Credit Default Swap Prices as Risk Indicators of Large German Banks

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Abstract

This paper explores empirically the usefulness of credit default swap (CDS) prices as market indicators. The sample of reference entities consists of large, internationally active German banks and the observation period covers three years.

By analysing the explanatory power of three risk sources, idiosyncratic credit risk, systematic credit risk, and liquidity risk, we gain important insights for modelling the dynamics of CDS spreads. The impact of systematic risk, for example, has two components, one related to the overall state of the economy and the other to a banking–sector specific component. Contrary to previous research for corporate bonds we find that CDS premia of German banks rise with an increasing risk–free interest rate, which may be explained by its impact on term transformation risk.

We compare default probabilities, inferred from a tractable reduced form model for CDS spreads, with expected default frequencies from the Moody's KMV model. The results provide empirical support to the hypothesis that structural models based on equity market prices may be less informative than reduced–form models of CDS spreads, especially for banks with major investment banking activities, because the leverage looses explanatory power.

Although the CDS market appears to have matured in the observation period, in certain periods premiums for liquidity risk can substantially increase which limits their value as market indicators. We conclude that equity prices and CDS premia should be considered together to fully exploit the information content of both market indicators and to mitigate their respective drawbacks.

Keywords: credit default swaps, credit risk, market indicators, reduced–form models

JEL classification: G 12, G 21, G 13, C 13

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1 Introduction

This paper explores the usefulness of credit default swap prices as market indicators of the riskiness of large German banks. There is a clear demand from equity investors, depositors, bond holders, business partners and supervisory agencies to assess the credit quality of banking institutions. However, banks are generally considered to be relatively opaque entities compared with firms in other business sectors. This is especially true for large, internationally active banks that are involved in a wide spectrum of highly specialized financial businesses. The annual and quarterly reports may not always provide the information that is desired for an accurate risk assessment. Furthermore, they do not allow a timely monitoring. Due to the immense information processing power of capital markets, market prices may be better suited to provide the desired information. Furthermore, they promise to provide this information on a current basis whereas accounting information is usually lagging.

There exists an extensive literature on the use of market prices to measure the riskiness of banks. The bulk of this literature focuses on credit spreads of subordinated debt issues. A smaller part uses equity prices to extract information.[1] However, prices in both markets are also affected by factors unrelated to credit risk. Bonds are subject to interest rate risk and liquidity risk which are difficult to separate in practice from credit risk. Share prices may provide misleading signals for debt holders and supervisors because the risk profile of equity differs from their risk profile. Since Black and Scholes (1973) equity is usually viewed as a call option on the value of the firm. Therefore, high–risk strategies can increase the value of this option and send a positive signal although the riskiness of the firm has increased.

Credit default swaps (CDS) are to some extent unaffected by the limitations of debt and equity issues as market indicators, because they represent insurance premia for default events and measure credit risk more directly. This attractive feature has been counterbalanced for some time by the fact that the market for this product type was still in its infancy. However, this situation has changed dramatically over the last three years. The amount of protection sold through credit derivatives has increased from USD 893bn in 2001 to USD 1,952bn in 2002.[2] These figures demonstrate the growing importance of this market, although the amount outstanding in credit derivatives in December 2002 was still less than 1.5% of the whole OTC derivatives market. The global banking industry has transferred USD 229bn of credit risk, primarily to the insurance sector.[3] The most popular credit derivatives are CDS that account for 70% of the market.

[1] See among others Hancock and Kwast (2001) who analyse subordinated debt issues and Krainer and Lopez (2001) who focus on equity prices.

[2] Source: British Bankers Association and JPMorgan.

[3] See FitchRatings (2003b).

However, just at the time when credit derivatives markets have entered a state of maturity, they are accused to sent false signals in the sense that they overprice credit risk in times of turbulences.[4] Another issue that can obscure the signal from CDS prices is the observation that these prices are also affected by factors other than credit risk. The work of Amato and Remolona (2003) suggests that corporate bond spreads are largely influenced by tax effects, liquidity risk and also that they may carry a significant risk premium for undiversifiable unexpected losses from credit risk. Considering that corporate bond spreads are closely related to CDS premia because bonds serve as hedge instruments for CDS, these factors may also help to explain why CDS prices exceed by far the expected losses observed ex post. Furthermore, the impact of market forces like the influence of certain market participants that have taken large gambles involving different credit instruments such as collateralized debt obligations (CDOs) and CDS has yet to be explored.[5] In summary, previous research efforts have provided encouraging as well as discouraging insights into using CDS prices as market indicators for credit risk.

