. The comparison reveals a common trend in the two indicators during the period 2006-2010 with some interesting differences.

3.1 Bank CDS spreads

European banking groups associated with five-year CDS spreads are considered. The limited number of banks contained in the sample (48) derives from the decision to focus on the banking sector within EU countries. Banks are distributed among European countries as follows:

Table 1 Number of banking groups per country

Country ³	AT	BE	DE	DK	ES	FR	GB	GR	IE	IT	NL	PT	SE
Number of banks	3	2	8	1	3	4	7	1	3	8	4	2	2

The analysis is divided into two periods: 2006-2010 and 2008-2010. Daily spreads coming from Bloomberg were available from January 2006 to December 2010 for the 48 banks. The average spread over the last 15 days of December of each year considered was taken since only annual data were available for balance sheet variables.

The following table shows average annual CDS spreads by country:

Table 2 Annual average CDS spreads per country

	2006	2007	2008	2009	2010
AT	0.0018	0.0077	0.0360	0.0232	0.0286
BE	na	na	0.0463	0.0207	0.0346
DE	0.0020	0.0090	0.0166	0.0163	0.0335
DK	0.0008	0.0054	0.0229	0.0129	0.0191
ES	0.0017	0.0090	0.0262	0.0175	0.0494
FR	0.0010	0.0070	0.0272	0.0160	0.0237
GB	0.0009	0.0075	0.0218	0.0121	0.0205
GR	na	na	na	0.0409	0.1451
IE	0.0011	0.0149	0.0427	0.0529	0.2414
IT	0.0010	0.0065	0.0413	0.0122	0.0276
NL	0.0010	0.0067	0.0999	0.0229	0.0280
PT	0.0015	0.0080	0.0170	0.0169	0.1312
SE	0.0021	0.0022	0.0187	0.0097	0.0112

³ AT=Austria, BE=Belgium, DE=Germany, DK=Denmark, ES=Spain, FR=France, GB=UK, GR=Greece, IE=Ireland, IT=Italy, NL=The Netherlands, PT=Portugal, SE=Sweden.

Average	0.0014	0.0082	0.0387	0.0198	0.0529
----------------	---------------	---------------	---------------	---------------	---------------

Values of average spreads are quite different among countries, ranging from a minimum value of 0.0014 in 2006 to a maximum of 0.0529 in 2010 (driven by high Greek and Irish values). The highest values are associated with Greece (only two years of available data) and Ireland, as expected.

3.2 Balance sheet ratios

Data about Italian banks are public data provided by FastBilanci.

The change in accounting methods due to introduction of International Accounting Standards at the end of 2005 do not allow to use data for the previous years, only from 2006 we have fully comparable balance sheet extractions.

The analysis involves all the FITD's member banks (around 300), which represent over 90 % of total eligible deposits as of June 2010 (693.5 billion €). This means that the dataset draws a complete picture of the Italian banking system. More specifically, the dataset contains 263 banks in 2006, 265 in 2007, 252 in 2008, 240 in 2009 and 208 in 2010. The original dataset was reduced by eliminating banks that benefit from exceptions (start-up banks, non-EU banks from G10 countries and banks with no reimbursable funds).

Descriptive statistics are provided in Table 3:

Table 3 Average values. Italian banks sample, 2006-2010

	2006	2007	2008	2009	2010
A1	7.57	7.77	9.19	12.82	17.47
B1	271.13	304.84	285.60	266.67	252.45
D1	62.00	63.17	72.87	82.70	80.47
D2	-1.38	13.01	-0.41	67.20	-196.80

Looking at annual average values, we notice a deterioration of ratios. In particular, A1 increases, B1 drops starting from 2007 and D1 increases until 2009. D2 doesn't show a clear tendency because of the large variability in D2 data. Its negative average values are driven by extreme negative values in the sample. Subsequently to the application of a winsoring procedure, D2 shows an increasing trend until 2009, which is consistent with the higher riskiness showed by the other indicators.

Table 4 provides details about correlations between indicators in the FITD sample. Correlation coefficients are computed both for 2006-2010 and for 2008-2010.

