Are Banks Different? Evidence from the CDS Market

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Abstract

This paper uses regression analysis to compare the market pricing of the default risk of banks to that of other firms. We study how CDS traders discriminate between banks and other type of firms and how their judgement changes over time, in particular, since the start of the recent financial turmoil. We use monthly data on the Credit Default Swaps (CDS) of 41 major banks and 162 non-banks. By means of panel analysis, we decompose the CDS premia into the expected loss and the risk premium. Our results indicate that market participants first believed that banks would be less risky then other firms. However, after the turmoil that started in August 2007 they drastically changed their mind and viewed banks to be at least as risky as other firms.

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1 Introduction

As the financial crisis which started in summer 2007 has amply demonstrated, banks differ in a number of characteristics from non-bank firms such as industrial firms. In particular, the structure and composition of banks' balance sheets, their central functions in the economy as well as their regulatory environment all set them apart from other firms. Bank loans as a bank's main assets or financing through retail deposits illustrate the unique structure of a bank balance sheet. Together with high leverage, the inherent maturity mismatch or the trading activities they create valuation uncertainty and agency problems which cannot easily be resolved by market discipline alone.[3] Due to these characteristics deposit-taking financial institutions are usually more heavily regulated than other firms. In addition, government mechanisms such as public safety nets or deposit guarantee schemes, which have continued to play a major rule in the financial crisis all distinguish banks from their peers in other sectors of the economy.

The empirical literature on banking does not reach unanimous conclusions on how financial markets discriminate between banks and other firms. Two of the most prominent papers are Morgan (2002) and Flannery et al. (2004). On the one hand, the significant disagreement between rating agencies on the riskiness of bank debt leads Morgan (2002) to conclude that banks are indeed perceived as inherently more opaque than other firms. On the other hand, Flannery et al. (2004) study the microstructure properties of U.S. bank stocks and find that the stock market does not see banking assets as unusually opaque.

The main purpose of this paper is to analyse how investors in the corporate debt market view banks. The credit market is of particular interest as it provides a

[3] Berger et al. (2009) survey research on banking. In particular, Allen and Carletti (2009) offer a detailed discussion of the roles of banks in financial systems.

more direct market assessment of a firm's credit risk than its stock price which rather represents an estimate of the firm's future profits. We compare the market pricing of banks to industrial firms and study whether investors discriminate between the riskiness of banks and other type of firms by requiring different risk premia or by modifying their expected loss measures. We also study how the financial turmoil has affected the market perception of the credit risk in bank debt.

We investigate these questions using information from the Credit Default Swap (CDS) market. CDS contracts are over the counter derivative securities providing insurance against the default of senior bonds or loans. Their "market price" is the so called CDS premium and can be interpreted as an estimate of a firm's credit spread. Due to a standardized contract design and the relatively high liquidity in the market the CDS premium is arguably the best measure of the market pricing of credit risk currently available (O'Kane and Sen, 2005). Our sample comprises monthly data on the CDS premium of 41 major banking groups and 162 non-banks for the period January 2003 to December 2007. Given that the financial crisis has had a particularly strong impact on CDS premia, our approach can draw on a rich information set in order to provide unique insights into the changed market perception of bank debt and corporate debt more generally.

Using the Moody's KMV empirical default frequency (EDF) as a real-world measure of default risk, we decompose the CDS premia into expected loss and risk premia. Our aim is to understand market pricing rather than to study the performance of alternative models for pricing CDS. Thus, our econometric specification is motivated by a commonly used approach, which while simple, captures the main features of CDS pricing.

Research on the determinants of CDS premia and credit spreads in general does either not distinguish between banks and other firms or excludes financial firms altogether. However, if market participants really think that the drivers of the default risk of banks are different then components of bank CDS premia should reflect this fact. This research includes Collin-Dufresne et al. (2001) on the determinants of bond-based credit spreads, Campbell and Taksler (2003) on the linkage between equity volatility and credit spreads, Zhang et al. (2005) on the linkage between jumps and credit spreads and Ericsson et al. (2008) on the determinants of CDS. Berndt et al. (2005) use intensity modelling to estimate default risk premia.

Our paper is also related to the literature on the market discipline of banks.[4] Market prices of banks' debt are available on a much higher frequency than accounting variables and aggregate the market's perception of a bank's credit risk. Hence, markets may provide valuable forward-looking information not revealed otherwise. Therefore, many supervisors have incorporated market prices into their early warning models.

For practioners, policy makers as well as academics, understanding the specific factors and their relative role in driving the variation in CDS premia is important because changes in the weight of credit- and non-credit related elements have different implications about market expectations. Furthermore, the sharp increase in banks' CDS which is a central feature of the turmoil in credit markets since summer 2007 has underlined the importance of understanding the market pricing of banks' credit risk.[5] In particular, indications about rising aversion to credit risk provide a different signal of market perceptions than forecasts of rising future expected losses in the banking system.

[4] Flannery (2001) offers a conceptual discussion, see also e.g. Gropp et al. (2006).
[5] BIS (2008) offers a detailed analysis of the subprime crisis.

Our analysis indicates that until July 2007 bank debt was perceived as being less risky than non-bank debt. After this date, the financial crisis manifested itself in a major repricing of bank default risk which led to a reduction in the differences between banks and non-banks. In particular, until August 2007, CDS traders thought that exposure to banks carried lower default risk than exposure to non-banks. However after the outbreak of the financial market turmoil, the market perceptions of bank and non-bank credit risk reached similar levels. Furthermore, uncertainty about the level of different banks' default risk also rose. We also find considerable variation in the explanatory power of our factors over time.

The rest of this paper is organised as follows. Section 2 describes the mechanics of CDS contracts and the decomposition of the CDS premium. Section 3 summarises our sample. Section 4 provides a time series perspective on CDS premia of banks and non banks. Section 5 contains our econometric analysis and section 6 concludes.

2 The CDS premium

In a standard single name CDS two parties enter into a contract terminating either at the stated maturity or earlier at the time when a specified credit event occurs. Typical credit events include failure to meet payment obligations when they are due, bankruptcy and some more technical credit events which are defined along with other terms of the contract by the International Swaps and Derivatives Association (ISDA). If a default event occurs the protection seller compensates the protection buyer for the incurred loss by either paying the face value of the bond in exchange for the defaulted bond (physical settlement) or by paying the difference between the post-default market value of the bond and the par value (cash settlement) where the post-default value of the bond is fixed by a dealer poll.

The annual insurance premium (in basis points as a fraction of the underlying notional) that the buyer pays for protection against default is the CDS premium. Like in a standard swap this premium is set such that the CDS has zero value at the time of origination of the contract. The CDS premium (C) can be split up into an expected loss (EL) component, which depends on the recovery rate (R) and the probability of default (PD) plus a risk premium (RP). This (approximate) decomposition (derived in appendix 1) can be written as

$$C = EL + RP = (1 - R)PD + RP. \tag{1}$$

In (1) the probability of default may depend on general economic conditions as well as on sector and firm specific conditions. Recovery rates may also vary with macroeconomic conditions, debt type, seniority and industry and may display a negative relationship with default rates (Altman et al., 2005). The risk premium compensates for the exposure to default risk, liquidity risk and possibly other non diversifiable sources of risk.

3 Data

We focus on single name CDS contracts with a maturity of five years because this is the most frequently traded type of contract in the CDS market. For this maturity we collected end of month CDS premia from the Bloomberg database for the period from January 2003 to December 2007. Decomposition (1) suggests that default probabilities should be closely related to CDS premia. Hence we need estimates of default probabilities. The empirical default probabilities (EDF) from the KMV database provide such estimates on a monthly basis. The EDF is an estimate of the probability of default based on the model of Merton (1974) and widely used in the financial industry. Kealhofer (2003) outlines the methodology to obtain the EDF in some detail but KMV does not fully disclose their procedure. [6]

After eliminating sovereign entities, companies not listed at a stock exchange and companies who disappeared through merger or went bankrupt we were able to match CDS premia for 213 firms with corresponding firm specific EDF's from the KMV database. Data on other control variables that we use in the regression analysis are also collected from the Bloomberg database.

