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Sovereign Risk and Bank-Specific CDS Pricing

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Abstract: Employing time series of single-name CDS market spreads from 29 European banks located in the EU-12 plus Switzerland and the UK over the period from January 2004 through September 2010 this paper analyses the relationship between increasing sovereign risk and bank-specific CDS pricing. Results from calculating relative CDS spread deviations (model minus market spreads) initially reveal a price bubble in the European CDS market until the beginning of the financial crisis in mid-2007. From this point in time the gap narrows remarkably during the financial crisis and sovereign debt crisis period. Corresponding to these findings, the empirical analysis reveals a negative impact of sovereign risk on calculated CDS spread differentials indicating a spill-over effect between sovereign risk and bank risk and hence, a positive effect on bank-specific CDS pricing. Further analyses reveal that the perception of sovereign risk is not crisis- but country-dependent suggesting that bank-specific CDS market spreads may already include a premium to cover sovereign risk from PIIGS countries during the pre-crisis period in Europe.

JEL classification: G01, G12, G14, G18, G21

Keywords: Sovereign risk, Structural credit risk models, bank-specific CDS pricing

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1. Introduction

Capital market investors' risk perception has been substantially enhanced due to the global financial crisis starting in the U.S. in mid-2007. The increase in bank defaults together with rising financial and economic uncertainty have fortified investors' risk aversion and caused market risk premiums to soar up (IMF, 2010a). Accordingly, a remarkable revaluation of bank default risks, indicated by an increase in single-name bank-specific Credit Default Swap (CDS) spreads, has been observed since mid-2007 in Europe. As shown in Figure 1, while the *EU Banks Sector CDS Index 5Y* was on the lowest level at 7 basis points in March 2007, it reached its peak in March 2009 at 320 basis points and remains comparatively high at 242 basis points at the end of September 2010.

Likewise, as many countries from the euro area were forced to take a number of measures to restore capital market confidence, fiscal imbalances have simultaneously increased since mid-2007. The first sovereign debt crisis has been observed in Greece in October 2009 but meanwhile, this crisis has fiercely affected the periphery economies of the European Monetary Union, i.e. the so-called PIIGS countries.[1] As reported by Figure 2, the increase in sovereign risk in PIIGs countries is reflected by an increase government bonds' absolute yield values and rising yield volatilities. However, as also shown, government bond yields from the EU-12[2] plus Switzerland and the UK are asymmetrically affected which might be due to the fact that capital market investors' flight to quality and safety has clearly depressed some European countries' bond yields more than other. Accordingly, while government bond yields from the EU-12 plus Switzerland and the UK have increased for the first time until end-2008 due to bailing-out distressed financial institutions such as Northern Rock, Hypo Real Estate, Fortis and Dexia, differences in spread levels between euro area countries have become more

[1] The PIIGS countries comprise Portugal, Ireland, Italy, Greece and Spain.

[2] The EU-12 includes Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain and Sweden.

distinct thereafter. In particular, spreads of government bonds from PIIGS countries, which face severe funding difficulties, widened much more than those of other European countries especially since the beginning of the first sovereign debt crisis in Greece in 2009.

Against this background, employing data from 29 European banks located in the EU-12 plus Switzerland and the UK over the period from January 2004 through September 2010 the analysis at hand investigates if increasing sovereign risk is likely to spill over to bank risk and hence, may affect bank-specific CDS pricing as a consequence. We complement and extend previous related studies (Imbierowicz, 2008; Tsesmelidakis and Schweikhard, 2011; see Section 2) on determinants of CDS pricing for three aspects. *First*, to the best of our knowledge this is the first study that explicitly focusses on banks as the most important market players and traders in the European CDS market. Therefore, as banks generally exhibit higher leverage ratios than non-financial firms we employ an adjusted structural credit risk model to address a likely overestimation bias when estimating fundamentally verified CDS model spreads for financial institutions by means of "standard" models. *Second*, we evaluate different transmission channels that help to explain how sovereign risk may spill over to bank risk finally inducing an increase in single-name bank-specific CDS market spreads. And *third*, employing dynamic panel regression techniques the impact of sovereign risk on bank risk and CDS pricing is empirically analyzed.

Results at hand initially reveal a price bubble in the European CDS market until the beginning of the financial crisis in mid-2007. From this point in time the gap between predicted model spreads and observed market CDS spreads narrows remarkably during the financial crisis and sovereign debt crisis period. Corresponding to these findings, the empirical analysis reveals a negative impact of sovereign risk on calculated CDS spread differentials suggesting a spill-over effect between sovereign risk and bank risk and hence, a positive effect on bank-specific CDS pricing. Results from sensitivity analyses further reveal that the perception of sovereign risk is not crisis- but country-dependent suggesting that bank-specific CDS market spreads may already include a premium to cover sovereign risk from PIIGS countries during the pre-crisis period in Europe.

The remainder of the paper is organized as follows. Theoretical reflections on the nexus between sovereign risk, bank risk and bank-specific CDS pricing are discussed in Section 2. Section 3 presents previous comprehensive studies on determinants of CDS pricing. The sample of bank-specific CDS market spreads employed is introduced in Section 4.1 and the structural credit risk models used are presented in Section 4.2. Results from calculating relative CDS spread deviations are discussed in Section 4.3 and illustrated in the Technical Appendix. Section 5 describes our empirical methodology. While Section 5.1 presents data and sources, the empirical model is introduced in Section 5.2. Empirical results are discussed in Section 5.3 and illustrated in the Statistical and Technical Appendix. Finally, Section 6 concludes.

2. Theoretical background

We follow relevant studies on determinants of sovereign bond yield spreads (e.g. Barrios et al., 2009) and define sovereign risk as credit risk and liquidity risk from holding government bonds. Accordingly, while credit risk is defined as the probability that the issuer fails to meet his obligations either on coupon payments or repayment of principal at maturity, liquidity risk describes the obstacle to convert bonds into cash (market depth) as well as the adverse effects of decreasing market liquidity on bond yields (market breadth). Obviously, credit risk and liquidity risk are related. While an increase in the supply of government bonds should result in a decline of liquidity premiums, a high supply may also be associated with an increase in public deficit and hence, a higher credit risk premium.

We evaluate three transmission channels that help explain how sovereign risk may spill over to bank risk (see also BIS, 2011; IMF, 2010b). If perceived by risk-averse capital market investors, the spill-over effect is assumed to be priced in single-name bank-specific CDS market premiums. The *first channel* describes the impact of decreasing sovereign creditworthiness on the bank's *earnings potential*. Initially, an increase in sovereign risk may affect bank risk due to the fact that debt from home and foreign sovereigns is directly held by the bank. Accordingly, losses on sovereign portfolios may weaken the bank's balance sheet and increase riskiness with the adverse effects on the bank's earnings potential. Haircuts, induced by multiple sovereign downgrades, as happened in the case of Greece, could additionally strain the asset side which becomes even more important since banks hold sizable exposures to sovereigns especially in countries with high public debt (BIS, 2011).

Obviously, the extent of the negative impact depends on whether securities from sovereigns are carried on the balance sheet at market values (held in the trading book) or at amortized costs (held in the banking book). In the first case, a decrease in the value of sovereign securities may have a direct and immediate effect on the bank's profit and loss statements as well as on the bank's equity capital and leverage. In the second case, accounting principles imply that losses are recorded only when the securities are impaired (e.g. when a sovereign default becomes likely). Nevertheless, one may argue that the bank's earnings potential may be affected prior to the credit event, to the extent that capital market investors become concerned about the bank's financial soundness.

Furthermore, banks may also hold exposures to sovereigns through OTC derivatives used by sovereigns to adjust the interest rate or the currency composition of their outstanding debt. In this context, an increase in sovereign risk may result in a reduction in the market value of the bank's derivatives transactions reported as mark-to-market losses in the income statement (e.g., counterparty credit risk valuation adjustments). And finally, from a regulatory point of view higher risk weights for government debt and derivatives transactions, as proposed by the Basel II framework and its enhancements into Basel III, may induce a higher backup with regulatory equity capital which may further reduce the bank's earnings potential.

The *second channel* describes the impact of rising sovereign risk on the bank's *funding costs*. Typically, banks use securities from sovereigns extensively as collaterals to secure wholesale funding from central banks, private repo markets and the issuance of covered bonds as well as to back OTC derivative positions. Obviously, an increase in sovereign risk may reduce the value of the collateral or in general, its availability or eligibility and hence, the bank's funding capacity and funding costs. Moreover in this context, a decrease in sovereign solvency and liquidity may also reduce the probability of implicit and explicit government guarantees as well as bailing-outs which again may provoke higher funding costs especially for systemically important banks.

Finally, the *third channel* describes the impact of sovereign rating downgrades on *bank ratings*. The common belief that banks cannot be rated better than their home sovereign may lead to co-downgrades in ratings under increasing sovereign risk. By end-2010, only three out of 172 European banks exhibited ratings above that of their home sovereign (BIS, 2011). Therefore, sovereign rating downgrades may also induce direct negative effects on the bank's earnings potential and funding costs as discussed above in detail.

3. Related literature

Comprehensive studies on determinants of bank-specific CDS pricing are scarce; only two (partly) related analyses have been identified. In addition, to the best of our knowledge the study at hand is the first to investigate the relationship between sovereign risk, bank risk and bank-specific CDS pricing.

To begin with, using data from 759 firms (127 financial firms) located in Europe, the U.S. and Asia over the period from January 2002 to April 2008 *Imbierowicz* (2008) employs the standard CreditGrades model and Zhou model to calculate relative CDS spread deviations (model minus market spreads). Performing dynamic panel regressions the following empirical analysis reveals that macroeconomic measures (industry production, inflation, unemployment), confidence indicators (business and consumer confidence) and CDS market characteristics (bid-ask-spread, implied volatility) may be significant determinants of a change in relative CDS spread deviations. However, building sub-samples for Europe, the U.S. and Asia and additionally splitting the entire sample into investment and non-investment grade firms, empirical evidence on the effects of macroeconomic variables and confidence indicators is not conclusive anymore as the estimated signs partially vary across regions. Additionally, this inconsistency is more pronounced for non-investment grade rated firms than for investment grade rated companies.

Similarly, employing data from 498 firms (27 banks) located in the U.S. over the period from January 2002 to September 2010 *Tsesmelidakis and Schweikhard* (2011) focus on CDS pricing effects associated with the too-big-too-fail hypothesis while controlling for further likely pricing determinants. Calculated relative CDS spread deviations are based on the standard CreditGrades model. Employing dynamic panel regressions the analysis reveals that macroeconomic indicators (interest rate term structure, slope of the yield curve), firm-specific factors (firm size, changes in firm ratings) and the U.S. “Troubled Asset Relief Program” (TARP) may be significant determinants of CDS pricing. In particular, evidence suggests that banks being forced to receive capital assistance under TARP may exhibit higher spread deviations than non-forced financial institutions. The authors suggest that findings may support the too-big-to-fail hypothesis since default probabilities are likely to be negatively affected by capital injections.