Table 4 Correlation coefficients between balance sheet ratios, FITD sample

	2006-2010				2008-2010			
	A1	B1	D1	D2	A1	B1	D1	D2
A1	1				1			
B1	-25 %	1			-32 %	1		
D1	2 %	18 %	1		-1 %	29 %	1	
D2	-5 %	0 %	-2 %	1	-6 %	0 %	-3 %	1

The four ratios are slightly correlated to each other, confirming that indicators are capturing different risk profiles, and their aggregation could offer a spread picture of banks' exposures. The largest

correlation values are represented by the correlations between B1 and A1 (-25 %) and between B1 and D1 (18 %). Such a behaviour is confirmed looking specifically at the central crisis period. Larger values are obtained considering D2 without extreme values.

The second sample of banks is composed of the 48 European banking groups issuing CDSs. The dataset contains 25 banking groups in 2006, 30 in 2007, 33 in 2008, 37 in 2009 and 40 in 2010.

Balance sheet ratios are computed using Bankscope™, a database containing balance sheet data for banks worldwide. The table below sets out average values for the sample of banks issuing CDSs.

Table 5 Balance sheet ratios average values, Bankscope sample, 2006-2010

	2006	2007	2008	2009	2010
A1	19.64	22.31	45.22	51.67	61.38
B1	140.45	136.26	140.34	166.55	181.87
D1	58.99	61.03	76.96	61.64	65.16
D2	119.71	377.75	-12.66	858.51	316.15

Comparing Table 3 to Table 5, the two samples differs in value range, but the tendency towards a deterioration of balance sheet ratios moving from 2006 to 2010 is confirmed.

Table 6 reports the correlation matrix for the Bankscope sample.

Table 6 Correlation coefficients between balance sheet ratios, Bankscope sample

	2006-2010				2008-2010			
	A1	B1	D1	D2	A1	B1	D1	D2
A1	1				1			
B1	-4%	1			-12%	1		
D1	6%	25%	1		2%	23%	1	
D2	6%	-3%	-9%	1	4%	-4%	-5%	1

Bold numbers signals the main differences with the previous correlation table. In particular, throughout the considered time period A1 and B1 display a slight negative correlation, whose magnitude increases significantly considering only the central period. This difference was not so definite in the previous sample. Moreover, the correlation between D2 and A1 (in 2006-2010 and 2008-2010) has a different sign than in the FITD data. If we consider D2 without extreme values, differences in signs still remain, at least in the period 2008-2010.