From the 213 companies in the dataset 41 belong to the banking industry.[7] They are among the largest banks in the US and Europe. We list them in Table A1 in the appendix. The remaining firms belong to a broad range of different industries, including many industrial firms but also other financial firms such as insurers or investment banks. Table 1 provides some statistics about the CDS premium on the industry level over the entire sample period. The average CDS premium in the sample is about 58 basis points and the median is around 37 basis points. In nearly all industries the median CDS premium is lower then the average premium reflecting the fact that the distribution of the premia is skewed to the right. It is striking that the average and median CDS premium of banks is only about 21 and 15 basis points, respectively, and hence among the lowest across all the industries in the sample.

4 CDS premia of banks and non banks over time

[6] Bharath and Shumway (2008) examine the accuracy of a simplified version of the KMV model.
[7] Hence, we use a narrow definition of banks as deposit-taking institutions.

Figure 1 displays how the CDS premium of banks and non banks evolved over time. Throughout the sample period the average CDS premium for banks was lower then the average premium for non banks. Both premia dropped sharply at the start of the sample period reflecting the recovery from the economic downturn at the beginning of the decade. Then between October 2003 and June 2007 the CDS premium was in both sectors rather stable. Finally, during the last six months of the sample the premium rose sharply in both sectors due to the turmoil that originated in the US sub-prime market. Moreover, the difference between the average CDS premium of the banking and non banking sector shrunk markedly in the turmoil months. Figure 2 shows the median of the CDS premia in both sectors. Unlike the mean this measure is robust to extreme observations. The message remains basically the same but here the difference in the premia essentially disappears during the turmoil.

Figure 3 shows the median CDS premia for banks and non banks together with the corresponding median EDF’s (expressed in basis points) from KMV. Two observations are striking. First, the EDF of non banks while clearly larger during the first half of the sample period converges more or less to the EDF of banks during the second part of the sample period. Second, the median EDF tracks the median CDS premium quite closely until the start of the turmoil in both industry sectors. But during the turmoil in both sectors a wide gap opens between the EDF and the CDS premium suggesting that the market demanded a huge risk premium for holding credit risk in general.

The EDF from KMV is an estimate of the real-world or actual probability of default but the pricing of credit risk requires risk-neutral default probabilities. Risk-neutral probabilities are typically larger than real-world probabilities to compensate for risk aversion (see Duffie and Singleton (2003), Ch. 5 for further discussion). The ratio between the risk-neutral and the actual default probabilities should therefore inform us about the risk perception of investors. Alternatively to (1) we can express the observed CDS premium C as

$$C = (1 - R)\lambda \tag{2}$$

where λ is the risk-neutral default probability (e.g. Hull et al., 2005). Making the simplifying but standard assumption of a constant recovery rate we can approximate the risk-neutral default probability by the quantity C/(1-R).

Figure 4 displays the ratio of the risk-neutral to the empirical default probability for banks and non banks. In the approximation of the risk-neutral probabilities we use the median CDS premium and set the recovery rate R to 40% as is commonly done by market participants. In both sectors the ratio rose from a value of about 4 to a value of roughly 20. Thus, although the actual default probabilities declined market participants became relatively more concerned about credit risk over time.

Note that the risk-neutral/empirical default probability ratio is about the same for bank and non banks during the recovery phase at the beginning of the sample period. Afterwards, during the stable phase, the ratio is most of the time markedly larger for non banks, however. Thus, the market either believed that banks are inherently less risky or the market expected to obtain a significantly higher recovery rate in case of a bank default. The CDS premium of banks *and* non banks shot up dramatically during the turmoil where announcements of spectacular losses of banks and other financial institutions were frequently released. During this time banks were even reluctant to lend money to each other as reflected by the sharp increase in overnight interest rates and the accompanying interventions of central banks to avoid a dry up of the inter bank market.

In order to illustrate the extent of the repricing of banks, figure 5 shows a histogram of the relative change in median CDS premia between period 2 and period 3. The chart indicates both the size of the repricing as well as the heterogeneity with 8 banks recording an increase of up to 80 % and 6 banks recording an increase between 150 and 170 %.

5 Regression analysis

5.1 Baseline model

The CDS premium can be decomposed into a loss given default component times the probability of default plus a risk premium. Using our sample of firm level data we now assess statistically whether this decomposition differs for banks and non banks. We start with a simple empirical model which we refine later. Assuming a constant risk premium, substituting the empirical default probability for the true but unobservable PD in (1), accounting for unobserved firm specific fixed effects ν_i, error terms ε_{it} as well as for differences between banks and non banks we obtain the empirical model

$$C_{it} = \alpha + \beta_1 EDF_{it} + \beta_2 BANK * EDF_{it} + \nu_i + \varepsilon_{it} . \qquad (3)$$

In (3) C is the CDS premium, EDF is the empirical default probability and BANK is a dummy variable that takes on the value of one if the firm is a bank (as defined above) and zero otherwise. The coefficients β_1 and β_2 have an interesting interpretation. The coefficient β_1 may be viewed as an estimate of the loss given default LGD for non banks and β_2 measures the difference in the estimated LGD for banks.

The baseline model that we will extend later on is admittedly simple. For example, figure 4 suggests that the risk premium varies over time. The assumption of a constant risk premium may therefore be unrealistic when the model is estimated over the full sample period and may still be too restrictive when the model is estimated over different sub-periods. The model just serves as a benchmark to see later to what extend various variables associated with the risk premium are able to explain the variation in CDS premia in addition to the EDF.

Table 2 shows the model coefficients estimated over the entire sample period as well as over the three sub periods which we distinguished in section 4. To account for possible presence of autocorrelation and heteroskedasticity we use panel robust estimates of the asymptotic variance-covariance matrix for inference (Cameron and Trivedi, 2005, Ch 21 provide details). The first column in table 2 contains the regression coefficients estimated over the full sample period. The simple model is able to explain about 50% of the variation in the CDS premium. The coefficient on the EDF implies an estimated LGD of about 60 % (i.e. a recovery rate of about 40%) for non banks. This estimate is quite close to the standard assumption made by market participants. The insignificance of the bank dummy variable implies that the coefficient on the EDF for banks is about the same as for non banks.

The analysis in section 4 suggests that the relationship between the EDF and the CDS premium may not be stable over time and the regression results obtained for the three sub periods confirm this conjecture. During the first period (1/2003 - 9/2003) we do not find statistically significant differences between banks and non banks. But in the second period (10/2003 - 6/2007) where CDS premia are relatively stable both β coefficients are lower. The coefficient for non banks is around 45 and the coefficient for banks is only about half as large. This difference is statistically significant at the 10% level. The last period (7/2007 - 12/2007) covers the first six months of the turmoil. Here both coefficients are extremely high. The coefficient for non banks is slightly above 100 and therefore already larger than theory permits but the coefficient on the bank dummy times the EDF is even four times larger. However, as the standard error of 280 indicates the coefficient is very imprecisely estimated and therefore not statistically significant. Moreover, the ability of the model to explain the cross sectional variation in the CDS premium drops sharply.

Table 3 provides summary statistics concerning the CDS premium and the EDF for banks in the three sub-periods. If we compare period 2 with period 3 it can be seen that the variability of the CDS premium measured by the standard deviation or the more robust inter-quartile range rises in the later turmoil period. At the same time the variability of the EDF declines quite a lot in the turmoil period. This helps to explain why the coefficient on the bank dummy times the EDF is estimated so imprecisely in the third period.