This paper makes an empirical contribution to the literature in exploring the information content of CDS prices for credit risk. The sample of reference entities consists of three large, internationally active German banks. By analysing the explanatory power of three risk sources, idiosyncratic credit risk, systematic credit risk, and liquidity risk, we gain useful insights for the modelling of credit spreads. Considering banks as reference entities directs the focus to an industry sector that has not received wider attention in the past but is interesting due to certain peculiarities. For example, CDS prices for reference entities from this sector are known to be relatively liquid which should further their usefulness as market indicators. Furthermore, due to substantial off–balance sheet activities and the well–known opaqueness of banks, structural models based on equity market prices may be less informative in this sector than reduced–form models of CDS spreads. To explore these issues we compare default probabilities (PDs), inferred from CDS, with expected default frequencies from the Moody's KMV model. The PDs are inferred from a tractable reduced form model, drawing from Hull and White (2004) and Houweling and Vorst (2003). The CDS prices are extracted from Bloomberg and cover the period from September 2001 to Februar 2005.

Empirical research of the credit derivatives markets is still scarce. Recent results by Hull and White (2004) have confirmed that CDS prices lead signals from rating announcements. A similar lead of CDS prices has been observed by Blanco et al. (2003) relative to investment–grade bond prices. To the best of our knowledge a comparison between CDS and equity market information is still missing. Our analysis intends to narrow this gap.

The paper is organized as follows. In section 2 we briefly review characteristics of CDS contracts and the model of Hull and White (2004) that is used to estimate PDs from CDS

[4]See FitchRatings (2003a).

[5]See Amato and Remolona (2003), p. 62.

prices. Section 3 describes the data on CDS prices. Section 4 discusses various factors that may drive CDS premia and section 5 presents the estimation results. A comparison of CDS prices and EDFs from the KMV model is presented in section 6. Section 7 summarizes and concludes.

2 Model setup

A CDS is a traded instrument that fulfils the economic function of a credit insurance contract. The protection buyer transfers the credit risk of a reference entity to the protection seller. The latter receives in turn a premium that is usually paid quarterly in arrears. The premium payments stop when a credit event occurs. Then, the protection buyer either receives a compensation payment that covers the credit loss of a certain obligation, issued by the reference entity, or he delivers the obligation to the protection seller and receives the par value in return. In the first case (*cash settlement*) a number of market participants have to be polled to determine the recovery rate of the obligation. The second case (*physical settlement*) seems to be the preferred procedure because it easily solves the problem to determine a recovery rate and facilitates arbitrage between the reference obligation and the CDS.

A broad variety of investor groups are active in the credit derivatives market. Some, like hedge funds, banks and corporates are active on both sides whereas others are predominantly on one side. Life insurance corporations usually act as protection sellers whereas derivative players are mostly protection buyers. The overwhelming market success of CDS was triggered by a standardization of the product by ISDA[6] in 1999 and a growing demand and supply from various investor groups. CDS are currently traded under an *ISDA Master Agreement* and documentation is based on the *2003 ISDA Credit Derivative Definitions*. Counterparty risk is mostly eliminated by bilateral collateral agreements which greatly facilitates the valuation of CDS contracts. The credit event includes bankruptcy, failure to pay and *modified restructuring*.[7]

In the following we present a tractable discrete–time valuation framework of CDS. We use a reduced–form model rather than a structural model since this type of model is probably more often used in CDS pricing. Further, the reduced–form approach does not model the process of the firm's asset value. We consider that in case of banks the distance to default derived from the asset value relative to the liabilities may not always serve as a good indicator for their true credit risk. Furthermore, some financial institutions increasingly include investment banking activities and derivative trading in their operations. These off–balance activities question the information content of balance–sheet ratios based on

[6] International Swaps and Derivatives Association, Inc.

[7] This is the new standard in the European CDS market since June 2003. It defines the limit of the maturity of deliverable obligations differently from the standard in the US market.

book values like, for example, the leverage of the firm. In our model we pose the usual assumptions of frictionless and arbitrage–free markets with continuous trading and with rational participants.

The term structure of interest rates of a credit–risk free obligor at time 0 is given by the prices $B(0,t)$ of standardized pure–discount bonds with a maturity of t years and a face value of 1. The term structure of interest rates of the credit–risky bond issuer is given by pure–discount bond prices $B'(0,t)$ that differ from $B(0,t)$ only in that they carry credit risk. The credit risk–free term structure can usually be inferred from market prices of Government bonds, swap rates or repo rates. However, the term structure of the credit–risky issuer cannot be inferred in this way because markets of these instruments either do not exist or they contain too small a number of instruments for a meaningful estimation of pure–discount bond prices. Therefore, we rely on the premiums of CDS to infer default probabilities and the credit–risky term structure of interest rates. These interest rates are the sum of the credit risk–free rate and a credit spread.