4. Calculation of relative CDS spread deviations (RSDs)

4.1 Sample of single-name bank-specific CDS market spreads

Although CDS contracts have been observed since the early 1990s, market liquidity has been extremely short until the beginning of the 21st century. In addition, due to the fact that CDS are traded over-the-counter, qualified databases have to aggregate quotes from several trading desks to build a composite CDS market spread for each trading day. To ensure consistency as regards European CDS market spreads, we exclusively retrieve CDS quotes from *Credit Market Analysis* (CMA) provided by *Thomson Reuters' Datastream* database. CDS quotes obtained refer to daily Euro denoted mid-rates. Furthermore, only those CDS contracts with a five-year term structure are employed since these contracts are the most frequently traded and hence, most liquid contracts. Reliable and complete CDS data have been provided by CMA since January 2004 denoting the starting point of our sample.[3] With the CMA license agreement as of October 2010 *Thomson Reuters* has restricted access to the CMA database via Datastream so that our sample ends in September 2010.

The analysis at hand exclusively focuses on systemically important financial institutions in Western Europe. Accordingly, our initial sample comprises 71 banks having participated in the end-2011 European Banking Association (EBA) stress test and includes another 5 financial institutions[4] not captured in the EBA survey but characterized as systemically relevant banks as well. Since we employ structural pricing models in order to estimate fundamentally verified CDS model spreads (Section 4.2), we initially have to exclude all banks that are not publicly listed European Stock Exchanges which reduces the sample to 55 banks. In addition, we have to exclude "high-illiquid" time series of CDS spreads, i.e. time

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[3] Note that CDS quotes from KBC, Danske Bank, Crédit Agricole and the Bank of Ireland are only available since mid-January 2004 while quotes from Swedbank and Standard Chartered are available since June 2004 and May 2005 respectively.

[4] These banks are Natixis, IKB Dt. Industriebank, UBS, Credit Suisse and Standard Chartered.

series of CDS spreads are omitted if observations are missing for more than five consecutive trading days. This adjustment finally reduces the sample to 29 major European banks located in the EU-12 plus Switzerland and the UK over the period from January 2004 to September 2010.

A detailed summary statistics of sample banks per country and respective CDS market spreads is provided in Table 1 in the *Statistical Appendix*. As further shown in Figure 1, comparing the sample's arithmetic mean with the EU Banks Sector CDS Index 5Y a correlation of 99.3 percent between absolute levels of both time series suggests that our sample of single-name bank-specific CDS market spreads is highly representative with regard to the European banking sector.

In line with Imbierowicz (2008) and Tsesmelidakis and Schweikhard (2011) we do not investigate "pure" CDS market spreads but rather employ *relative CDS spread deviations* (*RSDs*). Accordingly, the RSD is calculated as the difference between estimated structural credit risk model-implied spreads ($\widehat{\mathrm{CDS}}$) and market spreads (CDS) normalized by market spreads.

$$\mathrm{RSD} = \frac{\widehat{\mathrm{CDS}} - \mathrm{CDS}}{\mathrm{CDS}} \tag{1}$$

RSDs are included since they allow for greater comparability among different banks in our sample and in particular among varying time periods. Furthermore, employing RSDs during the empirical analysis addresses likely reverse causality between bank-specific CDS market spreads and changes in sovereign bond yields serving as a proxy of sovereign risk (Section 5.1).

4.2 Structural credit risk models

We employ two structural credit risk models in order to predict theoretically justified (fundamentally verified) CDS model spread. Both credit risk models are based on the structural framework provided by Black and Scholes (1973) and Merton (1974).

Bank-level fundamental data required to calculate and estimate the structural credit risk models is retrieved from *Datastream*. All observations are cross-checked with recent *financial statements* to ensure accuracy. Daily share prices, the number of common shares outstanding and the EURIBOR and LIBOR, serving as proxies of the risk-free interest rate, are also retrieved from *Datastream*. As regards daily share prices, we adjust data for stock splits, capital measures and outliers and conduct additional cross-checks with publicly available accounting information. Matching available time series of bank-specific CDS market spreads with data necessary to estimate both structural credit risk models our final sample comprises more than 50,000 daily CDS quotes over the period from January 2004 through September 2010.

4.2.1 The adjusted CreditGrades model (benchmark model)

The *CreditGrades model* (Finger et. al., 2002) constitutes our benchmark model since this model is considered as an industry benchmark and has been used frequently in related studies (e.g. Imbierowicz, 2008; Tsesmelidakis and Schweikhard, 2011; Cao et. al., 2010). In this model the bank's asset value is assumed to evolve as a geometric Brownian motion with zero drift[5] which reduces the process to

$$dV_t / V_t = \sigma_V dW_t, \tag{2}$$

[5] See Finger et al. (2002) for a justification of this assumption.

where V_t denotes the bank's asset value, σ_V is the asset volatility and W_t denotes a standard Brownian motion (Wiener process). The default event is defined as the first time the bank's asset value process V_t hits the bank-specific default barrier K_t observed at time t.

$$V_t < K_t, \tag{3a}$$

$$\text{with } K_t = LD_t. \tag{3b}$$

L denotes a log-normally distributed recovery rate of debt with mean $E(L) = \bar{L}$ and variance $Var(L) = \lambda$ revealed at the time of default. Corresponding to Finger et al. (2002) the moments are specified as $\bar{L} = 0.5$ and $\lambda = 0.3$. D_t describes the bank's debt per share while debt is defined as the sum of short-term debt and current proportion of long-term debt plus half of long-term debt at time t.

Due to the fact that the CreditGrades model relies on several input parameters that are not directly observable, the share price is reduced to its intrinsic value $S_0 = V_0 - \bar{L}D$. Under this assumption, the calibration of asset and equity volatility is derived as $\sigma_v = \sigma_s S^* / (S^* + \bar{L}D)$ where σ_v describes the annualized asset volatility, σ_s is the corresponding equity volatility and S^* is the reference share price. Following Finger et al. (2002) equity volatility is measured as the average annualized historical volatility based on a rolling window of the past (historical) 1,000 observations.

The survival probability, i.e. the probability that the bank's asset value process does not reach the default barrier up to time t, is approximated as

$$P^{approx}(t) = \Phi\left(-\frac{A_t}{2} + \frac{ln(d)}{A_t}\right) - d \cdot \Phi\left(-\frac{A_t}{2} - \frac{ln(d)}{A_t}\right), \tag{4a}$$

$$\text{with } A_t^2 = \sigma_v^2 t + \lambda^2 \text{ and } d = \frac{V_0 \exp(\lambda^2)}{LD}, \tag{4b}$$

where Φ denotes the cumulative standard normal distribution function.

Applying structural credit risk models to banks is not common – an aspect that has not yet been discussed sufficiently by related studies. Thus, as leverage ratios from banks are typically higher compared to non-financial firms, structural credit risk models are likely to underestimate bank-specific survival probabilities and hence, are likely to overestimate CDS spread levels (see Kiesel and Veraart, 2008). We address this potential estimation bias by substituting the *approximated* survival probability from equations (4a) and (4b) by an *exact* survival probability.

The exact survival probability is given as

$$P^{exact}(t) = \Phi_2\left(-\frac{\lambda}{2} + \frac{ln(d)}{\lambda}, -\frac{A_t}{2} + \frac{ln(d)}{A_t}; \frac{\lambda}{A_t}\right) - d \cdot \Phi_2\left(\frac{\lambda}{2} + \frac{ln(d)}{\lambda}, -\frac{A_t}{2} - \frac{ln(d)}{A_t}; -\frac{\lambda}{A_t}\right), \tag{5}$$

embedding a cumulative bivariate instead of a cumulative univariate normal distribution as assumed in the standard CreditGrades model.[6]

Converting the adjusted survival probability, the CDS price is calculated as the difference between discounted expected loss payments and discounted expected spread payments as follows

[6] We provide a verification of CDS model spreads estimated by means of the adjusted CreditGrades model in the Technical Appendix, Section 1.

$$CDS = (1-R)\left[1-P(0)+\int_0^t dsf(s)e^{-rs}\right]-c\int_0^t dse^{-rs}P(s). \tag{6}$$

R denotes the recovery rate on senior unsecured debt. The recovery rate is chosen as $R=0.4$ throughout all models which is consistent with related studies (Imbierowicz, 2008; Covitz and Han, 2004; Altman et al., 2005). $P(t)$ is the survival probability and r describes the risk-free interest rate proxied by the EURIBOR and LIBOR (as regards UK). All CDS contracts mature at $T = 5$.

The fundamentally verified CDS spread ($c*$) per bank is then calculated such that the expected loss payouts equal the expected spread payments on the CDS:

$$c* = r(1-R)\frac{1-P(0)+H(t)}{P(0)-P(t)\exp(-rt)-H(t)}, \tag{7a}$$

$$\text{where} \quad H(t)=\exp(r\xi)(G(t+\xi)-G(\xi)),\ \xi=\lambda^2/\sigma^2 \tag{7b}$$

$$\text{and} \quad G(t)=d^{z+0,5}\Phi\left(-\frac{\log(d)}{\sigma_v\sqrt{t}}-z\sigma_v\sqrt{t}\right)+d^{-z+0,5}\Phi\left(-\frac{\log(d)}{\sigma_v\sqrt{t}}+z\sigma_v\sqrt{t}\right) \tag{7c}$$

$$\text{with} \quad z=\left(0,25+2r/\sigma_v^2\right)^{\frac{1}{2}}. \tag{7d}$$

4.2.2 The Zhou model (verification model)

We verify CDS model spreads estimated by the adjusted CreditGrades model by means of the *Zhou model* (Zhou, 2001) which is based on less stringent assumptions concerning the underlying dynamics of the bank's asset value process. Instead, the Zhou model captures the dynamics of sudden jumps within the diffusion process of the bank's asset value which is even more relevant in times where markets are highly volatile and where unanticipated information suddenly occurs.

Accordingly, the bank's asset value is assumed to evolve as a jump-diffusion process given by

$$dV_t / V_t = (\mu - \lambda v)dt + \sigma dW_t + (\Pi - 1)dY_t, \tag{8}$$

where V_t denotes the bank's asset value with $V_t = S_t + D_t$, σ is a volatility measure, μ is a drift measure and W_t denotes a standard Brownian motion (Wiener process). μ , σ and v are positive constants. Y_t is a homogenous Poisson process with intensity parameter λ and jump amplitude Π. Jump events are assumed to occur only once between two consecutive sampling points and they are presumed to be log-normally distributed with $ln(\Pi) \sim N(\mu_\pi, \sigma_\pi^2)$ and $v = exp(\mu_\pi + \sigma_\pi^2 / 2) - 1$. Furthermore, W_t, Y_t and Π are assumed to be mutually independent.