5.2. Determinants of risk premia

In the simple model we assume that the risk premium is constant over the estimation period. If this assumption is violated the coefficients on the EDF may pick up effects from variables related to time varying risk premia that are correlated with the EDF. We now extend the model to account for the possibility of time varying components of the risk premium. The enlarged model is

$$C_{it} = \alpha + \beta_1 EDF_{it} + \beta_2 BANK * EDF_{it} + \boldsymbol{\gamma}\mathbf{x}_t + \nu_i + \varepsilon_{it} \, , \qquad (4)$$

where $\boldsymbol{\gamma}$ is a vector of parameters and $\mathbf{x}$ denotes a vector of additional control variables. The control variables are the risk-free five year interest rate, the slope of the yield curve, the implied stock market volatility, a measure of idiosyncratic equity volatility and the swap spread. The selection of these variables is based on the results in Campbell and Taksler (2003).

Risk-free rate: Changes in the risk-free rate in general are negatively related to credit spreads. The theoretical explanation within the Merton (1974) framework proceeds as follows: First, a rising risk-free rate decreases the present value of expected future cash flows, i.e. the price of the put option decreases. Second, a rising risk-free rate tends to raise the expected growth rate of the firm value and hence a higher firm value becomes more likely. In turn, this implies a lower price of the put option on the firm value. Both effects decrease the costs of insurance against default, which implies a lower credit spread. We use the five-year swap rate because interest rate swaps are commonly seen as the market participants' preferred measure of the risk-free rate (cf. Longstaff et al., 2005).

Slope of the yield curve: In the Longstaff and Schwarz (1995) structural credit risk model with stochastic interest rates, a rising slope of the term structure lowers credit spreads. In this model, in the long run, the short rate converges to the long rate. Hence an increasing slope of the term structure should lead to an increase in the expected future spot rate. This in turn, will decrease credit spreads through its effect on the drift of the asset value process. We define the slope of the term structure as the difference between the ten-year and the one-year euro and US dollar swap rates, respectively.

Stock market volatility: Spreads for credit-risky products compensate investors for more than pure expected losses from default (Berndt et al, 2005). These risk premia are typically assumed to be correlated with investor attitudes towards risk. Given its forward-looking character, the VIX implied volatility index derived from option prices on the S&P 500 equity index is commonly used to capture these effects (Coudert and Gex, 2008). For the European market, we use the VSTOXX index, which represents the implied volatility of the Euro Stoxx 50 index.

Idiosyncratic equity volatility: Campbell and Taksler (2003) find that the variation in the spreads on US corporate bonds is more strongly linked to idiosyncratic stock price volatility rather than aggregate stock price volatility. Like these authors we define a firm's idiosyncratic stock returns as the difference between its stock return and the market-wide stock return as represented by the S&P 500 or the EuroStoxx 50, respectively. The idiosyncratic volatility is then calculated as the monthly average of squared idiosyncratic stock returns. Idiosyncratic volatility measured in this way implicitly assumes a beta of one. Campbell and Taksler (2003) find that adjusting for beta has no effect on their findings.

Swap spread: Longstaff et al. (2005) show that risk premia in credit spreads are positively related to average bid-ask spreads, which in turn capture changes in market liquidity. As individual bid-ask spreads for the CDS are not readily available, we use US dollar and Euro 10 year swap spreads. These are known to contain a liquidity premium, along with a premium reflecting the default risk embedded in the Libor rate (which is known to have risen during the crisis), due to banks' funding operations in the interbank market (Huang and Neftci, 2003).

Table 4 reports the results from the fixed effects panel regressions of model (4). The first column contains the estimates over the entire sample period. The estimates for β_1 and β_2 in (4) differ slightly from the estimates in the simple model (3) but β_2 is again not significantly different from zero. The coefficients on the additional control variables are statistically different from zero at conventional significance levels. The only exception is the coefficient on the slope of the yield curve. Hence variables related to time varying risk premia help to explain CDS spreads but the modest increase of only 3% in the overall explanatory power suggests that their contribution relative to the EDF is rather small.

The other columns in table 4 show the estimates for the three sub periods. The results are again qualitatively similar to the ones for the simpler model (3). The coefficient β_2 is statistically insignificant in the first period, significantly lower in the second period and extremely large but imprecisely estimated in the turmoil period. The variables related to the risk premium help again to explain CDS spreads to some extent during the sub periods. Their additional explanatory power is rather modest in the first two periods. During the turmoil period, however, their contribution is quite large in relative terms. In particular, the simple model can only explain about 12% of the overall variation in the CDS spread during the turmoil period whereas the extended model can explain about 20%.

Finally, the explanatory value of factors also sheds some light on changes in the market perception of corporate credit risk. Figure 6 shows the variation in the R-squared measure across subperiods. Here, model 1 represents the specification with the EDF as the only right-hand side variable (table 2). In contrast, model 2 also contains the additional explanatory factors (table 4). We find a sharp decline in the R-squared measure with the lowest values observed in the last period.

One possible explanation of this finding is in terms of the ”credit spread puzzle” (see, for example, Amato and Remolona (2003)), which describes the observation that fundamental factors are usually found to explain only a small fraction of observed credit spreads. A similar result is documented by Collin-Dufresne et al.

(2001) for US corporate bonds. They show that the residuals from regressions on the spreads of individual bonds are heavily correlated. Their interpretation is that US corporate bond markets are segmented from stock and Treasury markets and driven by large supply/demand shocks. This interpretation could also be applied to CDS. Given that the market has only been active for a few years, supply – demand imbalances and technical factors, which are not captured by the liquidity proxies in the equations, may be present. In addition, the market may exhibit “clientele” effects, i.e. demand may differ across firms due to investors’ risk appetite. Similar clientele effects based on heterogeneous investors have also been observed in other segments of the credit market. [8]

5.3 Bank specific risk premia

In (4) we assume that the variables that help to determine the risk premium affect the CDS premia of banks and non banks to the same extent. Now we relax this assumption and allow for differences between both types of firms. Thus we estimate the model

$$C_{it} = \alpha + \beta_1 EDF_{it} + \beta_2 BANK * EDF_{it} + \boldsymbol{\gamma}\mathbf{x}_t + \boldsymbol{\delta}\mathbf{x}_t BANK + \nu_i + \varepsilon_{it} \qquad (5)$$

in which we interact all explanatory variables with the bank dummy. Table 4 summarizes the results for this model.

When we estimate (5) over the full sample period only the interaction term on idiosyncratic volatility is statistically significant. The estimated coefficient on the idiosyncratic volatility for non banks is about plus one and the estimated coefficient

[8] For a study of these effects in the commercial paper market see Covitz and Downing (2007).

on the associated bank interaction term is about minus one suggesting that idiosyncratic volatility does not affect the CDS premia for banks. However, the pattern on the interaction terms differs over the three sub periods. In period 1 no interaction term is statistically significant. We find significant interaction terms on the risk free rate, the market volatility and the idiosyncratic volatility in period 2. The size and sign of the estimated interaction coefficients suggest that these three variables affect bank CDS premia only to a small extent in the second sub period. Only the interaction term on the slope of the yield curve is significant in period 3 and the associated coefficient again suggests that this variable is less important for the CDS premia of banks.

Up to now we accounted for unobserved heterogeneity of firms in a fixed effects panel regression framework. This has the advantage that the coefficients can be consistently estimated if some of the explanatory variables are correlated with the unobserved effects. However, the fixed effects specification prevents the identification of marginal effects of qualitative variables. Thus we cannot assess whether the simple fact of being a bank helps to explain differences in the CDS premium for banks and non banks.

In order to assess this possibility we estimate the model

$$C_{it} = \alpha_1 + \alpha_2 BANK + \beta_1 EDF_{it} + \beta_2 BANK * EDF_{it} + \boldsymbol{\gamma}\mathbf{x}_t + \boldsymbol{\delta}\mathbf{x}_t BANK + \nu_i + \varepsilon_{it} \qquad (6)$$

in which we treat unobserved heterogeneity ν_i as a random effect (i.e. ν_i is assumed to be random and uncorrelated with the explanatory variables). This enables us to use the random effects estimator which allows for qualitative variables. We can therefore include the bank dummy variable BANK as an additional qualitative explanatory variable in (6).