We assume that the credit spreads are constant for all maturities. As a consequence they are completely determined by a single parameter, the hazard rate h_0. The assumption of maturity–invariant credit spreads is in line with empirical findings that no clear relation exists between the size of the CDS premium and maturity.[8] Previous empirical findings do not rule out a complex, highly non–linear relation. However, in the absence of meaningful CDS prices for a range of maturities, our parsimonious approach seems to be appropriate.

The CDS is characterized by a fixed spread premium s, a time to maturity of T years, and a notional principal that is a credit–risky coupon bond. This reference obligation pays a fixed coupon c on a yearly basis and redeems the face value at maturity. Its time to maturity T' equals or exceeds the maturity of the CDS.

We evaluate the CDS at time 0. By assumption the issuer of the reference bond can default at every trading date. In case of default at time τ the protection seller pays the notional value N of the reference bond and the accrued interest since the last coupon payment date τ'^{-}. In return the protection buyer delivers the reference bond and pays the CDS premium for the time between the last premium payment and τ. $K(\tau,s)$ denotes the payment from the protection seller, π the recovery rate and τ^{-} the time of the last CDS premium payment before τ. The payment of $K(\tau,s)$ is assumed to be made immediately after default has occurred:

$$K(\tau,s) = \begin{cases} N \ \left((1-\pi)\,(1+(\tau-\tau'^{-})\,\frac{c}{100}) - s\,(\tau-\tau^{-})\right) & \text{if } \tau \le T \\ 0 & \text{if } \tau > T. \end{cases} \tag{1}$$

During the life–span of the CDS the CDS buyer pays a fixed credit spread s, usually on a quarterly basis. These payments constitute the *fixed leg* of the CDS. Let $t_1^*, \ldots, t_{n^*}^*$ denote

[8] See Houweling and Vorst (2003) and Aunon-Nerin et al. (2002).

the payment dates of the CDS premium, t_j trading day j, m_j^* the number of trading days up to t_j^*, and $q(t_a, t_b, t_c)$ the probability of default between t_b and t_c conditional on the information set available at time t_a. The value $\bar{V}_0(s, h_0)$ at time 0 of the fixed leg is given as follows:

$$\begin{aligned} \bar{V}_0(s, h_0) &= N\ s \sum_{j=1}^{n^*} B(0, t_j^*) \prod_{i=1}^{m_j^*} (1 - q(0, t_{i-1}, t_i)) \\ &= N\ s \sum_{j=1}^{n^*} B'(0, t_j^*) \\ &= N\ s \sum_{j=1}^{n^*} B(0, t_j^*) \prod_{i=1}^{m_j^*} \frac{1}{1 + (t_i - t_{i-1})\ h_0}. \end{aligned} \tag{2}$$

The *floating leg* consists of the payment by the protection seller in case of default at time τ. The CDS insures every default event that occurs at one of the n trading days up to its maturity T. The value $\tilde{V}_0(s, h_0)$ of the floating leg is determined as follows:

$$\begin{aligned} \tilde{V}_0(s, h_0) &= \sum_{j=1}^{n} B(0, t_j)\ K(t_j, s) \left(\prod_{i=1}^{j-1} (1 - q(0, t_{i-1}, t_i)) \right) q(0, t_{j-1}, t_j) \\ &= \sum_{j=1}^{n} B'(0, t_j)\ K(t_j, s)\ (t_j - t_{j-1})\ h_0 \\ &= \sum_{j=1}^{n} B(0, t_j)\ K(t_j, s)\ (t_j - t_{j-1})\ h_0 \prod_{i=1}^{j} \frac{1}{1 + (t_i - t_{i-1})\ h_0}. \end{aligned} \tag{3}$$

By a simple arbitrage argument the risk–neutral expected value of the fixed leg equals the value of the floating leg. Therefore, by equating the values of the fix and the floating leg,

$$\bar{V}_0(s, h_0) = \tilde{V}_0(s, h_0), \tag{4}$$

we can infer the hazard rate h_0 as long as the CDS premium s is observable in the market. The probability of default for a one–year horizon is defined as follows:

$$q(0, 0, 1) = \frac{h_0}{1 + h_0}. \tag{5}$$

The default probability from (5) is denoted PD and compared with the EDF of the Moody's KMV model. However, both are conceptually different because the PD is determined under the risk–neutral measure. Therefore, the default probabilities inferred from CDS prices serve as an upper bound of the default probabilities under the physical measure.