4. Results

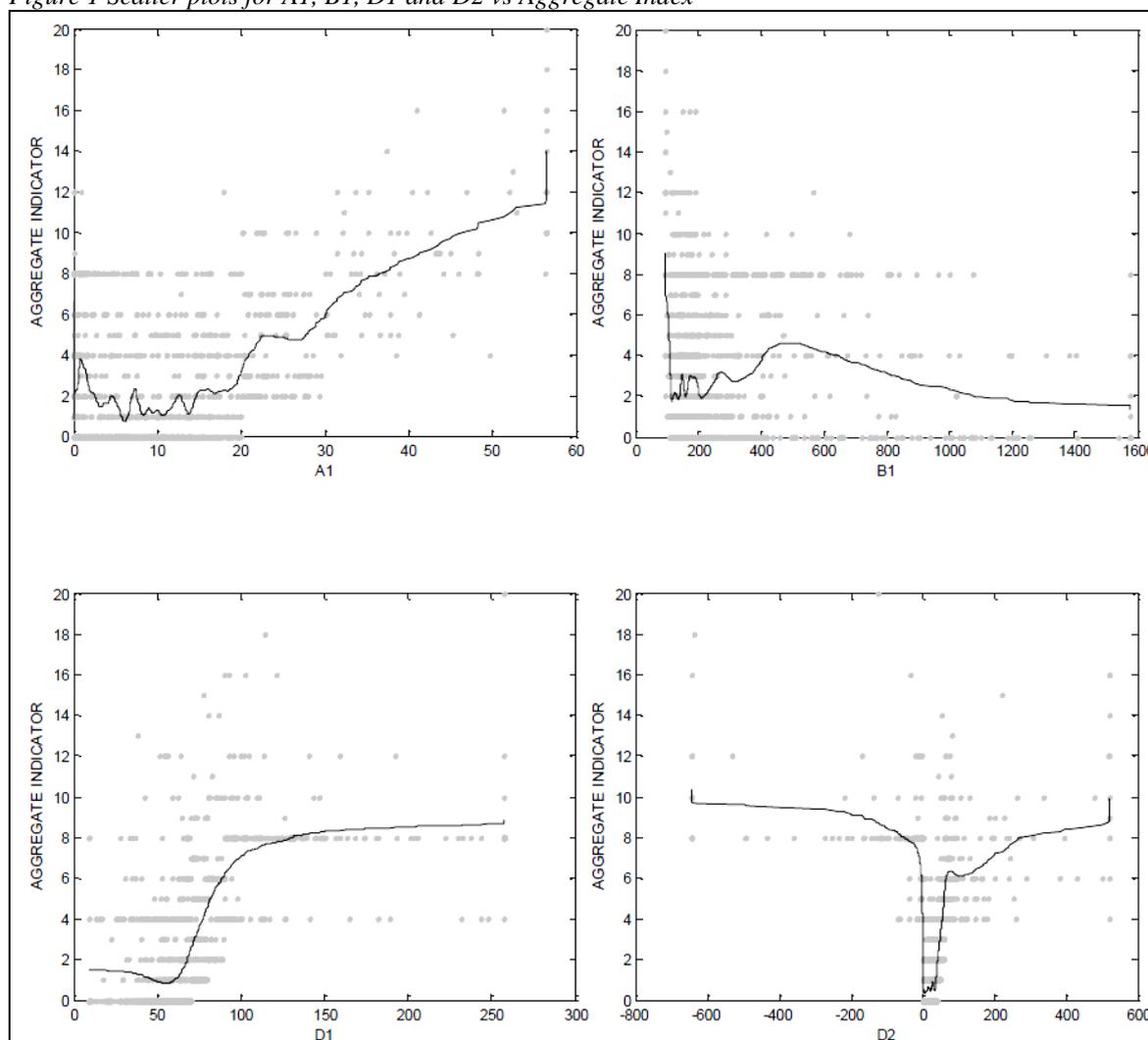
4.1 Sensitivity analysis

Sensitivity analysis results are reported here following both in graphical and numerical terms.

The scatter plots in Figure 1 graphically show the relationship between the composite indicator (AI) and the sources of uncertainty (ratios) over the period 2006-2010.

In order to avoid the plots being influenced by extreme values, both the left and the right 2.5% of the distribution extremes of the distributions were replaced with the nearest “non extreme” value.

Figure 1 Scatter plots for A1, B1, D1 and D2 vs Aggregate Index



The second scatterplot show that B1 has a rather flat behaviour, meaning that the aggregate indicator is not relevantly affected by movements in B1, while the other figures show a more clear pattern, giving evidence of their relative importance in the variability of the composite indicators. All of them have a rather monotonic behaviour, except for D2, which shows non-monotonicity coherently with its

peculiar definition: a bank is considered riskier either when D2 is negative or it takes large positive values.

For the numerical analysis, first-order sensitivity indices for the four ratios calculated using the algorithm of Ratto and Pagano (2010) are computed for evaluating the influence of each variable to the aggregate index. Sensitivity indices are reported presented in Table 7.

Table 7: Sensitivity indices for A1, B1, D1 and D2. FITD sample, 2006-2010

Sensitivity index	
A1	0.4096
B1	0.0885
D1	0.4904
D2	0.7458

Results confirm that B1 lacks of informative power. Furthermore, the important role given to A1 by its double weight is not confirmed by its sensitivity index, which is even lower than the one associated with profitability ratios.

4.2 Relationship between CDS spreads and balance sheet ratios used at the FITD in a sample composed of 48 European banks issuing CDSs

To determine whether CDS spreads can be explained by balance sheet ratios, a regression was performed, in which the explanatory variables are represented by balance sheet ratios and the dependent variable is the CDS spread, as shown in the equation below:

$$CDS_{jt} = \beta x_{jt} + \varepsilon_{jt}$$

Regressions were conducted over the sample of 48 EU banking groups, for which the four FITD ratios were constructed using Bankscope data.