Table 6 reports the results from the random effects model. The coefficient on the bank dummy variable is negative and statistically significant when the model is estimated over the full sample period. Its numerical value suggests that the CDS premium is about 35 basis points lower for banks. However, this effect results mainly from the second sub period. In the first period the bank dummy is much smaller and statistically insignificant. Interestingly, the bank dummy is positive and numerically large in the third period. However, similar to the coefficient on the EDF for banks the estimate is very imprecise and therefore not statistically significant. The results for the other coefficients are very similar to the results from the fixed effects model (5) as reported in table 5. Only the coefficient on the swap spread is quantitatively but not qualitatively different in period 1 and period 3.

5.4 Robustness tests

We perform a number of robustness tests. First, the results of the regression analysis are similar if we add the investment banks to our group of banking companies. Second, we use the money market spread (defined as the difference between unsecured rates and the yields on short term government paper) instead of the swap spread. Again, results are materially unchanged.

A striking observation is that the EDF does not increase with CDS spreads at the end of the sample period (see e.g. figure 1). Given that the KMV model is proprietary it is difficult to exactly explain why this is the case. Ideally, we therefore would like to re-estimate our model with a second proxy for the real world default probability. However, this is not feasible as, to the best of our knowledge, KMV is the only provider of real world default probability estimates for banks as well as non-banks. [9]

6. Conclusions

The existing literature emphasizes a number of major differences between banks and non-banks. First, solvent commercial banks always have access to central bank discount window operations, where they can obtain emergency liquidity when they are unable to raise funding on the interbank market. Hence the central bank as a lender of last resort has no equivalent among industrial firms. Second, the opacity in banks' assets makes them different from plain-vanilla industrials. In particular, bank loans are an example for an asset category which makes exogenous bank valuation particularly difficult. This argument can be summarised as the view that "Banks are black boxes" (cf. Morgan, 2002). Furthermore, the capital structure of banks and non-bank differs due to the fact that a part of banks' liabilities are government guaranteed retail deposits. However, despite these structural differences, the CDS remain comparable as market prices of banks' default risk as they always reference senior unsecured debt.

By means of regression analysis we study how CDS traders discriminate between banks and other type of firms and how their assessment has varied over time. Our results illustrate the substantial repricing of banks' CDS relative to the CDS of other firms during the subprime turmoil. In contrast to previous episodes of financial market stress such as the LTCM collapse in 1998 the subprime crisis has had a particularly severe and protracted impact on the banking system. This rise in systemic risk was to a large extent due to the fact that reliable pricing for the large exposures to

[9] For instance, Fitch offers estimates of the real world default probability through its Equity Implied Rating and Probability of Default methodology but the database does not cover banks (cf. Liu et al., 2007).

securitisation instruments which banks had built up during the boom period of the credit risk transfer markets had become almost impossible. [10] Hence, banks were faced with the problem that they were holding large positions on their books for which no reliable valuation was available and selling into the market was also impossible due to the collapse in market liquidity. [11] Depending on the quality of a bank's risk management, the extent of these positions varied considerably across banks. The uncertainty about the value as well as about the size of these credit market exposures led to general uncertainty about the valuation of banks themselves. This general reassessment of credit risk spilt over money markets in August 2007. [12]

Our analysis captures some of the main features of the market turmoil. First, we find that the market unconditionally perceived banks to have lower default risk only in the second period. Second, the regressions as well as the time series plots show from August 2007 onwards that the perception of bank credit risk approached the level of non-banks which in our second sample period had been seen as being more risky.

Third, the increased valuation uncertainty is illustrated by the increase in the standard error of the coefficient on Bank x EDF. In this context, an alternative interpretation is that investors may also have had increasing doubt about the quality of the KMV EDF as a predictor of default risk. Thus, part of the increase in the coefficient on Bank x EDF may also be due to the fact that investors attached a higher likelihood to a bank default than the estimate of the KMV model. Support for this argument is provided by the fact that the EDF is an estimate for the probability of

[10] Examples are asset-backed securities or collateralised debt obligations (cf. Scheicher, 2008).
[11] See e.g. Borio (2008) or Gorton (2008).
[12] Given the importance of counterparty risk in money markets, interbank rates rose sharply, making bank funding ever more difficult (Taylor and Williamson, 2008).

default whereas the CDS also provides insurance for other adverse credit events such as restructuring.

Finally, we find that the risk premium which investors require for exposure to bank credit risk differs across time as well as across the two types of firms. In particular, effects on the risk premium of banks are weaker than on the risk premium of non-banks.

Appendix 1: Decomposition of the CDS premium

A standard CDS contract has two legs. The fee leg consists of the present value of the CDS premium payments that a protection buyer makes to the protection seller. The contingent leg is the present value of the payment that the protection seller makes in case of default. We assume for simplicity that the hazard rate λ (i.e. the probability of default per year conditional on no earlier default) is constant. We further assume no counterparty default risk and continuous premium payment. The value of the contingent leg at time s > t is then

$$\int_t^T (1-R)\lambda D(s)S(s)ds$$

where S(s) = exp(-λs) is the survival probability, R is the recovery rate and D(s) is the discount factor. The value of the fee leg is

$$C\int_t^T D(s)S(s)ds$$

where C is the CDS premium per annum. Subtracting the fee leg from the contingent leg yields

$$V(t) = \left[(1-R)\lambda - C\right]\int_t^T D(s)S(s)ds.$$

At origination of the contract at t = 0 the present value of both legs are equated and the CDS has a market value V(0) = 0. Consequently the CDS premium is

$$C = (1 - R)\lambda.$$

Note that λ is a risk neutral probability which incorporates the risk aversion of investors. Risk neutral probabilities are therefore usually larger than actual default probabilities denoted as PD. Hence using PD instead of λ for pricing would lead to CDS premium C* that is smaller than the one actually observed in the market. The difference between C and C* is just the risk premium RP that the market requires for holding credit risk. Thus

$$C = (1 - R)PD + RP$$

is a decomposition of the CDS premium if we use objective probabilities. This decomposition is of course only approximate if we relax the assumption of a constant hazard rate and a deterministic recovery rate. Hull and White (2000) and Duffie and Singleton (2003) provide further details on CDS pricing.

Appendix 2: Banking companies in the dataset

Table A1: Banks included in the dataset

company name	country
ERSTE BANK	aut
FORTIS BANK A.S.	bel
DEXIA	bel
CREDIT SUISSE GROUP	che
UBS AG	che
DANSKE BANK AS	dnk
BNP PARIBAS	fra
SOCIETE GENERALE	fra
CREDIT AGRICOLE SA	fra
BARCLAYS PLC	gbr
HSBC HOLDINGS PLC	gbr
ROYAL BANK OF SCOTLAND GROUP PLC	gbr
STANDARD CHARTERED PLC	gbr
LLOYDS TSB GROUP PLC	gbr
BAYERISCHE HYPO- UND VEREINSBANK AG	Ger
COMMERZBANK AKTIENGESELLSCHAFT	ger
DEUTSCHE BANK AKTIENGESELLSCHAFT	ger
ALLIED IRISH BANKS PLC	irl
BANK OF IRELAND	irl
UNICREDITO ITALIANO SPA	ita
MEDIOBANCA SPA	ita
INTESA SANPAOLO SPA	ita
BANCA POPOLARE DI MILANO	ita
CAPITALIA SPA	ita
BANCA MONTE DEI PASCHI DI SIENA SPA	ita
BANCA POPOLARE ITALIANA	ita
ABN AMRO HOLDING N.V.	nld
BANCO ESPIRITO SANTO SA	prt
BANCO COMERCIAL PORTUGUES, S.A.	prt
BANCO SABADELL	sm
BANCO BILBAO VIZCAYA ARGENTARIA SA	sp
BANCO POPULAR ESPANOL	sp
BANKINTER, S.A.	sp
SKANDINAVISKA ENSKILDA BANKEN	swe
JPMORGAN CHASE & CO	us
WACHOVIA CORP	us
BANK OF AMERICA CORP	us
WELLS FARGO & CO	us
CITIGROUP INC	us
WASHINGTON MUTUAL INC	us
CAPITAL ONE FINANCIAL CORP	us