Furthermore, let K_t denote the default threshold with $K_t = D_t$. Setting the bank's asset value relative to the default barrier so that $X_t = V_t / K_t$ follows a jump-diffusion process given as

$$dX_t / X_t = (\mu - \lambda v)dt + \sigma dW_t + (\Pi - 1)dY_t. \tag{9a}$$

Applying Ito's lemma to $x_t = \ln(X_t)$ yields

$$dx_t = \left(\mu - \sigma^2 / 2 - \lambda v\right)dt + \sigma dW_t + \ln(\Pi)dY_t. \tag{9b}$$

The parameter vector $\theta = (\mu, \sigma, \lambda, \mu_\Pi, \sigma_\Pi)$, specifying the process from equation (9b), is obtained from maximum likelihood estimations for each bank in our sample. Due to the fact that the probability of more than one jump within two sampling-points is of marginal importance (Wong and Li, 2006), the resulting likelihood function is given as

$$L(\theta) = \prod_{i=2}^{k} g\left(x_i \middle| x_{i-1}, \theta\right), \tag{10}$$

where k is the number of observations for each bank and $g(x_i | x_{i-1})$ is the density function of $x_t = \ln(X_t)$ conditioning on x_{t-1}. The density function is approximated by

$$g\left(x_i \middle| x_{i-1}, \theta\right) = (1 - \lambda \Delta t) f_x\left(x_i \middle| x_{i-1}, \theta\right) + \lambda \cdot \Delta t \cdot f_{xy}(x_i | x_{i-1}, \theta), \tag{11a}$$

where

$$f_x\left(x_i \middle| x_{i-1}, \theta\right) = \frac{1}{\left(2\pi\sigma^2 \Delta t\right)^{1/2}} \exp\left(-\frac{\left(x_i - x_{i-1} - \left(\mu - \sigma^2/2 - \lambda\nu\right)\Delta t\right)^2}{2\sigma^2 \Delta t}\right), \tag{11b}$$

$$f_{xy}\left(x_i \middle| x_{i-1}, \theta\right) = \int_{-\infty}^{+\infty} f_x\left(x_i - y \middle| x_{i-1}, \theta\right) f_y(y)\, dy, \tag{11c}$$

$$f_y(y) = \frac{1}{\left(2\pi\sigma_\pi^2\right)^{1/2}} \exp\left(-\frac{(y - \mu_\pi)^2}{2\sigma_\pi^2}\right). \tag{11d}$$

Estimates of the parameter vector $\theta = (\mu, \sigma, \lambda, \mu_\Pi, \sigma_\Pi)$ resulting from maximum likelihood regressions are employed in a Monte Carlo approach which is based on simulated samples of the discrete time version of x_t from equation (9b) under the risk-neutral measure. Starting values for the parameter estimation of θ are obtained from an equally-spaced grid. The Monte Carlo simulation process is given as

$$\tilde{x}_i = (r - \sigma^2 / 2 - \lambda \nu)T / m + \sigma\sqrt{T / m} \cdot \varepsilon_i + \ln \Pi \cdot (Y_i - Y_{i-1}) + \tilde{x}_{i-1}. \tag{12}$$

m is the size of the simulated sample, $\tilde{x}_0$ is the starting value of the simulation process and ε_i is a standard normally distributed white noise with $i = 0, \ldots , m$. Y_i are Bernoulli-type random variables with $P(Y_i - Y_{i-1} = 0) = 1 - \lambda \cdot T / m$ and $P(Y_i - Y_{i-1} = 1) = \lambda \cdot T / m.$

The Monte Carlo simulation process requires 3·m·M pseudo random variables for each observation with *m* denoting the number of reiterations and *M* denoting the number of replications. We choose *m* = 1,000 and *M* = 5,000 for computation. For each observation of x_t we generate a simulated sample using the current observations as starting values.

Let $\tilde{x}_{i,j}$ denote the *i-th* simulated observation from the *j-th* sample of the process given in equation (12) and let τ_j describe the hitting time satisfying $\tau_j = \min\left\{ i \mid \tilde{x}_{i,j} \le 0 \right\}$ with *i = 1,…,m* and *j = 1,…,M.* The fundamentally verified CDS spread *c*(0,T)* per bank is then obtained by

$$c^*(0,T) = -1 / T \cdot \ln\left(1 - \sum_{j=1}^{M} z_j / M \right), \tag{13a}$$

$$\text{where } z_j = (1 - R)\exp(\tilde{x}_{\tau_j, j}) \text{ if } \left\{ \tau_j \right\} \ne \left\{ \ \right\} \text{ and } 0 \text{ otherwise.} \tag{13b}$$

4.3 Discussion of calculated CDS model spreads and relative CDS spread deviations

Fundamentally verified CDS model spreads obtained from the adjusted CreditGrades and the Zhou model are matched with respective single-name bank-specific CDS market spreads in order to calculate relative CDS spread deviations (RSDs) as shown in Section 4.1.

As regards the performance of the pricing models employed, Table 2a indicates that *on average* CDS model spreads predicted by the Zhou model exceed CreditGrades-implied spread levels throughout the entire sample period which may be plausible for the following aspects. Assuming sudden jumps in the diffusion process of the bank's asset value, the Zhou model is likely to respond more sensitively to market dynamics than the CreditGrades model. In particular, the presence of high-volatile markets during the crisis period might have contributed to higher predicted CDS spreads obtained from the Zhou model compared to the CreditGrades model (see also Table 2b). In contrast, comparatively lower CDS spreads predicted by the adjusted CreditGrades model over the entire sample period might be due to the fact that the historical volatility employed in this model may act as a smoothing parameter (in particular during times of financial distress in the crisis period). Additionally, findings may also result from adjusting the CreditGrades model for higher bank leverage ratios addressing a likely underestimation of bank-specific survival probabilities and hence, a likely overestimation of CDS spread levels during the crisis period (Section 4.2.1). Nevertheless, as Figure 3 illustrates, a clear co-movement between both time-series of calculated RSDs is observed throughout the entire sample period with a correlation between absolute values of both time series at 79.5 percent. Accordingly, as estimated CDS model spreads from the adjusted CreditGrades are sufficiently validated by the Zhou model, we suggest that adjusting the CreditGrades model is adequate.

Furthermore, Table 2b reveals that predicted model spreads are time-dependent. As shown, predicted model spreads exhibit lower values during the pre-crisis period compared to the crisis period. In addition, while CDS spreads predicted by the Zhou model are lower (on average 143 bps) than spread levels from the CreditGrades model (on average 175 bps) during the pre-crisis period, the reverse pattern is observed during the crisis period, i.e. Zhou model-implied spreads exceed CreditGrades-implied spreads by 190 bps on average. Taking this into account, results again suggest that the Zhou model responds more sensitively to market distortions than the adjusted CreditGrades model.

Finally, turning to changes in calculated RSDs over time, Figure 3 and Table 2b point to a bubble in the European CDS market during the pre-crisis period (Jan. 2004 – Jun. 2007) suggesting the willingness of market participants to accept lower CDS premiums than theoretically predicted. In contrast, given large-scale RSDs until the beginning of the subprime crisis in mid-2007, we observe a fast and strong convergence of model and market spreads resulting in a significant narrowing of CDS pricing differentials during the financial crisis period (Jul. 2007 – September 2010). In this context, the convergence of model and market spreads is found to be stronger for the CreditGrades model indicating that the CreditGrades model is less sensitive during periods of financial distress.

5. Empirical analysis

CDS model spreads may rise due to an increase in market volatilities during the crisis period, which are captured by specific parameters implemented in both structural credit risk models employed. In contrast, the increase in bank-specific CDS market spreads as illustrated in Figure 1 may rather depend on a change in capital market investors' risk perception and risk tolerance during this time period. Furthermore, while bank default risks are reflected by estimated CDS model spreads, calculated RSDs and hence, the residuum between model and market spreads should be affected by risks other than bank default. In this context we are interested in sovereign risk that is assumed to spill over to bank risk and thus may have a positive impact on CDS pricing following different transmission channels as elaborated in Section 3 in detail. Accordingly, the relationship between sovereign risk and CDS pricing is empirically investigated in a next step.

5.1 Data and sources

Notes on variables and data sources are presented in Table 3. Table 4 reports descriptive statistics for the entire set of variables included and a prediction of the impact on calculated RSDs. The correlation matrix is presented in Table 9. Variables are retrieved from *Datastream*, the *OECD Statistics Database* and the *Worldbank* database. All variables are employed on a quarterly basis.

To begin with, corresponding to our time series of *five-year single name bank-specific CDS market spreads* we include the change in *five-year government bond yields* as a proxy of sovereign risk. As suggested in related studies (e.g., Barrios et al., 2009) an increase in government bond yields is associated with rising funding costs due to higher credit risk and liquidity risk indicating a decline in the overall soundness of public finances and government's creditworthiness (IMF, 2010b). Accordingly, taking possible transmission channels into account (Section 3), an increase in sovereign risk is expected to be negatively correlated with RSDs and positively related to bank-specific CDS market spreads given that model spreads (on average) exceed market spreads.

However, if it is true that sovereign risk may spill over to bank risk but that an increase in bank risk may also affect the government's creditworthiness (e.g., due to bail-outs), the relationship between bank-specific CDS spreads and government bond yields is not clear but may suffer from reverse causality. We generally mitigate this problem by regressing on relative CDS spread deviations rather than absolute bank-specific CDS market spreads. In addition, since model spreads already include bank default related components while market spreads are assumed to reflect default related market information, relative spread deviations define a residuum that is primarily determined by capital market investors' perceptions of risks other than bank default risk.

Recent studies (e.g., Ericsson et. al., 2009; Chen and Wei, 2007; Collin-Dufresne et. al., 2001) have highlighted the importance of further *non-bank-specific* determinants when explaining the variation in bank-specific CDS spread levels. Accordingly and in order to address omitted-variable biases, we consider macroeconomic as well as capital market- and CDS market-specific measures as further control variables.

To begin with, as regards *macroeconomic control variables* we include the *rate of real GDP growth*, the *annual change of inflation rates* and *short term interest rates* as well as *credit growth* to capture changes in a country's macroeconomic environment. We lag some of these variables to avoid multicollinearity. The *rate of real GDP growth* is a control variable since the banks' investment opportunities may be correlated with business cycles. Hence, we expect a positive impact of this measure on calculated RSDs if investment opportunities and banking stability rise under economic booms (Borio et al., 2001). Moreover, borrowers' solvency may be higher under increasing economic performance which in turn raises the banks' asset quality. In addition, banks may pro-cyclically widen their capital under economic booms and hence engage in precautionary measures in anticipation of forthcoming economic downturns.

The effect of changes in *inflation rates* and *short-term interest rates* depends on whether a change in inflation and interest rates is anticipated by banks or not and whether these changes coincide with general economic fragility. Since interest rates tend to rise in the presence of inflation, inflation is probably associated with a higher realization of net interest margins. However, as the banks' funding costs may also increase under inflation and rising interest rates, the effect on profitability and bank capital ratios depends on the net effect from increasing net interest margins and costs, the average maturity of assets and liabilities and the bank's capability to reprice assets and liabilities (Hortlund, 2005). Accordingly, we expect an ambiguous effect of both measures.[7]

Finally, *credit growth* is included as a control variable since excessive credit lending (fiercer credit market competition) is associated with decreasing capital ratios and hence, financial soundness (Dell'Ariccia and Marquez, 2006). If this is true, we expect a negative impact of this measure on calculated RSDs.