As a first step, two regressions were performed over the entire period 2006-2010: one regression includes the four FITD ratios and the second one includes also a dummy variable that identifies the last three years, these being the most turbulent years according to CDS values (we can call them the core crisis period). Subsequently regressions were run specifically on those three years. For all the regressions the final sample consists of 165 observations for 48 banks (years with missing data were eliminated).The results are set out in Table 8:

Table 8 Regressions results, Bankscope sample

	2006-2010	2006-2010 with dummy	2008-2010
A1	0.0455 ^{***} (0.0054)	0.0413 ^{***} (0.0053)	0.0442 ^{***} (0.0066)
B1	0.0056 (0.0049)	-0.00055 (0.0048)	0.0064 (0.0062)
D1	-0.00062 (0.0112)	-0.00208 (0.0169)	0.0049 (0.0141)

D2	-0.00018 (0.00016)	-0.0002* (0.00016)	-0.00017 (0.0002)
Dummy		1.862*** (0.0068)	
Number of observations	165	165	110
Number of banks in the sample	48	48	48
Adjusted R-squared	0.4623	0.4813	0.4807

The dependent variable is CDS spreads, which is strictly related to the probability of default. Explanatory variables are four balance sheet ratios referring to risk (A1), solvency (B1) and profitability (D1 and D2). Standard errors of estimated coefficients are in brackets below the estimated coefficient; *** denotes coefficients statistically different from zero (1 %, 2.5 %, 5 % levels)

Results show that A1 is the most significant variable. The high explanatory power of A1 was expected since it is focused on credit risk, and CDSs are strictly linked to that specific banking risk. B1 is only significant at the 20 % level and the introduction of the dummy makes its significance level further decreasing. D1 is never significantly different from zero (the t-statistic ranges from -0.055 in the first regression to 0.349 in the regression with the dummy). Since D2 has non-monotonic behaviour, new regressions are performed after replacing D2 negative values with the 95th percentile of its distribution.

Table 9 Regressions results after modification of D2. Bankscope sample

	2006-2010	2006-2010 with dummy	2008-2010
A1	0.0469*** (0.0055)	0.0428*** (0.0055)	0.046*** (0.0067)
B1	0.00522 (0.0049)	-0.0015 (0.0053)	0.0061 (0.0061)
D1	0.0015 (0.017)	0.0005 (0.0111)	0.0081 (0.0142)
D2	-0.00027 (0.00018)	-0.0003* (0.00018)	-0.0003 (0.0002)
Dummy		2.009*** (0.7058)	
Number of observations	165	165	110
Number of banks in the sample	48	48	48
Adjusted R-squared	0.465	0.487	0.487

The modification of D2 slightly increases its significance (it is always significant at the 10 % level, and it reaches significance at 5 % only in the regression with the dummy). Still, there are not large differences between the two regression results.

Looking at the results the following observations can be made:

- A1, which represents the credit risk profile, is the ratio mostly connected to CDS spreads. So, a DGS system that wants to emphasize the bank's capacity to face losses without becoming insolvent

should give more importance to this ratio. The choice of the Italian DGS to assign more importance to A1 through a double coefficient is coherent with this.

- B1 loses importance with the introduction of a dummy variable identifying the most turbulent crisis period. Without the dummy variable, B1 is significant at the 20 % level (with and without the modification of D2).
- D1 is not significantly different from zero. In the first set of regressions, the sign of its relationship with CDS spreads doesn't emerge clearly. The introduction of a modified version of D2 doesn't change its significance. Even if this ratio measures the same bank profile as D2 (efficiency/profitability), it cannot be discarded from the analysis. The low correlations between D1 and D2 evidence that the two ratios do not measure the same riskiness profile. Further research on this ratio is needed.
- D2 has a non-monotonic behavior that calls for a partial modification. By design, high riskiness is measured either by negative values (thanks to the denominator) or by large positive values. After modifying the variable, transforming the negative values into positive values that represent the 95th percentile of D2's distribution, D2 is always significant at the 10 % level and at the 5 % level with the introduction of the dummy variable. Nevertheless, regression coefficients always have a negative sign, which was not expected.
- The four ratios explain about 48 % of CDS spreads. This result confirms what was found by previous literature: CDS spreads are strictly connected with balance sheet ratios. For this reason, they can be used as a benchmark for composite indicators intended to represent banks' riskiness.
- The choice of balance sheet ratios needs to be better explored. Taking into account previous literature, it emerges that liquidity and leverage are not considered in the current Italian model.