Appendix 3: Variables used in the regression analysis

Table A2 : Variables in dataset

variable	description	source
CDS	Annual premium for a five year credit default swap	Bloomberg
EDF	Empirical Default Frequency (in percent)	KMV
RF	Risk free five year interest rate (swap rate, in percent)	Bloomberg
YSLOPE	Slope of the yield curve (difference between ten year and three month yield, in percent)	Bloomberg
VOLM	Implied stock market volatility (S&P 500, STOXX)	Bloomberg
VOLID	Idiosyncratic equity volatility	Bloomberg
SWAP	Spread between 10 year swap rate and government bond rate	Bloomberg
BANK	Dummy variable for banks	

Figures

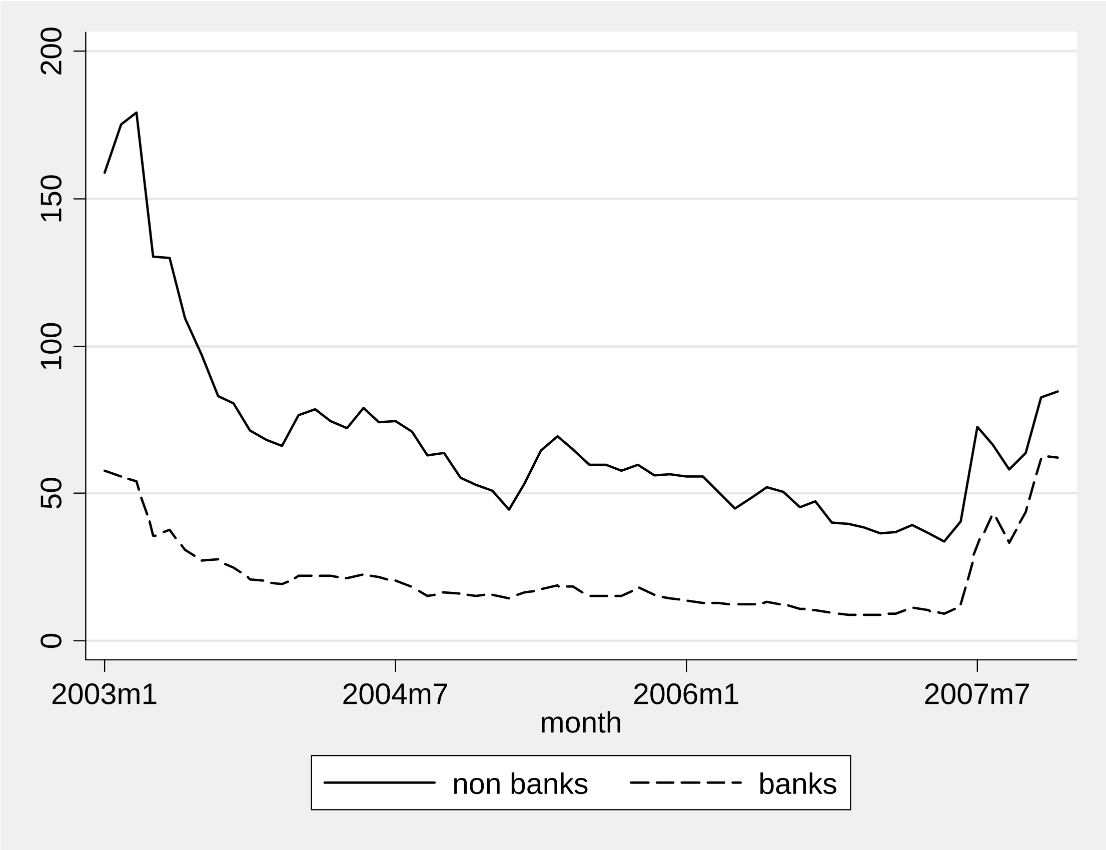

Figure 1: Average CDS premium of banks and non banks

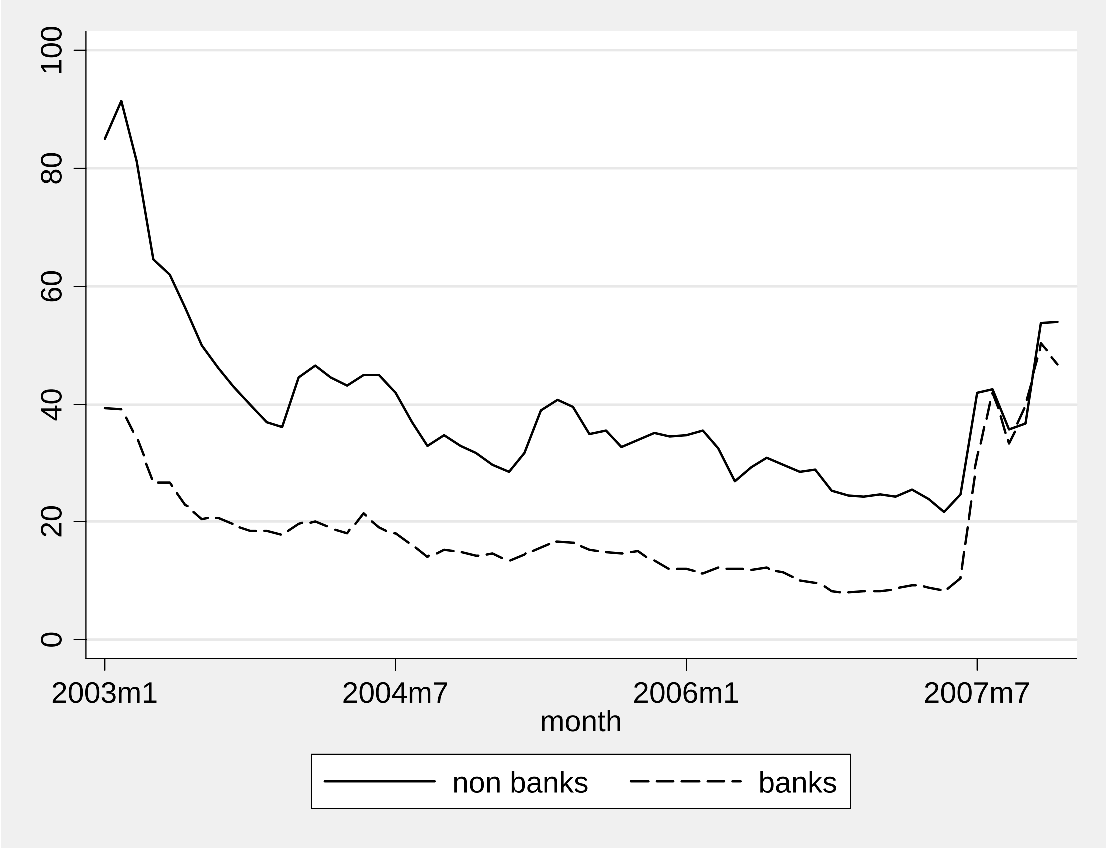

Figure 2: Median CDS premium of banks and non banks

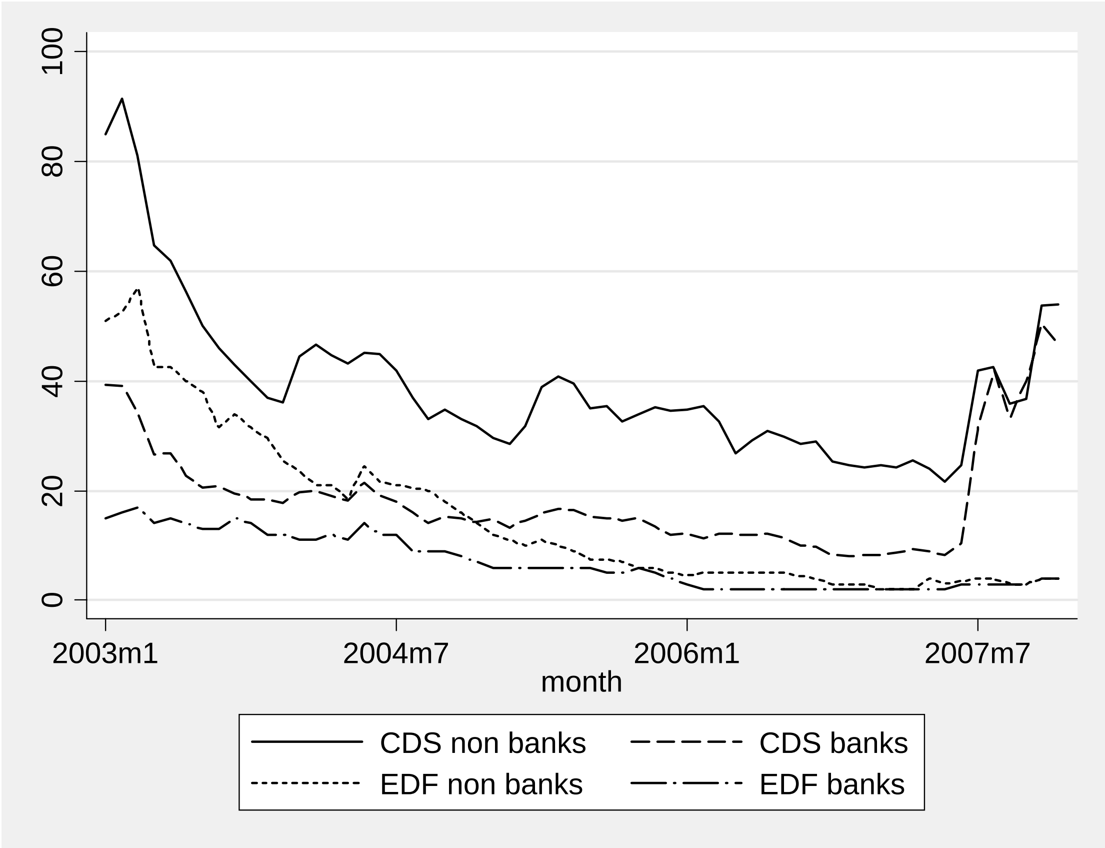

Figure 3: Median CDS premia and EDF's of banks and non banks

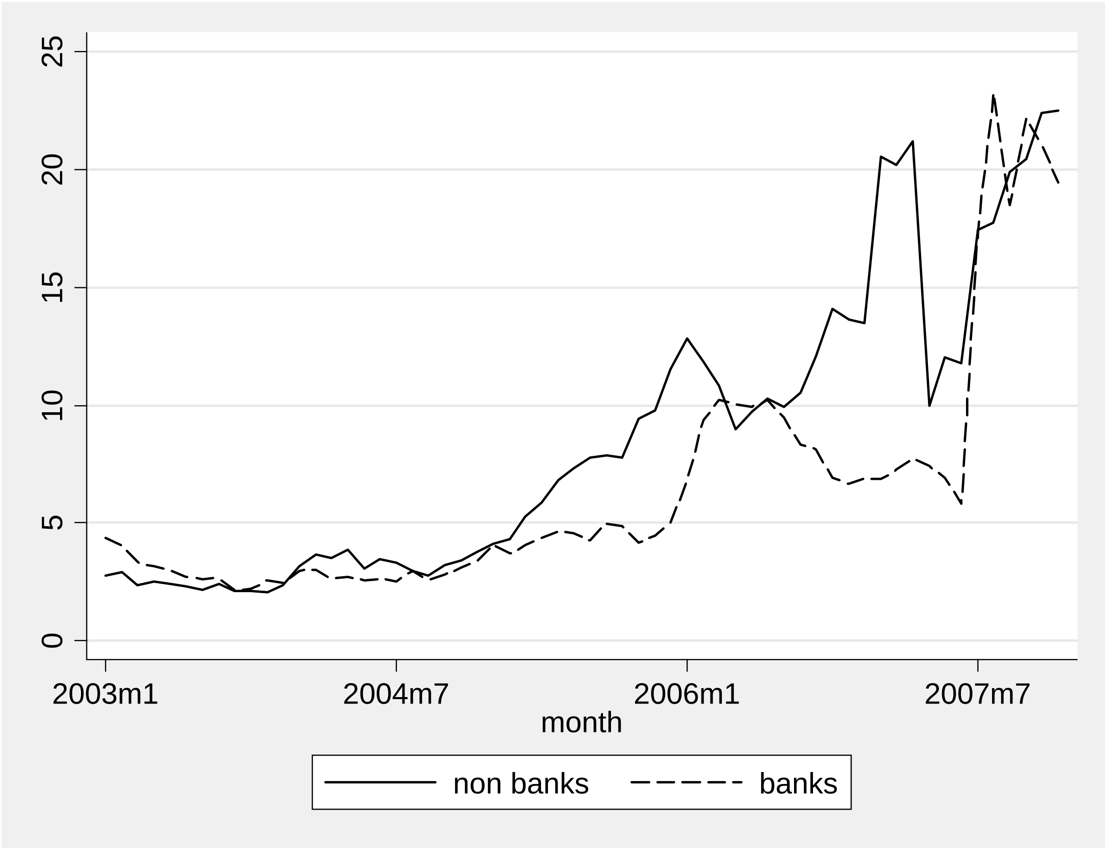

Figure 4: Ratio of risk-neutral to real-world default probabilities

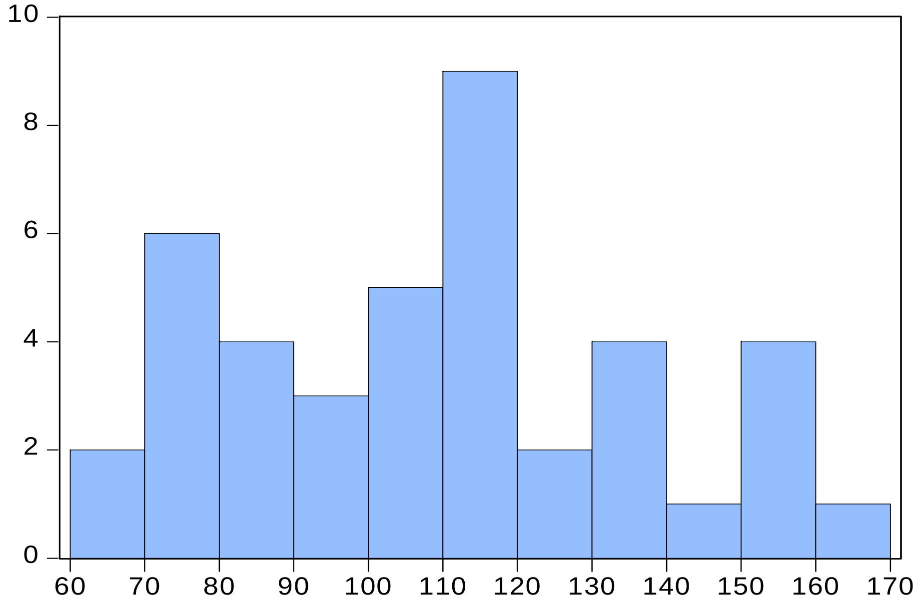

Figure 5: Histogram of changes in banks' CDS premia (log changes of period 2 vs. period 3)