Next to macroeconomic measures we further include two variables controlling for *capital market and CDS market characteristics*. *Implied volatility* is proxied by the VSTOXX Volatility Index and is employed as a measure of market investors' risk aversion reflecting the degree of market uncertainty. Higher index levels are associated with greater uncertainty concerning the future state of the economy suggesting a negative impact of this index measure on calculated RSDs. However, as our sample comprises top CDS market players, i.e. large and systemically relevant banks, the too-big-to-fail hypotheses may also play an important role especially during the crisis period. In this context, Tsesmelidakis and Schweikhard (2011) suggest that especially in times of highly volatile markets, investors may stronger rely on governments to bail-out systemic relevant banks resulting in lower bank default risk and lower CDS premiums respectively. Taking this into account, a positive impact of the measure of implied volatility on calculated RSDs is also conceivable. Finally, differences between *CDS bid- and ask-spreads* are included while larger differences indicate a decrease in CDS market liquidity. Accordingly, we expect a negative impact of an increase in bid-ask spreads on calculated RSDs.

[7] Technically, a rise in short-term interest rates may also increase the risk-neutral drift in structural credit risk models provoking a decline in bank-specific default risk.

5.2 Empirical model

To test our hypothesis that sovereign risk may spill over to bank risk and hence, affect bank-specific CDS pricing, we employ the difference Generalized Method of Moments (GMM) estimator for dynamic panel data models suggested by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998).[8] Accordingly, we estimate the following dynamic regression model on panel data

$$RSD_{i,t} = \beta RSD_{i,t-1} + \gamma \Delta SovereignRisk_{k,t} + \delta X_{i,k,t} + \varepsilon_{i,t}, \tag{14}$$

where $RSD_{i,t}$ represents calculated relative CDS spread deviations for bank i at quarter t, $\Delta SovereignRisk_{k,t}$ is the country-specific, quarterly change in government bond yields, $X_{i,k,t}$ denotes a vector of control variables as discussed above and $\varepsilon_{i,t}$ is the error term. β, γ and δ are the parameters to be estimated. We use a robust estimation procedure for the covariance matrix to obtain standard errors that are robust to heteroskedasticity and autocorrelation within our panel data.

Employing a dynamic regression model with a difference GMM estimator is a consequent strategy for two reasons. *First*, the presence of unobserved time-invariant effects on the individual bank level gives rise to autocorrelation resulting in inconsistent Ordinary Least Squares (OLS) estimates. In contrast, the first-differences transformation, as performed in the Least Squares Dummy Variable (LSDV) estimator and the difference GMM estimator for dynamic panel data, mitigates this problem by purging out the fixed effects. *Second*, related theoretical and empirical studies suggest a significant level of persistence in bank risk (e.g., Black and Hazelwood, 2012; Delis and Kouretas, 2011). Since RSDs are calculated as the

[8] The difference GMM estimates are obtained from employing Stata's "xtabond2" module provided by Roodman (2006).

difference between market and model CDS spreads, i.e. the difference between a fundamentally verified and a perceived risk of bank default, we suggest persistence in calculated RSDs as well. If this is true, a dynamic estimation model is necessary. Under an autoregressive framework, however, estimated coefficients of the lagged RSD variable on the right hand side will be upward biased using OLS if this variable is positively correlated with the fixed effects in the error term. Similarly, estimated coefficients of the transformed lagged RSD variable will be downward biased under the LSDV estimator if this variable is negatively correlated with the transformed error term.[9] Taking this into account, the application of a GMM-style dynamic panel model is more appropriate when estimating an autoregressive-distributed lag model (Blundell and Bond, 1998; Bond, 2002; Roodman, 2006).

Nevertheless, given that calculated RSDs are *highly* persistent, i.e. the coefficient of the lagged RSD variable is close to the value of 1 while T is *sufficiently* small (as it is the case for our sample), the difference GMM estimator may suffer from poor finite sample properties (Blundell and Bond, 1998). Thus, to avoid biased estimation results, we specify our dynamic regression model as follows. We employ second lags of the dependent RSD variable as instruments within the GMM regression specification and let remaining exogenous variables (including the bond yield measure) serve as standard instruments. The validity of the instruments is tested using the Hansen's J test statistic of over-identifying restrictions, which is robust to heteroskedasticity and autocorrelation.[10] Furthermore, we employ the Arellano-Bond test to control for serial correlation in the first differenced residuals. As shown across all

[9] We provide evidence that GMM-style estimated coefficient values of lagged RSD variables are between their OLS and LSDV counterparts while the OLS (LSDV) estimates serve as an upper (lower) bound. Hence, results indicate the appropriateness of the GMM estimator following Bond (2002).We do not include results from OLS and LSDV estimates into this paper but provide them on request.

[10] Although instrument proliferation may significantly weaken the Hansen test, we obtain p-values smaller than one and greater than 0.25 suggesting that the set of instruments employed is valid (Roodman, 2006, 2007).

regressions in Tables 5-8 respective test statistics indicate that the instruments included are valid (not correlated with residuals) and that the residuals in the first difference regression do not exhibit serial correlation serial correlation of order two.

5.3 Empirical results

We present baseline results in Table 5. Results from robustness checks (different bond yield term structures, inclusion of further determinants of bank-specific CDS pricing) are shown in Tables 6a and 6b. Tables 7 and 8 report results from sensitivity analyses (exclusion of the pre-crisis period and simultaneous exclusion of PIIGS countries). The correlation matrix is shown in Table 9.

5.3.1 Baseline regressions

As shown in Table 5, the change in five-year *government bond yields* enters regression specification (1) significantly negative at the one-percent level indicating that an increase in government bond yields has a negative impact on calculated RSDs based on model spreads from the adjusted CreditGrades model. As the increase in sovereign risk may not be captured by structured credit risk models by definition, results rather reveal a decrease in RSDs due to an increase in bank-specific CDS market spreads. Accordingly, evidence suggests that sovereign risk may spill over to bank risk while this effect may be perceived and priced into bank-specific CDS market premiums by capital market investors.

Among the control variables the coefficient of *credit growth* turns out to be significantly negative at the one-percent level suggesting that fiercer credit market competition is associated with a decline in bank financial soundness (Dell'Ariccia and Marquez, 2006). In particular, an increase in loan transactions during the crisis period may have turned out to be a severe impediment to banking stability since credit lending to less solvent borrowers may have directly increased the banks' overall credit risk exposure (e.g., Delis and Kouretas, 2011; Altunbas et al., 2010). Furthermore, *implied volatility* turns out to be significantly positive at the ten-percent level. Although an increase in implied volatility is generally associated with greater uncertainty concerning the future state of the economy, we observe a positive impact of a higher implied volatility on calculated RSDs. Results confirm empirical findings provided by Tsesmelidakis and Schweikhard (2011) for a sample primarily comprising non-financial firms. Given that our sample exceptionally includes large and systemically relevant European banks, we suggest that investors may stronger rely on governments to bail-out systemic relevant banks in times of high-volatile markets resulting in lower bank default risk and lower bank-specific CDS premiums respectively.

In order to draw accurate statistical inference concerning the identification of a spill-over effect between sovereign risk and bank risk, calculated RSDs based on model spreads from the adjusted CreditGrades model are substituted by calculated RSDs from the Zhou model in regression specification (2). As Table 5 reports, baseline findings are reconfirmed even when employing RSDs from the Zhou model while we observe a lower coefficient value of the government bond yield measure compared to regression specification (1).[11] The lower coefficient value might be explained by the fact that calculated RSDs from the Zhou model are on average lower compared to RSDs from the CreditGrades model over the entire sample period (Figure 3, Table 2a).

As further shown, signs and significances of control variables remain robust in regression (2). Additionally, one-period lagged *real GDP growth* turns out to be significantly positive at the five-percent level indicating a decrease in bank risk during economic boom phases. Results suggest that investment opportunities may rise during economic booms (Borio et al.,

[11] We control for the significance of net differences in estimated coefficients applying the difference-in-means t-test. We do not comment test results separately in this paper but provide them on request.

2001) and that borrowers' solvency may be higher under increasing economic performance which in turn may raise the banks' asset quality.

5.3.2 Robustness checks

The analysis proceeds by investigating the robustness of our baseline findings. As regressions on RSDs from the adjusted CreditGrades model are verified by regressions on RSDs from the Zhou model throughout all robustness checks, we do not separately comment results from the Zhou model regressions. Similarly, since control variables do not remarkably differ in signs and significances we do not comment on them separately in the following.

To begin with, changes in five-year government bond yields are included as a proxy of sovereign risk during baseline regressions in order to be consistent with time series of five-year bank-specific CDS market spreads. Nevertheless, since this choice may be arbitrary to some extent, we control for *different term structures* and substitute five-year government bond yields by two-year and ten-year government bond yields. As shown in Table 6a, both government bond yield measures enter regression specifications (1a) and (1c) significantly negative at the five- and one-percent level respectively. Thus, empirical results reconfirm baseline findings and further suggest that not only medium-term but also short- and long-term sovereign risk may be anticipated and priced into bank-specific CDS premiums. However, as estimated coefficient values of both bond yield measures turn out to be lower compared to the coefficient value of five-year government bond yields, we suggest a higher risk tolerance by capital market investors as regards medium-term sovereign risk.

We further investigate if sovereign risk may be a robust explanatory variable even when including further determinants that are assumed to affect calculated RSDs as well (e.g., Imbierowicz, 2008; Tsesmelidakis and Schweikhard, 2011; Arora et al. 2012). Due to high correlations between these determinants (Table 9) and in order to avoid simultaneity, we include these variables in turn in separate regressions in Table 6b. As a general result, baseline findings remain robust even when controlling for further determinants of CDS pricing.

To begin with, we include the change in the *US Banks Sector CDS Index 5Y* as a proxy of the degree of risk and uncertainty inherent in the U.S CDS market. In addition, we employ a *counterparty risk indicator* that is built from the average *Distance-to-Default* of the global top five CDS trading banks per year, mainly represented by U.S. banks (Table A4 in Section 2 in the *Technical Appendix*). As an increase in counterparty risk (an increase in the Distance-to-Default) is associated with a decrease in bank-specific CDS market premiums we expect the counterparty risk indicator to be positively correlated with calculated RSDs.

As shown in Table 6b, the *US Banks Sector CDS Index 5Y* enters regression (1a) insignificantly negative while the *counterparty risk indicator* turns out to be significantly positive at the one-percent level in regression (2a). Taking into account that the *US Banks Sector CDS Index 5Y* turns out to be significantly negative at the one-percent level in regression specification (1b), empirical results imply that risk and uncertainty inherent in the U.S. banking market may have spilled over to the European counterpart due to a strong interconnection of both CDS markets.

We further include three indicators that proxy country-specific future economic development and the level of market confidence. The *composite leading indicator* (*CLI*) is an aggregated sentiment indicator from standardized OECD survey data for early stages of production that anticipates turning points in economic activity per quarter and country relative to trend. Positive deviations from the long-term average (index = 100) indicate higher levels of expected future economic activity. As shown in Table 6b, the CLI enters regression significantly positive at the one-percent level. Empirical results reconfirm findings that the banks' investment opportunities (in particular lending activities) may rise under a prospering economy resulting in a decrease in bank-specific CDS market premiums.

Next to the CLI two confidence indicators are employed. The *business confidence indicator* (*BCI*) is a composed indicator that is based on standardized OECD survey data capturing expectations on order books, production levels and turning points in production per quarter and country of the manufacturing sector (relative to trend). Positive deviations from the long-term average (index = 100) indicate higher levels of expected output. The *consumer confidence indicator* (*CCI*) is an aggregated indicator that is based on standardized OECD survey data reflecting expected levels of household consumption and household behavior (relative to trend). Positive deviations from the long-term average (index = 100) indicate higher levels of consumption.