The present contribution aims to propose a critical approach to existing DGSs: comparing current approaches using balance sheet ratios with quantities priced on the market is useful to gain an idea of what kind of situation is actually measured.

Considering the regression coefficients presented earlier, it is possible to construct an aggregated indicator of banking riskiness for the 48 EU banks issuing CDSs and using the same coefficient to construct another indicator for the FITD sample.

4.3 Correction of (Italian) bank riskiness indicator using regression coefficients found in the previous step. Comparison of the performance of the new indicators with the current indicator applied in the Italian DGS

The coefficients found in the first and second group of regressions for the whole period 2006-2010 were selected and an aggregate indicator was constructed for bank riskiness.

Coefficients were chosen taking into account the magnitude of the four coefficients found in the above regressions. When D2 is modified to eliminate negative values, the coefficient associated with D1 changes its sign. The two aggregate indicators are constructed for the sample composed of 48 EU

banks and two series are obtained that exhibit a correlation with the CDS spread series of, respectively, 55% and 56%. The average values of the two aggregate indicators over the five years considered show a clear increasing trend, as CDS spreads. Applying the same weights for the four indicators constructed for the FITD sample yields the following values:

Table 10 Annual average values of aggregate indicators over 2006-2010. FITD sample

	Average values	
	AI	AI with D2 modified
2006	328.641	332.948
2007	363.187	368.163
2008	355.499	359.994
2009	361.702	368.425
2010	398.036	392.298

The increasing trend is evident also taking the FITD sample, with the exception of 2008, when there is a decrease in average values.

The following table highlights the behaviour of new aggregate indicators in the six classes of risk identified by the aggregate indicator currently used at the FITD.

Table 11 Annual average values of the new aggregate indicator in the six risk classes identified by the aggregate indicator currently used at the FITD. FITD sample, 2006-2010

Risk classes	Average AI				
	2006	2007	2008	2009	2010
Normal	316.058	320.280	330.506	332.971	358.122
Attention	358.214	534.453	388.798	376.513	332.632
Warning	300.894	277.504	390.245	346.656	389.634
Penalty	428.445	513.517	426.075	396.660	462.995
Severe imbalance	529.237	267.311	431.414	538.230	775.293
Expulsion	-	541.097	644.949	747.514	719.131
Tot. average	328.641	363.187	355.499	361.702	398.036

Table 12 Annual average values of the new aggregate indicator (obtained with D2 modified) in the six risk classes identified by the aggregate indicator currently used at the FITD. FITD sample, 2006-2010

Risk classes	Average AI (with D2 modified)				
	2006	2007	2008	2009	2010
Normal	321.542	325.703	336.332	339.197	364.701
Attention	361.202	539.048	394.819	386.692	339.174
Warning	307.755	282.497	397.705	353.890	397.012
Penalty	419.983	514.861	423.124	400.384	464.905
Severe imbalance	528.697	274.060	399.484	545.874	403.320
Expulsion	-	549.141	653.367	762.018	628.146
Tot. average	332.948	368.163	359.994	368.425	392.298

It is clear from the above results that both the new aggregate indicators exhibit an increasing trend along the six risk classes. The AI rises in the six risk classes with the exception of 2007, when both AIs show fluctuating behaviour. A closer look at original data reveals that such behaviour is caused by the ratio B1, which in 2007 takes on really extreme (positive) values for ten banks, probably because of the beginning of the crisis. In particular, averages are influenced by extremes in the Normal,

Attention and Penalty classes that for this reason take on really high values. The exclusion of extreme values for B1 allows an increasing trend to be obtained also for the year 2007. For the same reason the annual average values do not increase monotonically: the large rise in 2007 is driven by the ten extreme values of B1.

The behaviour of annual average values of the new AI shows that the current Italian model and the AI derived from CDSs go in the same direction. This is not so evident looking at minimum and maximum values of new aggregate indicators: they do not rise univocally along risk classes and they show huge variability.

5. Conclusions

We analysed risk-based contributions to DGSs based on the relationship between balance sheet ratios and CDS spreads during the period 2006-2010, considering the four balance sheet ratios currently employed at the Italian DGS, and evaluated for 48 EU banks issuing CDS.

Regressions reveal that only three out of four ratios have some explanatory power. In particular, the ratio that refers to banks' risk profile is always significant in explaining CDS spreads.