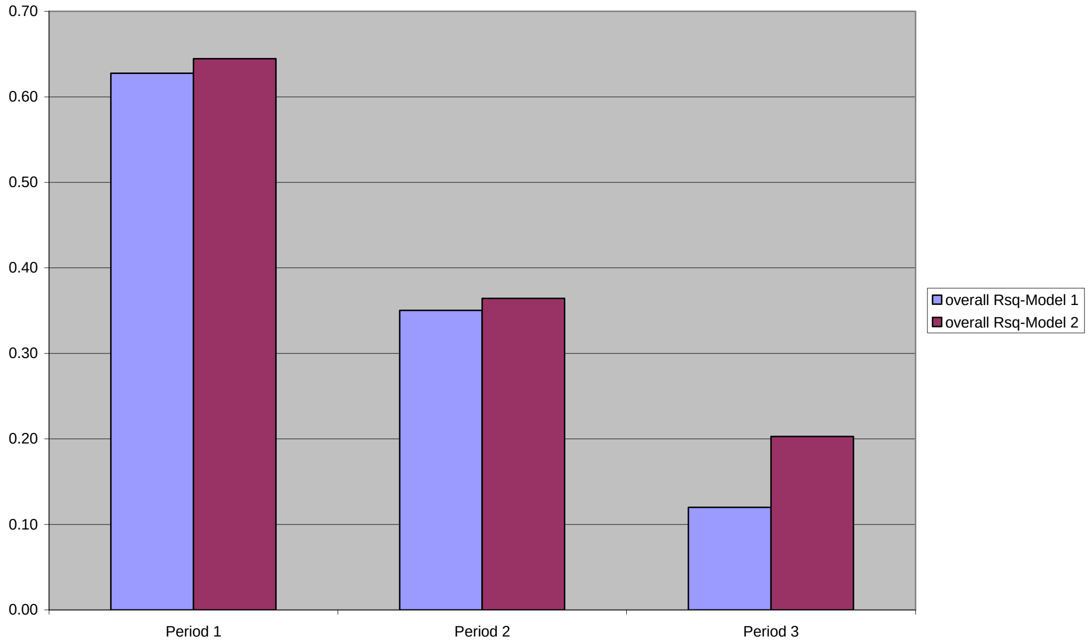

Figure 6: Comparison of R-squared measures across sub-periods. Model 1 includes only the EDF, model 2 also the risk appetite proxies.

Tables

Table 1: Summary statistics of CDS premia

industry	mean	median	min	max	N
aerospace&defense	41.5	32.4	12.9	288.3	289
air transportation	205.9	107.2	35.0	925.0	240
automotive	75.0	43.9	8.9	893.8	588
banks and s&lb	21.4	15.0	3.8	394.3	2332
business products whsl	30.0	28.3	19.4	57.0	48
business services	78.6	45.7	15.6	450.0	279
chemicals	79.2	30.0	8.8	739.6	466
construction	38.3	34.9	17.2	101.7	119
construction materials	74.0	45.9	20.3	515.0	274
consumer durables	40.6	34.5	15.2	125.2	60
consumer durables retl/whsl	59.0	53.0	27.0	155.9	120
consumer product	82.9	61.1	23.0	336.3	120
electrical equipment	62.4	65.1	32.2	115.9	60
electronic equipment	69.4	39.1	8.6	1062.5	349
entertainment & leasure	225.4	182.0	119.7	555.0	56
finance nec	47.9	30.2	9.0	324.7	171
food & beverage	31.1	29.0	3.4	82.8	347
food & beverage retl/whsl	74.4	49.3	7.7	1084.4	360
furniture & appliances	42.9	42.3	28.5	63.8	60
hotels & restaurants	84.1	60.2	19.1	756.3	240
insurance-life	25.8	23.4	6.1	118.8	567
insurance-prop/cas/health	51.0	36.3	6.5	605.2	1061
investment management	25.8	23.8	17.4	45.0	60
machinery & equipment	165.5	117.1	20.0	1525.0	162
measure & test equipment	418.4	419.4	88.5	1120.8	60
mining	23.0	21.7	10.5	98.3	106
oil refining	22.0	14.6	3.7	166.5	240
oil, gas & coal	27.6	19.9	5.6	97.5	120
paper	94.5	45.0	14.7	640.5	279
pharmaceuticals	21.1	13.2	4.1	170.8	180
publishing	45.3	41.1	17.5	159.0	240
real estate	39.7	36.3	15.2	115.0	120
real estate investment trusts	45.9	42.8	16.5	122.0	60
security brokers & dealers	37.9	31.2	16.2	179.8	300
semiconductors	35.9	30.7	21.5	115.0	60
steel & metal products	188.1	151.8	8.7	2001.8	228
telephone	74.2	42.4	17.5	825.0	645
tobacco	49.6	47.1	7.7	115.6	180
transportation	163.3	148.3	27.5	475.0	108
trucking	31.5	27.5	19.3	83.7	58
unassigned	24.3	23.2	9.7	54.3	51
utilities electric	32.0	26.1	8.2	180.0	480
utilities gas	27.5	24.2	13.0	62.7	60
utilities nec	34.0	27.9	10.2	146.6	282
Total	57.9	32.6	3.4	2001.8	12285

Notes: Mean, cv, min, max and N denote the mean, median, minimum, maximum and number of observations, respectively.

Table 2: Fixed effects panel regression of CDS premium on empirical default probability

	Full sample	Period 1	Period 2	Period 3
EDF	61.20***	68.92***	44.50***	113.54***
	(9.63)	(8.22)	(8.84)	(28.49)
EDF x BANK	-7.11	0.17	-20.54*	414.73
	(12.12)	(8.47)	(11.43)	(280.29)
Const.	40.21***	47.16***	38.93***	54.99***
	(2.59)	(6.93)	(1.81)	(3.09)
R-sq:				
within	0.51	0.58	0.26	0.36
between	0.49	0.63	0.46	0.09
overall	0.48	0.63	0.35	0.12
N firms	213	183	213	209
N obs	12237	1537	9462	1238

This table shows the estimated coefficients of the regression $C_{it} = \alpha + \beta_1 EDF_{it} + \beta_2 BANK*EDF_{it} + \nu_i + \varepsilon_{it}$. EDF denotes the empirical default probability and BANK is a dummy variable which takes on the value 1 if the firm is a bank and zero otherwise. Heteroskedasticity and autocorrelation robust standard errors are in parenthesis below coefficients. The full sample period ranges from 1/2003 – 12/2007. Period 1 ranges from 1/2003 – 9/2003, period 2 ranges from 10/2003 – 6/2007 and period 3 ranges from 8/2007 – 12/2007.

Table 3: Summary statistics of CDS premia and empirical default frequencies for banks in the three sub periods

	Period 1		Period 2		Period 3	
	CDS	**EDF**	**CDS**	**EDF**	**CDS**	**EDF**
mean	38.2	0.28	15.3	0.10	46.4	0.05
std	43.5	0.53	9.3	0.15	36.0	0.06
median	25.7	0.14	13.0	0.05	40.3	0.03
iqr	20.7	0.20	8.1	0.08	17.5	0.03
min	12.4	0.02	3.8	0.01	9.3	0.01
max	363.3	5.3	116.3	1.83	394.3	0.49

Notes: CDS denotes the CDS premium and EDF denotes the empirical default probability of banks. Mean, std, median, iqr, min and max denote the mean, standard deviation, median, inter-quartile range, minimum and maximum, respectively. Period 1 ranges from 1/2003 – 9/2003, period 2 ranges from 10/2003 – 6/2007 and period 3 ranges from 8/2007 – 12/200

Table 4: Fixed effects panel regression of CDS premium on empirical default probability and control variables