As regressions (4a) and (5a) in Table 7b report, both measures turn out to significantly positive at the one-percent level respectively. Based on findings from including the CLI, empirical results additionally reveal that increasing *expectations* on rising industrial productivity and household consumption may be anticipated as a positive signal resulting in a decrease in bank-specific CDS market premiums.

5.3.3 Sensitivity analyses

As shown by Figure 3 and Table 2b, the gap between model and market spreads has rapidly narrowed since the beginning of the financial crisis in mid-2007. In addition, Figure 2 and Table 2b indicate that baseline results may be driven by comparatively higher absolute yield values and yield volatilities during the crisis period as regards government bonds from PIIGS countries. Taking this into account, we perform sensitivity analyses as follows. In a first step, the analysis is focused on the crisis period only as we omit the pre-crisis period from the entire sample. In a second step, data from PIIGS countries is additionally excluded during the crisis period. As control variables exhibit reasonable signs and significances and do not distinctly differ from baseline results, we do not comment on them separately in the following.

To begin with, referring to the rapid decrease of calculated RSD values during the U.S. subprime mortgage crisis starting in mid-2007 and in particular the following phases of financial market disruptions, we repeat baseline regressions while omitting the pre-crisis period (2004:Q1 to 2007:Q2) from the entire sample. As shown by regression specifications (1) and (2) in Table 7, both government bond yield measures turn out to be significantly negative at the one-percent and five-percent level respectively while estimated coefficient values are lower compared to baseline findings (Table 5). Results generally reconfirm that sovereign risk may spill over to bank risk but that this effect is priced to a smaller extent by capital market investors during the crisis period. Accordingly, evidence suggests that capital market investors' risk perception and tolerance are not time-dependent, i.e. bank-specific CDS market spreads may already and partly include a sovereign risk premium independent from the start of the financial crisis and sovereign debt crises in Europe.

In this context, it is also plausible that the lower impact of sovereign risk on calculated RSDs may result from an increase in CDS model spreads due to higher bank default risks during the crisis period. However, as Table 2b reports that the percentage growth of model spreads (CreditGrades model at 29 percent and Zhou model at 190 percent) is distinctly lower than the percentage growth of market spreads (892 percent) between the pre-crisis and crisis period, we rule out that the statistical lower effect of increasing sovereign risk on bank-specific CDS pricing may be due to rising model spreads during the crisis period.

In a final step it is investigated if baseline results are driven by comparatively higher absolute government bond yield values and yield volatilities during the financial crisis and sovereign debt crisis period as regards bonds from PIIGS countries. Accordingly, we still focus on the crisis period but additionally exclude PIIGS countries from the sample. As shown by regressions (1) and (2) in Table 8, both government bond yield measures turn out to be significantly positive at the one-percent level respectively while estimated coefficient values are higher compared to values reported in Table 7. As model spreads exhibit significantly lower growth rates than market spreads between the pre-crisis and crisis period additionally excluding PIGGS countries (Table 2b), evidence indicates that the positive effect on calculated RSDs is due to a decrease in bank-specific CDS market spreads. Accordingly, results suggest that capital market investors' risk tolerance may be higher as regards non-periphery countries exhibiting sounder fiscal budgets. As a consequence, the spill-over effect between sovereign risk and bank risk may be less priced into bank-specific CDS premiums in non-PIIGS countries during the crisis period. In sum, the perception of sovereign is not crisis- but country-dependent suggesting that bank-specific CDS market spreads may already and partly include a sovereign risk premium for PIIGS countries during the pre-crisis period in Europe.

6. Conclusion

Employing time series of single-name CDS market spreads from 29 European banks located in the EU-12 plus Switzerland and the UK over the period from January 2004 through September 2010 this paper analyses the relationship between increasing sovereign risk and bank-specific CDS pricing. Results from calculating relative CDS spread deviations (RSDs; model minus market spreads) initially reveal a price bubble in the European CDS market until the beginning of the financial crisis in mid-2007. From this point in time the gap between predicted model spreads and observed market CDS spreads narrows remarkably during the financial crisis and sovereign debt crisis period. Corresponding to these findings, the subsequent empirical analysis reveals a negative impact of sovereign risk on calculated CDS spread differentials suggesting a spill-over effect between sovereign risk and bank risk and hence, a positive effect on bank-specific CDS pricing.

Baseline findings remain robust when controlling for different bond yield term structures and when including further likely determinants of bank-specific CDS pricing. Sensitivity analyses further reveal that capital market investors' perception of sovereign risk is not time-dependent since the impact on CDS pricing turns out to be weaker during the financial crisis and debt crisis period whereas the effect becomes stronger when simultaneously excluding debt-crisis countries (PIIGS countries) from the entire sample. Accordingly, we provide evidence that the perception of sovereign risk is not crisis- but country-dependent suggesting that bank-specific CDS market spreads may already include a premium to cover sovereign risk from PIIGS countries during the pre-crisis period in Europe.

Against this background, the analysis at hand provides policy and regulatory implications as follows. *First*, as we provide evidence from calculated RSDs that CDS market efficiency is time-dependent, bank-specific CDS market premiums may act as a reliable indicator of bank risk and upcoming financial fragility during crisis periods whereas market discipline may be less effective during sound periods and hence, CDS spreads may be carefully employed as a risk indicator during these time periods.

Second and related to the previous point, as we provide empirical evidence that an increase in sovereign risk may spill over to bank risk, we stress the necessity of rethinking possible interactions between sovereign risk and bank risk as regards macroprudential supervision. Accordingly, we suggest that credit risk should not be priced without accounting for sovereign risk. This postulation is clearly underlined by the recent European sovereign debt crisis, which has revealed some important insights regarding the (negative) effect of sovereign risk on banking stability.

Third, as the analysis suggests that the nexus between sovereign risk and bank risk may convolve, i.e. banking bail-outs may increase sovereign risk which in turn may increase bank risk, the government's role as a "rescuer of last resort" seems to be much more questionable than before. Thus, rather than providing explicit guarantees and capital assistance to banks, adequate regulatory standards should be generated and enforced. In this context, employing market-based credit valuation adjustments (CVA) for OTC-traded derivatives as proposed by the forthcoming Basel III framework is a step in the right direction, even it is likely that the pro-cyclical CVA capital charge may create a feedback loop in the CDS market. Accordingly, as we find that structural credit risk models may not (fully) capture further risk factors next to bank risk, a market-based CVA approach may be an accurate instrument given that market efficiency is also ensured beyond periods of financial distress.

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Statistical Appendix

Figure 1: Sampled CDS market spreads and EU Banks Sector CDS Index 5Y (in bps)

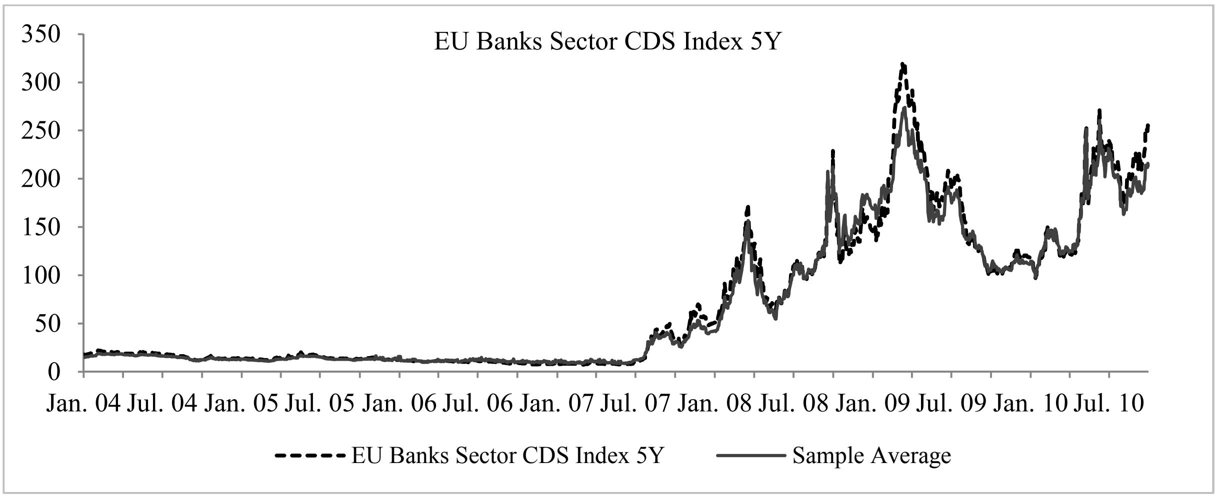

Figure 2: Quarterly Changes in 5Y Government Bond Yields (in percentage points)

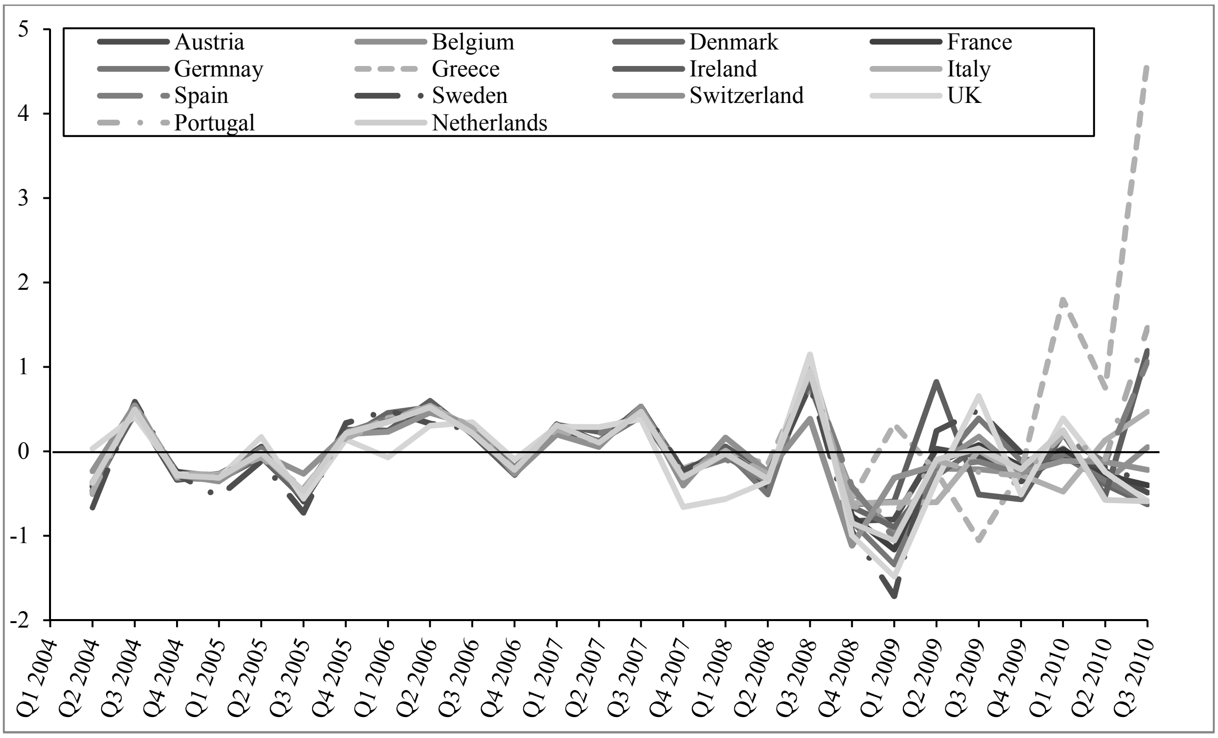

Table 1: Descriptive statistics of sample banks by country and respective CDS market spreads