In a second step we construct an aggregate index representing banks' riskiness by applying regression coefficients to the sample of Italian banks available at the Italian DGS. The comparison between the average values of both the new aggregate index and the one currently adopted reveals that they are coherent at least in the extreme risk classes (low risk and high risk).

Results confirm that CDS spreads are strictly connected to balance sheet ratios, in line with what was pointed out by previous literature, so that these ratios and aggregate indicators could be employed in DGSs procedures to proxy the risk actually priced on the market.

Our analysis also suggests that some points are worth to be better addressed in future research. In particular, the different characteristics the two samples exhibit can be related to the different dimension of the considered banks: banks issuing CDSs are typically top-tier banking groups, whereas the sample of Italian banks is mainly composed by individual banks of small dimensions. This point should be better addressed, together with a more close assessment of the adequacy of the ratios used at FITD. More, Additional ratios that exhibit a possible explanatory power of CDS spreads must be investigated, in order to find if different variables can improve the banks riskiness approximation.

References

- Almer, T., Heidorn T. & Schmaltz C. (2008). *The Dynamics of Short- and Long- Term CDS-spreads of Banks*. Frankfurt School Working Paper Series No 95.
- Amato, J. & Remolona E.M. (2005). *The Pricing of Unexpected Credit Losses*. BIS Working Papers No 190.
- Annaert, J., De Ceuster M., Van Roy M. & Vespro C. (2009). *What Determines Euro Area Bank CDS Spreads?* National Bank of Belgium Working Paper No 190.
- Aunon-Nerin, D., Cossin D., Hricko T. & Huang Z. (2002). *Exploring the Determinants of Credit Risk in Credit Default Swap Transaction Data: is Fixed-Income Markets' Information Sufficient to Evaluate Credit Risk?* Working Paper, HEC-University of Lausanne and Fame.
- Avramov, D., Gergana J. & Philipov A. (2007). *Understanding Changes in Corporate Credit Spreads*. Financial Analysts Journal 63, 90-105.
- Blanco, R., Brennan S. & Marsh I.W. (2005). *An Empirical Analysis of the Dynamic Relation Between Investment-Grade Bonds and Credit Default Swaps*. Journal of Finance 60, 2255-81.
- Calice, G. & Ioannidis C. (2009). *An Empirical Analysis of the Impact of the Credit Default Swap Index Market on Large Complex Financial Institutions*. School of Management, University of Bath.
- Campbell, J.Y. & Taksler G.B. (2003). *Equity Volatility and Corporate Bond Yields*. Journal of Finance 58, 2321-50.
- Cariboni, J. & Schoutens W. (2009). *Levy Processes in Credit Risk*. New York: John Wiley & Sons Ltd.
- Chiaromonte, L. & Casu B. (2010). *Are CDS spreads a good proxy of bank risk? Evidence from the financial crisis*. Centre for Banking Research Working Papers WP-CBR-05.
- Collin-Dufresne, P., Goldstein R.S. & Martin J.S. (2001). *The Determinants of Credit Spread Changes*. Journal of Finance 51, 2177-208.
- Cremers, M., Driessen J., Maenhout P.J. & Weinbaum D. (2004). *Individual Stock-Option Prices and Credit Spreads*. Yale ICF Working Paper No 04-14.
- Di Cesare, A. & Guazzarotti G. (2010). *An analysis of the determinants of credit default swap spread changes before and during the subprime financial turmoil*. Bank of Italy Temi di Discussione No 749.
- Diamond, D. & Dybvig P. (1983). *Bank Runs, Deposit Insurance and Liquidity*. Journal of Political Economy 91, 401-419.