	Full sample	Period 1	Period 2	Period 3
EDF	54.71***	60.34***	40.11***	86.98***
	(9.75)	(6.45)	(8.49)	(19.60)
EDF x BANK	-14.54	-2.42	-34.25***	318.89
	(12.51)	(7.64)	(8.50)	(243.96)
RF	-15.80***	21.53**	-10.18***	-16.45***
	(1.80)	(8.60)	(1.89)	(5.03)
YSLOPE	-0.64	-39.26***	2.41**	21.63***
	(1.18)	(10.94)	(1.12)	(2.95)
VOLM	0.99***	0.47*	0.72***	-0.58**
	(0.32)	(0.28)	(0.17)	(0.29)
VOLID	0.66**	0.61	0.24	0.69**
	(0.30)	(0.38)	(0.15)	(0.27)
SWAP	103.33***	42.31*	28.99	114.39***
	(17.82	(24.19)	(18.69)	(20.93)
Const.	46.51***	19.60	52.88***	74.59***
	(7.19)	(17.52)	(6.78)	(25.40)
R-sq:				
within	0.56	0.63	0.29	0.49
between	0.52	0.64	0.49	0.16
overall	0.50	0.64	0.36	0.20
N firms	213	183	213	207
N obs	12219	1537	9454	1228

This table shows the estimated coefficients of the regression $C_{it} = \alpha + \beta_1 EDF_{it} + \beta_2 BANK{*}EDF_{it} + \gamma_1 RF_t + \boldsymbol{\gamma}\, \mathbf{x}_t + \nu_i + \varepsilon_{it}$. EDF denotes the empirical default probability and BANK is a dummy variable which takes on the value 1 if the firm is a bank and zero otherwise. The vector **x** contains the risk free rate (RF), the slope of the yield curve (YSLOPE), the implied stock market volatility (VOLM), the idiosyncratic volatility (VOLID) and the swap spread (SWAP). Heteroskedasticity and autocorrelation robust standard errors are in parenthesis below coefficients. The full sample period ranges from 1/2003 – 12/2007. Period 1 ranges from 1/2003 – 9/2003, period 2 ranges from 10/2003 – 6/2007 and period 3 ranges from 8/2007 – 12/2007.

Table 5: Fixed effects panel regression of CDS premium on empirical default probability, control variables and interaction terms

	Full sample	Period 1	Period 2	Period 3
EDF	52.21***	59.57***	38.67***	88.19***
	(9.77)	(6.43)	(8.48)	(19.84)
EDF x BANK	-2.88	4.90	-28.61***	279.25
	(12.50)	(6.70)	(9.88)	(233.62)
RF	-16.40***	23.28**	-12.08***	-11.80**
	(2.10)	(10.28)	(2.29)	(5.18)
YSLOPE	-0.81	-43.68***	2.25*	25.29***
	(1.42)	(13.36)	(1.34)	(3.40)
VOLM	0.88**	0.56*	0.68***	-0.80**
	(0.34)	(0.33)	(0.19)	(0.32)
VOLID	1.08***	0.64	0.62***	0.67**
	(0.23)	(0.40)	(0.11)	(0.31)
SWAP	94.19***	47.59*	34.61	126.58***
	(21.06)	(27.57)	(23.14)	(24.24)
RF x BANK	4.35	-12.08	10.07***	-27.72
	(2.83)	(10.64)	(2.36)	(18.18)
YSLOPE x BANK	1.36	21.17	0.83	-19.13***
	(1.83)	(14.11)	(1.42)	(5.09)
VOLM x BANK	-0.22	-0.45	-0.43**	1.09
	(0.38)	(0.35)	(0.19)	(0.73)
VOLID x BANK	-0.97***	-0.52	-0.60***	-0.03
	(0.25)	(0.40)	(0.11)	(0.45)
SWAP x BANK	29.30	-3.98	-37.13	-57.01
	(25.41)	(34.29)	(24.23)	(37.47)
Const.	44.21***	22.63	50.25***	78.05***
	(6.84)	(16.40)	(6.50)	(27.01)
R-sq:				
within	0.57	0.63	0.29	0.50
between	0.53	0.65	0.43	0.10
overall	0.51	0.65	0.34	0.13
N firms	213	183	213	207
N obs	12219	1537	9454	1228

This table shows the estimated coefficients of the regression $C_{it} = \alpha + \beta_1 EDF_{it} + \beta_2 BANK*EDF_{it} + \gamma_1 RF_t + \boldsymbol{\gamma}\, \mathbf{x}_t + \boldsymbol{\delta}\, \mathbf{x}_t\, BANK + \nu_i + \varepsilon_{it}$. EDF denotes the empirical default probability and BANK is a dummy variable which takes on the value 1 if the firm is a bank and zero otherwise. The vector **x** contains the risk free rate (RF), the slope of the yield curve (YSLOPE), the implied stock market volatility (VOLM), the idiosyncratic volatility (VOLID) and the swap spread (SWAP). Heteroskedasticity and autocorrelation robust standard errors are in parenthesis below coefficients. The full sample period ranges from 1/2003 – 12/2007. Period 1 ranges from 1/2003 – 9/2003, period 2 ranges from 10/2003 – 6/2007 and period 3 ranges from 8/2007 – 12/2007.

Table 6: Random effects panel regression of CDS premium on empirical default probability, control variables and interaction terms

	Full sample	Period 1	Period 2	Period 3
EDF	52.38***	60.22***	39.28***	89.82***
	(9.71)	(6.64)	(8.50)	(21.72)
EDF x BANK	-3.07	4.77	-29.02***	251.51
	(12.47)	(6.97)	(9.89)	(228.14)
RF	-16.16***	19.01**	-12.07***	-11.21**
	(2.09)	(8.77)	(2.28)	(4.93)
YSLOPE	-1.13	-40.28***	2.01	22.91***
	(1.42)	(12.54)	(1.37)	(3.31)
VOLM	0.88**	0.48	0.68***	-0.66**
	(0.34)	(0.34)	(0.19)	(0.33)
VOLID	1.11***	0.68*	0.65***	0.74**
	(0.23)	(0.39)	(0.12)	(0.31)
SWAP	89.52***	81.07***	32.61	108.25***
	(20.25)	(31.21)	(21.85)	(20.10)
RF x BANK	4.24	-10.71	9.92***	-28.38
	(2.84)	(9.39)	(2.35)	(17.75)
YSLOPE x BANK	1.47	19.77	1.28	-14.99**
	(1.83)	(13.34)	(1.44)	(5.83)
VOLM x BANK	-0.20	-0.39	-0.46**	0.84
	(0.38)	(0.36)	(0.19)	(0.66)
VOLID x BANK	-1.00***	-0.54	-0.63***	-0.06
	(0.25)	(0.39)	(0.12)	(0.46)
SWAP x BANK	30.86	-19.57	-30.79	-29.02
	(24.85)	(34.43)	(23.00)	(31.62)
BANK	-34.13***	-13.52	-44.89***	93.39
	(10.26)	(19.68)	(10.25)	(80.05)
Const.	51.37***	27.46	58.96***	61.88**
	(9.14)	(17.03)	(10.09)	(24.45)
R-sq:				
within	0.57	0.63	0.29	0.50
between	0.54	0.65	0.45	0.22
overall	0.53	0.65	0.39	0.25
N firms	213	183	213	207
N obs	12219	1537	9454	1228

This table shows the estimated coefficients of the regression $C_{it}= \alpha_1 + \alpha_2$ BANK $+ \beta_1 EDF_{it} + \beta_2 BANK{*}EDF_{it} + \gamma_1 RF_t + \boldsymbol{\gamma}\, \mathbf{x}_t + \boldsymbol{\delta}\, \mathbf{x}_t$ BANK $+ \nu_i + \varepsilon_{it}$. EDF denotes the empirical default probability and BANK is a dummy variable which takes on the value 1 if the firm is a bank and zero otherwise. The vector **x** contains the risk free rate (RF), the slope of the yield curve (YSLOPE), the implied stock market volatility (VOLM), the idiosyncratic volatility (VOLID) and the swap spread (SWAP). Heteroskedasticity and autocorrelation robust standard errors are in parenthesis below coefficients. The full sample period ranges from 1/2003 – 12/2007. Period 1 ranges from 1/2003 – 9/2003, period 2 ranges from 10/2003 – 6/2007 and period 3 ranges from 8/2007 – 12/200

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