Country	Bank	Mean CDS market spreads	STD	Min	Max
Austria	Erste Group	80.77	89.51	1.00	487.13
Belgium	Dexia	103.25	124.56	2.50	550.00
	KBC Group	75.49	83.61	6.90	343.30
Denmark	Danske Bank	43.16	50.62	1.00	225.00
France	BNP Paribas	36.69	34.60	5.00	155.38
	Crédit Agricole	47.04	46.87	5.50	237.81
	Natixis Bank	81.85	93.52	6.30	390.18
	Société Générale	46.81	45.32	5.70	208.55
Germany	Commerzbank	49.23	38.93	7.40	170.52
	Deutsche Bank	52.33	45.98	8.70	187.95
	IKB Dt. Industriebank	220.85	285.59	1.00	1109.86
Greece	Alpha Bank	109.79	209.75	10.80	1048.80
Ireland	Bank of Ireland	113.65	143.55	5.00	670.28
Italy	Unicredito	54.63	53.47	7.00	278.74
Netherlands	ING Bank	45.72	45.60	4.00	188.30
Portugal	Banco BPI	70.63	95.30	10.50	507.20
	Banco Comr. Portugues	72.72	98.50	8.00	572.28
Spain	Banco Bilbao Vizcaya Arg.	54.27	58.86	7.10	295.16
	Banco Popolar Espanol	86.16	108.48	7.50	437.70
	Santander	52.77	52.83	7.00	260.51
Sweden	Nordea Bank	40.18	37.82	1.50	165.00
	Swedbank	72.86	81.43	10.95	362.00
Switzerland	Credit Suisse	55.31	51.39	9.20	262.88
	UBS	61.91	71.77	4.00	360.00
UK	Barclays Bank	57.14	60.49	5.30	270.00
	HSBC	40.32	38.43	4.90	170.59
	Lloyds	58.95	66.94	3.50	248.06
	Royal Bank of Scotland	65.64	70.43	3.50	299.60
	Standard Chartered	66.19	67.60	5.50	352.06

Figure 3: Relative CDS spread deviations (RSDs) calculated as model spread minus market spread normalized by the market spread

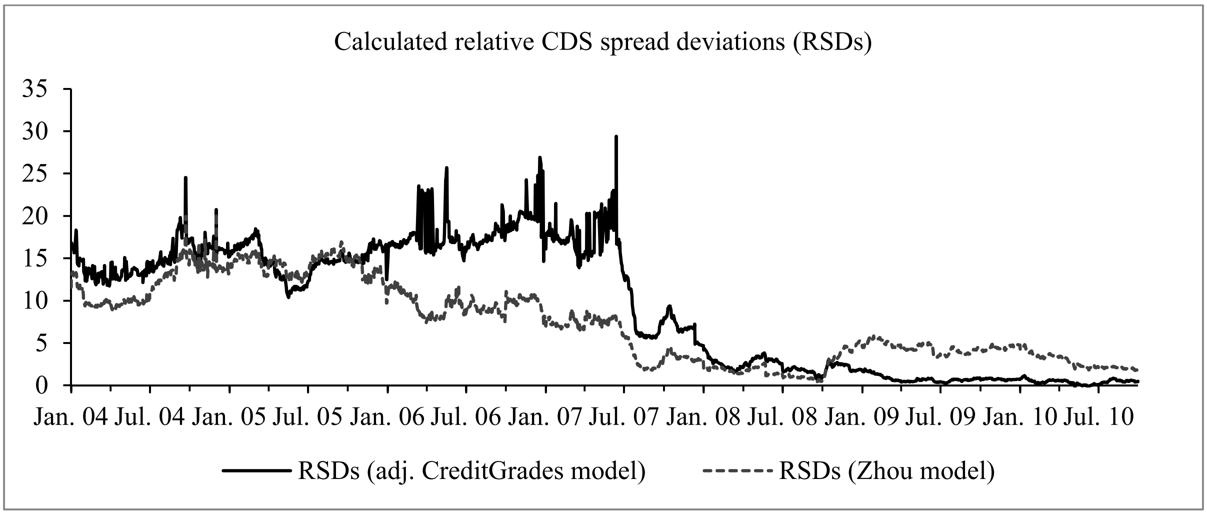

Table 2a: Average CDS spreads and average calculated RSDs (full period)

Full period	Model Spread	Market Spread	RSDs
CreditGrades	199	69	7
	(56)	(72)	(6)
Zhou	274	69	6
	(222)	(72)	(4)
Models combined	237	69	7
	(124)	(72)	(5)

Note: Values in parentheses indicate average standard deviations of the respective time series of model and market spreads as well as calculated RSDs. Model spreads from the adjusted CreditGrades model are adjusted for outliers (IKB Dt. Industriebank) by Windsorizing at a 0.5% level.

Table 2b: Average CDS spreads and average calculated RSDs (pre-crisis period, crisis period, exclusion of PIIGS countries)

	Pre-Crisis Period (Jan. 2004 - Jun. 2007)			Crisis Period (Jul. 2007 - Sep. 2010)			Crisis Period (Jul. 2007 - Sep. 2010) and exclusion of PIIGS		
	Model Spread	Market Spread	RSDs	Model Spread	Market Spread	RSDs	Model Spread	Market Spread	RSDs
CreditGrades	175	13	13	225	129	1	251	124	2
	(20)	(3)	(2)	(70)	(61)	(2)	(78)	(59)	(2)
Zhou	143	13	10	415	129	2	362	124	2
	(48)	(3)	(3)	(248)	(61)	(1)	(239)	(59)	(1)
Models combined	159	13	11	320	129	2	307	124	2
	(33)	(3)	(2)	(132)	(61)	(1)	(127)	(59)	(1)

Note: Values in parentheses indicate average standard deviations of the respective time series of model and market spreads as well as calculated RSDs. Model spreads from the adjusted CreditGrades model are adjusted for outliers (IKB Dt. Industriebank) by Windsorizing at a 0.5% level.

Table 3: Notes on variables and data sources

Variable	Definition	Source
RSD (CreditGrades)	Relative CDS spread deviation (RSD). Calculated as the bank's CreditGrades-implied CDS model spread minus the respective market spread, normalized by the market spread. Further details and an in-depth technical discussion of the calculation of RSDs are provided in Section 4.2.1.	Datastream, own calc.
RSD (Zhou)	Relative CDS spread deviation (RSD). Calculated as the bank's Zhou-implied CDS model spread minus the respective market spread, normalized by the market spread. Further details and an in-depth technical discussion of the calculation of RSDs are provided in Section 4.2.2.	Datastream, own calc.
GDP growth	Rate of real GDP growth. Quarterly percentage change per country.	Datastream
Credit growth	Domestic credit provided by banks to the private sector in percent of GDP per anno and country.	World Development Indicators
Interest rate	Short term interest rate; 3-month Inter Bank Offered Rate (IBOR) per quarter and country.	Datastream
Inflation	GDP deflator per quarter and country.	Datastream
Implied volatility	VSTOXX Volatility Index (EUR) per quarter and country.	Datastream
Bid-ask spread	Averaged daily CDS ask-spread minus bid-spread per quarter and bank.	Datastream
Government bond yield (2Y; 5Y; 10Y)	Two year, five year and ten year sovereign bond yields (constant maturity) per quarter and country.	Datastream
US CDS index	US Banks Sector CDS Index 5Y per quarter.	Datastream
Counterparty risk indicator	Average Distance-to-Default of the global top-five CDS counterparties according to FitchRatings (per year). Further details and an in-depth technical discussion of the construction of this indicator are provided in Section 2 in the Technical Appendix.	Datastream, own calc.
Composite leading indicator (CLI)	Aggregated sentiment indicator from standardized OECD survey data for early stages of production that anticipates turning points in economic activity per quarter and country relative to trend. Positive deviations from the long-term average (index = 100) indicate higher levels of future economic activity.	Datastream, OECD Statistics
Business confidence indicator (BCI)	Composed sentiment indicator that is based on standardized OECD survey data capturing expectations on order books, production levels and turning points in production per quarter and country of the manufacturing sector (relative to trend). Positive deviations from the long-term average (index = 100) indicate higher levels of expected output.	OECD Statistics
Consumer confidence indicator (CCI)	Composed sentiment indicator that is based on standardized OECD survey data reflecting expected levels of household consumption and household behavior (relative to trend). Positive deviations from the long-term average (index = 100) indicate higher levels of consumption.	OECD Statistics

Table 4: Descriptive statistics

Variable		N	Mean	SD	Min	Max
RSD (CreditGrades)		777	9.3528	11.2374	-0.8207	67.3859
RSD (Zhou)		777	7.3098	10.3257	-1	68.2775
GDP growth	+	783	1.3393	2.8423	-8.3	7
Credit growth	−	783	143.1598	43.0278	70.7886	235.9324
Interest rate	+/−	756	2.8063	1.6328	0.06	6.3052
Inflation	+/−	729	1.9282	1.3233	-6.1	5.59
Implied volatility	+/−	783	22.1837	9.0876	11.94	43.87
Bid-ask spread	−	771	7.1007	11.2191	0	150
Government bond yield (2Y)	−	783	2.9616	1.2661	0.3279	11.1221
Government bond yield (5Y)	−	783	3.4846	0.9360	0.8022	10.5635
Government bond yield (10Y)	−	783	3.9495	0.7561	1.8108	10.8682
US CDS index	−	783	84.6815	89.5101	12.2	363.08
Counterparty risk indicator	+	783	4.0576	1.7898	1.2252	6.1880
Composite leading indicator (CLI)	+	729	102.9441	3.2865	92.3725	113.1972
Business confidence indicator (BCI)	+	773	99.9908	1.5756	94.3144	102.8261
Consumer confidence indicator (CCI)	+	773	99.9262	1.3078	95.8864	103.5736

Table 5: Baseline regressions

	(1)	(2)
RSD (CreditGrades) $_{(t-1)}$	0.7887 ***	
	(0.0638)	
RSD (Zhou) $_{(t-1)}$		0.7810 ***
		(0.1037)
GDP growth $_{(t-1)}$	0.0641	0.3324 **
	(0.1423)	(0.1509)
Credit growth	−0.1891 ***	−0.2058 ***
	(0.0499)	(0.0694)
Δ Interest rate $_{(t-1)}$	0.4806	−0.0574
	(0.3038)	(0.4164)
Δ Inflation	0.3863	0.2745
	(0.3121)	(0.2639)
Implied volatility	0.0837 *	0.1629 ***
	(0.0415)	(0.0574)
Bid−ask spread	−0.0220	−0.0457
	(0.0271)	(0.0350)
Δ Government bond yield (5Y)	−1.5460 ***	−1.0737 ***
	(0.4161)	(0.3817)
No. of obs.	620	620
Hansen test	0.434	0.823
AR (1)	0.024	0.005
AR (2)	0.148	0.570

Note: The dynamic panel model estimated is $RSD_{i,t} = \alpha + \beta RSD_{i,t-1} + \gamma \Delta SovereignRisk_{k,t} + \delta x_{i,k,t} + \varepsilon_{i,t}$. Regression specification (1) includes calculated relative CDS spread deviations based on CDS model spreads estimated by means of the adjusted CreditGrades model as the benchmark model. Regression specification (2) includes calculated relative CDS spread deviations based on CDS model spreads estimated by means of the Zhou model as a validation model. Constant included but not reported. Heteroscedasticity consistent P-values are in parenthesis. ***, **, * indicate significance at the 1, 5 and 10% level.