- Driessen, J. (2005). *Is default event risk priced in corporate bonds?* Review of Financial Studies 18(1), 165-195.
- Eichengreen, B., Mody A., Nedeljkovic M. & Sarno L. (2009). *How the Subprime Crisis Went Global: Evidence from Bank Credit Default Swap Spreads*. NBER Working Paper Series 14904.
- Elton, E.J., Gruber M.J., Agrawal D. & Mann C. (2001). *Explaining the Rate Spread on Corporate Bonds*. Journal of Finance 56, 247-77.
- Ericsson J., Jacobs K. & Oviedo R. (2009). *The Determinants of Credit Default Swap Premia*. Journal of Financial and Quantitative Analysis 44, 109-32.
- European Commission (2010). *Impact Assessment: Accompanying document to the proposal for a Directive of the European Parliament and of the Council on Deposit Guarantee Schemes and to the Report from the Commission to the European Parliament and to the Council*. Available at http://ec.europa.eu/internal_market/bank/docs/guarantee/20100712_ia_en.pdf
- Guazzarotti, G. (2004). *The determinants of changes in credit spreads of European corporate bonds*. Mimeo, Bank of Italy.
- Gropp, R., Vesala J. & Vulpes G. (2002). *Equity and Bond Market Signals as Leading Indicators of Bank Fragility*. ECB Working Paper No 150.
- Hart, O. & Zingales L. (2009). *A New Capital Regulation For Large Financial Institutions*. University of Chicago, NBER & CEPR.
- Huang, X., Zhou H. & Zhu H. (2008). *A Framework for Assessing the Systemic Risk of Major Financial Institutions*. CAREFIN Working Paper No 11.
- Jarrow, R.A. & Protter P. (2004). *Structural versus Reduced Form Models: a New Information Based Perspective*. Journal of Investment Management 2(2), 1-10.
- Ketcha, N.J. (2007). *Deposit Insurance System Design and Implementation*. BIS Policy Paper.
- Paruolo, P., A. Saisana and A. Saltelli (2011), *Ratings and rankings: Voodoo or Science?* Mimeo.
- Ratto, M. and Pagano A. (2010), *Recursive algorithms for efficient identification of smoothing spline ANOVA models*, Advances in Statistical Analysis, 94-4, pp. 367-388
- Saltelli, A. and Tarantola S. (2002), *On the relative importance of input factors in mathematical models: safety assessment for nuclear waste disposal*, Journal of American Statistical Association 97, pp. 702-709.
- Sahajwala R. & Van den Bergh P. (2000). *Supervisory Risk Assessment and Early Warning System*. Basel Committee on Banking Supervision Working Paper No 4.

Schich, S. (2008). *Financial Crisis: Deposit Insurance and Related Financial Safety Net Aspects*. OECD Journal of Financial Market Trends 95(2).

Stulz, R.N. (2009). *Credit Default Swaps and the Credit Crisis*. Social Science Research Network (SSRN) Paper.

Zhang, B.Y., Zhou H. & Zhu H. (2005). *Explaining Credit Default Swap Spreads with Equity Volatility and Jump Risks of Individual Firms*. BIS Working Paper No 181.

European Commission

EUR 25510 EN – Joint Research Centre – Institute for the Protection and Security of the Citizen

Title: European Deposit Guarantee Schemes: revision of risk based contributions using CDS spreads

Authors: Clara Galliani, Riccardo De Lisa, Stefano Zedda

Luxembourg: Publications Office of the European Union

2012 – 26 pp. – 21.0 x 29.7 cm

EUR – Scientific and Technical Research series –ISSN 1831-9424 (online), ISSN 1018-5593 (print),

ISBN 978-92-79-26414-6

doi:10-2788/49174

Abstract

Deposit Guarantee Schemes (DGS) aim at protecting depositors of all credit institutions against bank failures. One of the most critical issues about DGS concerns the criteria to be used to assess the risk- based contribution that each member bank should pay to the Scheme. We propose an alternative model for risk-based contributions based on CDS spreads. We construct the same balance sheet ratios used in the Italian DGSs for a sample of EU banks issuing CDSs. Subsequently we perform panel regressions to explore the relationship between CDS spreads and balance sheet indicators. Results are used to construct an Aggregate Indicator of bank riskiness that is compared with the Aggregate Indicator currently used in the analyzed DGS.

As the Commission's in-house science service, the Joint Research Centre's mission is to provide EU policies with independent, evidence-based scientific and technical support throughout the whole policy cycle.

Working in close cooperation with policy Directorates-General, the JRC addresses key societal challenges while stimulating innovation through developing new standards, methods and tools, and sharing and transferring its know-how to the Member States and international community.

Key policy areas include: environment and climate change; energy and transport; agriculture and food security; health and consumer protection; information society and digital agenda; safety and security including nuclear; all supported through a cross-cutting and multi-disciplinary approach.