Table 6a: Robustness checks (bond yield term structures)

	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
RSD (CreditGrades) $_{(t-1)}$	0.7847 ***	0.7887 ***	0.7624 ***			
	(0.0645)	(0.0638)	(0.0706)			
RSD (Zhou) $_{(t-1)}$				0.7850 ***	0.7810 ***	0.7715 ***
				(0.1024)	(0.1037)	(0.1100)
GDP growth $_{(t-1)}$	0.0867	0.0641	0.0438	0.3499 **	0.3324 **	0.3114 **
	(0.1349)	(0.1423)	(0.1401)	(0.1583)	(0.1509)	(0.1404)
Credit growth	−0.1941 ***	−0.1891 ***	−0.2035 ***	−0.2037 ***	−0.2058 ***	−0.2146 ***
	(0.0516)	(0.0499)	(0.0556)	(0.0703)	(0.0694)	(0.0718)
Δ Interest rate $_{(t-1)}$	0.4946	0.4806	0.3401	−0.0199	−0.0574	−0.1413
	(0.3027)	(0.3038)	(0.2960)	(0.4093)	(0.4164)	(0.4347)
Δ Inflation	0.4012	0.3863	0.3059	0.3084	0.2745	0.2278
	(0.3228)	(0.3121)	(0.3082)	(0.2694)	(0.2639)	(0.2674)
Implied volatility	0.0877 **	0.0837 *	0.0687	0.1634 ***	0.1629 ***	0.1605 ***
	(0.0415)	(0.0415)	(0.0428)	(0.0552)	(0.0574)	(0.0562)
Bid-ask spread	−0.0235	−0.0220	−0.0123	−0.0465	−0.0457	−0.0366
	(0.0280)	(0.0271)	(0.0253)	(0.0350)	(0.0350)	(0.0337)
Δ Gov. bond yield (2Y)	−1.0846 **			−0.9333 ***		
	(0.4139)			(0.2708)		
Δ Gov. bond yield (5Y)		−1.5460 ***			−1.0737 ***	
		(0.4161)			(0.3817)	
Δ Gov. bond yield (10Y)			−1.5290 ***			−0.9604 **
			(0.5372)			(0.3880)
No. of obs.	620	620	620	620	620	620
Hansen test	0.477	0.434	0.410	0.871	0.823	0.770
AR (1)	0.022	0.024	0.024	0.005	0.005	0.005
AR (2)	0.130	0.148	0.129	0.520	0.570	0.529

Note: The empirical model and estimation parameters are defined in Table 6. Controlling for the effect of different bond yield term structures 2-year and 10-year government bonds are additionally included in regressions (1a), (1c) and (2a), (2c) respectively. Constant included but not reported. Heteroscedasticity consistent P-values are in parenthesis. ***, **, * indicate significance at the 1, 5 and 10% level.

Table 6b: Robustness checks (further determinants)

	(1a)	(1b)	(2a)	(2b)
RSD (CreditGrades) $_{(t-1)}$	0.7878 ***		0.8078 ***	
	(0.0641)		(0.0567)	
RSD (Zhou) $_{(t-1)}$		0.7772 ***		0.7792 ***
		(0.1048)		(0.1046)
GDP growth $_{(t-1)}$	0.0560	0.3017 **	−0.0227	0.3249 **
	(0.1406)	(0.1427)	(0.1620)	(0.1507)
Credit growth	−0.1900 ***	−0.2133 ***	−0.1612 ***	−0.2065 ***
	(0.0520)	(0.0705)	(0.0432)	(0.0681)
Δ Interest rate $_{(t-1)}$	0.4493	−0.1737	0.2288	−0.0985
	(0.3063)	(0.4438)	(0.2886)	(0.4556)
Δ Inflation	0.4081	0.3323	0.3551	0.2512
	(0.3041)	(0.2699)	(0.3122)	(0.2727)
Implied volatility	0.0827 *	0.1733 ***	0.0799 *	0.1640 **
	(0.0440)	(0.0571)	(0.0445)	(0.0595)
Bid-ask spread	−0.0206	−0.0446	−0.0199	−0.0455
	(0.0277)	(0.0332)	(0.0279)	(0.0353)
Δ Gov. bond yield (5Y)	−1.5211 ***	−0.9399 **	−1.8217 ***	−1.1362 **
	(0.4371)	(0.3621)	(0.4549)	(0.4225)
Δ US CDS Index	−0.0011	−0.0050 ***		
	(0.0017)	(0.0016)		
Δ Counterparty risk indicator			1.0474 ***	0.1169
			(0.2683)	(0.2193)
No. of obs.	620	620	620	620
Hansen test	0.464	0.878	0.458	0.843
AR (1)	0.024	0.005	0.028	0.004
AR (2)	0.150	0.499	0.228	0.486

Note: The empirical model and estimation parameters are defined in Table 6. Regressions (1a) and (1b) include the US Banks Sector CDS Index 5Y while regressions (2a) and (2b) include the counterparty risk indicator, i.e. the average distance to default of the global top five CDS trader per year. Constant included but not reported. Heteroscedasticity consistent P-values are in parenthesis. ***, **, * indicate significance at the 1, 5 and 10% level.

Table 6b (continued)

	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
RSD (CreditGrades) $_{(t-1)}$	0.7516 ***		0.7765 ***		0.7652 ***	
	(0.0740)		(0.0667)		(0.0659)	
RSD (Zhou) $_{(t-1)}$		0.7707 ***		0.7684 ***		0.7588 ***
		(0.1048)		(0.1097)		(0.1063)
GDP growth $_{(t-1)}$	−0.1893	0.2924 *	−0.2036	0.3922 *	−02900	0.3242 *
	(0.2186)	(0.1745)	(0.2630)	(0.2053)	(0.2752)	(0.1954)
Credit growth	−0.2102 ***	−0.2166 ***	−0.2089 ***	−0.2139 ***	−0.1840 ***	−0.2137 ***
	(0.0531)	(0.0732)	(0.0542)	(0.0741)	(0.0514)	(0.0708)
Δ Interest rate $_{(t-1)}$	0.9294 **	0.0938	1.2657 **	−0.1346	1.7596 ***	0.1508
	(0.3765)	(0.3717)	(0.5025)	(0.3131)	(0.4886)	(0.3945)
Δ Inflation	0.4825 *	0.2385	0.1504	0.2614	0.5616 **	0.3079
	(0.2810)	(0.2807)	(0.3475)	(0.2844)	(0.2653)	(0.2950)
Implied volatility	0.1014 *	0.1670 ***	0.1099 **	0.1616 ***	0.0660	0.1571 **
	(0.0495)	(0.0550)	(0.0470)	(0.0542)	(0.0500)	(0.0633)
Bid-ask spread	−0.0145	−0.0412	−0.0148	−0.0514	−0.0072	−0.0462
	(0.0217)	(0.0356)	(0.0284	(0.0366)	(0.0292)	(0.0381)
Δ Gov. bond yield (5Y)	−1.5974 ***	−1.1412 **	−1.7810 ***	−1.1211 **	−1.9721 ***	−1.2725 **
	(0.4371)	(0.4521)	(0.4482)	(0.4629)	(0.5205)	(0.5357)
Δ Composite leading indicator (CLI)	1.0797 ***	0.1331				
	(0.2620)	(0.4181)				
Δ Business confidence indicator (BCI)			1.5084 ***	0.0396		
			(0.4987)	(05365)		
Δ Consumer confidence indicator (CCI)					2.4165 ***	0.7543
					(0.5650)	(0.8100)
No. of obs.	572	572	610	610	610	610
Hansen test	0.718	0.719	0.429	0.852	0.610	0.890
AR (1)	0.030	0.005	0.024	0.005	0.027	0.004
AR (2)	0.187	0.505	0.158	0.504	0.171	0.492

Note: The empirical model and estimation parameters are defined in Table 6. Regressions (3a)-(5b) include indicators that proxy economic outlook and market confidence. Regressions (3a) and (3b) include the Composite Leading Indicator (CLI), regressions (4a) and (4b) include the Business Confidence Indicator (BCI) and regressions (5a) and (5b) include the Consumer Confidence Indicator (CCI). Constant included but not reported. Heteroscedasticity consistent P-values are in parenthesis. ***, **, * indicate significance at the 1, 5 and 10% level.

Table 7: Sensitivity analyses (financial crisis period)

	(1)	(2)
RSD (CreditGrades) $_{(t-1)}$	0.7740 ***	
	(0.0564)	
RSD (Zhou) $_{(t-1)}$		0.6815 ***
		(0.0496)
GDP growth $_{(t-1)}$	0.1550	0.1344
	(0.1165)	(0.0996)
Credit growth	−0.1351	−0.1067 **
	(0.1123)	(0.0497)
Δ Interest rate $_{(t-1)}$	0.2651	0.3584
	(0.2619)	(0.2759)
Δ Inflation	0.6876 ***	−0.1347
	(0.2172)	(0.3267)
Implied volatility	0.1106 **	0.1024 *
	(0.0445)	(0.0591)
Bid-ask spread	−0.0228	−0.0563
	(0.0228)	(0.0437)
Δ Government bond yield (5Y)	−1.3499 ***	−0.6297 **
	(0.4008)	(0.2675)
No. of obs.	338	338
Hansen test	0.655	0.870
AR (1)	0.038	0.003
AR (2)	0.837	0.332

Note: The empirical model and estimation parameters are defined in Table 6. Regressions are based on observations from the crisis period (2007:Q3 to 2010:Q3). Constant included but not reported. Heteroscedasticity consistent P-values are in parenthesis. ***, **, * indicate significance at the 1, 5 and 10% level.

Table 8: Sensitivity analyses (financial crisis period and exclusion of PIIGS)

	(1)	(2)
RSD (CreditGrades) $_{(t-1)}$	0.7467 ***	
	(0.0603)	
RSD (Zhou) $_{(t-1)}$		0.6082 ***
		(0.0610)
GDP growth $_{(t-1)}$	0.1082	0.1034
	(0.1790)	(0.1382)
Credit growth	−0.2150	−0.1028
	(0.1660)	(0.0637)
Δ Interest rate $_{(t-1)}$	0.0284	0.2018
	(0.3887)	(0.2771)
Δ Inflation	0.9056 ***	−0.3950
	(0.2872)	(0.4692)
Implied volatility	0.0948	0.0250
	(0.0597)	(0.0397)
Bid-ask spread	−0.0245	−0.0355
	(0.0304)	(0.0235)
Δ Government bond yield (5Y)	−1.6798 ***	−0.8887 ***
	(0.5340)	(0.2758)
No. of obs.	273	273
Hansen test	0.729	0.990
AR (1)	0.034	0.013
AR (2)	0.992	0.977

Note: The empirical model and estimation parameters are defined in Table 6. Regressions are based on observations from the crisis period (2007:Q3 to 2010:Q3) while observations from PIIGS countries are excluded. Constant included but not reported. Heteroscedasticity consistent P-values are in parenthesis. ***, **, * indicate significance at the 1, 5 and 10% level.

Table 9: Correlation matrix

	Δ Government bond yield (2Y)	Δ Government bond yield (5Y)	Δ Government bond yield (10Y)	GDP growth $_{(t-1)}$	Credit growth	Δ Interest rate	Δ Inflation	Implied volatility	Bid-ask spread	Δ US CDS Index	Δ Counterparty risk indicator	Δ Composite leading indicator	Δ Business confidence indicator	Δ Consumer confidence indicator
Δ Government bond yield (2Y)	1.00													
Δ Government bond yield (5Y)	0.94***	1.00												
Δ Government bond yield (10Y)	0.72***	0.83***	1.00											
GDP growth $_{(t-1)}$	0.26***	0.18***	0.12***	1.00										
Credit growth	-0.08**	-0.04	0.00	-0.04	1.00									
Δ Interest rate	0.43***	0.32***	0.21***	0.37***	-0.16 ***	1.00								
Δ Inflation	0.34***	0.25***	0.19***	0.43***	-0.04	0.39 ***	1.00							
Implied volatility	-0.44***	-0.33***	-0.21***	-0.35***	0.23 ***	-0.61 ***	-0.46 ***	1.00						
Bid-ask spread	-0.16***	-0.12***	-0.04	-0.12***	0.03	-0.29 ***	-0.21 ***	0.48 ***	1.00					
Δ US CDS Index	0.01	0.06	0.18***	-0.20***	0.00	-0.08 **	-0.01	0.09 **	0.02	1.00				
Δ Counterparty risk indicator	0.32***	0.25***	0.25***	0.28***	-0.12 ***	0.37 ***	0.25 ***	-0.38 ***	-0.17 ***	0.13 ***	1.00			
Δ Composite leading indicator	0.17***	0.12***	0.07*	0.40***	-0.10 ***	-0.01	0.20 ***	-0.35 ***	-0.20 ***	-0.25 ***	0.29 ***	1.00		
Δ Business confidence indicator	0.20***	0.17***	0.16***	0.44***	0.01	-0.09 **	0.27 ***	-0.21 ***	-0.09 **	-0.14 ***	0.19 ***	0.77 ***	1.00	
Δ Consumer confidence indicator	0.02	0.06*	0.06*	0.17***	-0.04	-0.30 ***	-0.11 ***	0.04 ***	-0.04	-0.11 ***	0.09**	0.63 ***	0.60 ***	1.00

Technical Appendix

1. Validation of the adjusted CreditGrades model

Results from the adjusted CreditGrades model for banks as employed in this paper are verified as follows.

The *first table* is identical to that outlined in Finger et al. (2002), p. 49 and reports spreads (in basis points) estimated by means of the standard CreditGrades model given a constant set of input parameters. The *second table* displays credit spreads estimated by the adjusted CreditGrades model including the exact survival probability and the same input parameters as in Finger et al. (2002). Finally, the *third table* presents the differences between spread levels shown in Table 1 and Table 2, i.e. the differences between CDS spreads estimated by the standard CreditGrades model and those estimated by the adjusted model.

As shown in Table 3, given that S_0 / D expresses different levels of the financial leverage, positive spread differentials in the first row indicate that the standard CreditGrades model is likely to overestimate bank-specific CDS spreads. Accordingly, lower estimated CDS spreads from the adjusted CreditGrades model suggest that the modification of the model is adequate to address potential estimation biases when estimating CDS spreads for banks exhibiting higher leverage ratios than non-financial firms.

Table A1: Conventional CreditGrades spreads as outlined in Finger et al. (2002), p. 49

	Equity volatility (percent)												
S_0/D	20	25	30	35	40	45	50	55	60	65	70	75	80
0.5	55	85	125	175	232	297	367	441	520	602	687	774	865
1.0	8	22	46	82	130	188	253	326	403	486	572	662	755
1.5	2	8	22	48	85	134	193	260	333	412	495	583	675
2.0	1	3	12	30	59	101	153	214	283	358	438	523	612
2.5	0	2	7	20	43	78	124	180	244	315	392	474	561
3.0	0	1	4	13	32	62	103	154	214	282	355	434	518
3.5	0	0	3	9	24	50	86	133	190	254	325	401	483
4.0	0	0	2	7	19	41	73	117	169	230	298	373	452
4.5	0	0	1	5	15	34	63	103	152	211	276	348	425
5.0	0	0	1	4	12	28	55	91	138	194	257	326	401
5.5	0	0	1	3	10	24	48	82	126	179	240	307	381
6.0	0	0	0	2	8	20	42	74	115	166	224	290	362

Table A2: Adjusted CreditGrades spreads based on the exact survival probability

	Equity volatility (percent)												
S_0/D	20	25	30	35	40	45	50	55	60	65	70	75	80
0.5	48	77	116	165	221	284	352	425	501	580	661	745	832
1.0	8	22	47	83	132	190	257	330	409	492	579	670	765
1.5	2	8	22	48	86	136	196	263	338	418	502	591	684
2.0	1	3	12	30	60	102	155	217	287	363	444	530	620
2.5	0	2	7	20	44	79	126	183	248	320	398	481	568
3.0	0	1	4	14	33	63	104	156	217	285	360	441	526
3.5	0	0	3	10	25	51	88	135	192	257	329	407	489
4.0	0	0	2	7	19	41	74	118	172	234	303	378	458
4.5	0	0	1	5	15	34	64	104	155	213	280	353	431
5.0	0	0	1	4	12	29	55	93	140	196	260	331	407
5.5	0	0	1	3	10	24	48	83	127	181	243	311	386
6.0	0	0	0	2	8	21	43	75	117	168	228	294	367

Table A3: Spread differentials: Conventional CreditGrades spreads minus adjusted CreditGrades spreads

	Equity volatility (percent)												
S_0/D	20	25	30	35	40	45	50	55	60	65	70	75	80
0.5	7	8	9	10	11	13	15	16	19	22	26	29	33
1.0	0	0	-1	-1	-2	-2	-4	-4	-6	-6	-7	-8	-10
1.5	0	0	0	0	-1	-2	-3	-3	-5	-6	-7	-8	-9
2.0	0	0	0	0	-1	-1	-2	-3	-4	-5	-6	-7	-8
2.5	0	0	0	0	-1	-1	-2	-3	-4	-5	-6	-7	-7
3.0	0	0	0	-1	-1	-1	-1	-2	-3	-3	-5	-7	-8
3.5	0	0	0	-1	-1	-1	-2	-2	-2	-3	-4	-6	-6
4.0	0	0	0	0	0	0	-1	-1	-3	-4	-5	-5	-6
4.5	0	0	0	0	0	0	-1	-1	-3	-2	-4	-5	-6
5.0	0	0	0	0	0	-1	0	-2	-2	-2	-3	-5	-6
5.5	0	0	0	0	0	0	0	-1	-1	-2	-3	-4	-5
6.0	0	0	0	0	0	-1	-1	-1	-2	-2	-4	-4	-5

Note: The spread calculations outlined in the tables above are based on the standard CreditGrades assumptions, i.e. an average global recovery rate of 50 percent, a recovery rate volatility of 30 percent and R=0.5. The risk-free interest rate is assumed to be at five percent.

2. Calculation of the counterparty risk indicator

According to the Merton framework (1974) the market value of a bank's equity capital can be modeled as a contingent claim on the residual value of its assets. In the event of a default, the bank shareholder receives no returns if the market value of bank assets falls below the market value of bank liabilities. Otherwise the bank shareholder receives the difference between the market value of assets and liabilities. Hence, the contingent claim on the residual value of bank assets can be modeled as a call option on the underlying bank using standard option-pricing models. Corresponding to Black and Scholes (1973), the market value of a bank's assets is assumed to follow a geometric Brownian motion:

$$dV_A = \mu V_A dt + \sigma_A V_A dz, \qquad \text{(A1)}$$

where dV_A is the change in the value of assets, V_A is the current value of assets, μ is the drift rate of assets, σ_A is standard deviation of assets and finally, dz is a Wiener process. The *Distance-to-Default* is designed to indicate the number of standard deviations that the bank is away from the default point within a given time horizon (one year).

According to Crosbie and Bohn (2003) the *Distance-to-Default* is defined as

$$DtD = \frac{ln\left(\frac{V_A}{DB}\right) + \left(\mu - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}}, \qquad \text{(A2)}$$

where DB denotes the default threshold (sum of short-term plus half the long-term debt). The unobservable parameters V_A and σ_A can be calculated by simultaneously estimating the following system of equations:

$$V_E = V_A N(d_1) - DBe^{-rT} N(d_2), \tag{A3}$$

$$\sigma_E = N(d_1) \frac{V_A}{V_E} \sigma_A, \tag{A4}$$

with σ_E denoting the respective share price volatility and

$$d_1 \equiv \frac{ln\left(\frac{V_A}{DB}\right) + \left(\mu + \frac{1}{2}\sigma_A^2\right)T}{\sigma_A \sqrt{T}} = \frac{ln\left(V_A\, exp\left(\left(\mu + \frac{1}{2}\sigma_A^2\right)T\right)\right) - ln\, DB}{\sigma_A \sqrt{T}}, \tag{A5a}$$

$$d_2 \equiv d_1 - \sigma_A \sqrt{T}. \tag{A5b}$$

For the numerical procedure, we use values of the annualized quarterly share price volatility and market capitalization plus debt as starting values for σ_A and V_A respectively. Finally, we plug in the estimated values for V_A and σ_A in equation (A2) to obtain the *Distance to Default.*

The composition of the *counterparty risk indicator* is outlined in Table A4. Note that FitchRatings does not report the top-five counterparties for the years 2007 and 2010. For those years we assume the composition of top-counterparties to remain unchanged and use information from the previous year.

Table A4: Composition of the counterparty risk indicator

Top-five counterparties in CDS contracts according to FitchRatings (2010, 2009).

2010	JP Morgan	Goldman Sachs	Barclays	Deutsche Bank	Morgan Stanley
2009	JP Morgan	Goldman Sachs	Barclays	Deutsche Bank	Morgan Stanley
2008	JP Morgan	Goldman Sachs	Credit Suisse	Deutsche Bank	Morgan Stanley
2007	JP Morgan	Goldman Sachs	Barclays	Deutsche Bank	Morgan Stanley
2006	JP Morgan	Goldman Sachs	Barclays	Deutsche Bank	Morgan Stanley
2005	JP Morgan	Goldman Sachs	UBS	Deutsche Bank	Morgan Stanley
2004	JP Morgan	Goldman Sachs	UBS	Deutsche Bank	Morgan Stanley