The value of the reference obligation at default depends on the term structure of interest rates. Following Hull and White (2000) we do not model interest rate as stochastic and assume instead that the term structure of risk–free interest rates is deterministic and can reasonably well be approximated by the swap rate curve at the time when the CDS is evaluated. The work by Houweling and Vorst (2003) suggests that swap rates are preferable to the use of the term structure of Government bonds. The values of the pure–discount bonds are determined recursively from the swap curve by pure–discount bond stripping. Swap rates are observable for maturities between one and ten years on a yearly basis and also for 12, 15, 20, 25 and 30 years. We assume that the credit risk–free pure–discount bond rate is constant for maturities up to one year and for over 30 years. Between these boundaries we interpolate the swap rates linearly.

3 Dataset of CDS prices

The CDS prices and the bid–ask spreads are extracted from Bloomberg Financials and cover the time period from 5 September 2001 to 16 February 2005 on a daily basis. We analyse three large German private banks serving as reference entities in the CDS contracts: Commerzbank, Deutsche Bank and Bayerische Hypo- und Vereinsbank (HypoVereinsbank). The CDS premia are based on the quoted bid and ask prices. The bid price and the ask price is determined by Bloomberg as the average of the quoted bid and ask prices of the day, if at least five quotations are contributed that day. The highest ask and the lowest bid price are removed. The CDS premium is defined as the average of the bid and ask price. The bid–ask spread is the difference between the bid and the ask price of the day.

We choose 5–year CDS prices on senior debt, since these contracts are reportedly most actively traded. Furthermore, CDS contracts with other maturities are not available for the whole observation period but appeared at a later stage, for example in April 2003 for the 1– and 3–year maturities, in February 2004 for the 10–year and in April 2004 for the 7–year maturities (the latter only for Commerzbank and HypoVereinsbank). Most of the CDS transactions are in Euro 5m contracts of notional principal, but there are also traded in contract volumes of Euro 10m, 15m and 20m. The CDS premium is paid quarterly, on the 20th of the months March, June, September and December. Therefore, the 5–year CDS mature on a payment day between 5 and 5.25 years measured from the transaction date. The usual market convention is to assume an average recovery rate of 40%.[9] However, Hamilton et al. (2001) report recovery rates of 50–60% for defaulted banks. We assume in the following an expected recovery rate of 50% which takes a middle ground.

The CDS premia for corporate bonds issued by Deutsche Bank, Commerzbank and HypoVereinsbank are shown in panel A of Figure 1. We differentiate between three time periods. From September 2001 to August 2002 the CDS prices traded in a region of 20–30bp in the first period. The highest and most volatile CDS spreads were observed

[9] Bloomberg assumes a 40%–recovery rate for the analysed institutions.

in the second period between September 2002 and July 2003. Joint peaks of the CDS premia of all three banks occurred on 9 October 2002 and on 17 March 2003. The CDS spreads increased strongly but to different levels, with the premia for Commerzbank and HypoVereinsbank rising considerably higher than the premia for Deutsche Bank. The diagram also shows considerable differences in investors' credit risk perception concerning the three institutions. On 9 October 2002 this distance was of about 200bp, with Commerzbank at 261 and HypoVereinsbank at 182bp compared to Deutsche Bank at 75bp. In the third period after August 2003 the CDS premia returned to their initial range of 20–30bp in the first time period.

Table 1 summarizes descriptive statistics of the CDS premia. Their mean and standard deviation in levels (panel A) are around 34bp higher for Commerzbank and HypoVereinsbank than for Deutsche Bank which is consistent with their lower rating. The time series of log–returns are characterized by large excess kurtosis and positive skewness, so that the sample distribution is skewed to the right and has thick tails. There is high correlation among the CDS premia with pair–wise correlation coefficients between 0.7 and 0.8 (panel C), indicating that the implied default risk for these institutions may be to a large extent driven by a common factor in the banking sector.

4 Determinants of CDS premia and data sources

In this section we discuss selected risk factors that may affect the CDS premia. We differentiate between three sources of risk: idiosyncratic credit risk of the reference entity, systematic risk and liquidity risk. In the following we present various observable factors which will enable us to measure the impact of these three risk sources. Concerning the selection of the risk factors we draw from previous literature, especially from Aunon-Nerin et al. (2002).

Firm–specific credit risk is measured by stock price returns adjusted for dividend payouts and other corporate actions like stock splits.[10] The systematic risk factors are the German stock index DAX and the risk–free interest rate. As a proxy for liquidity risk we rely on bid–ask spreads of the CDS premia. Stock prices data were provided by Datastream, while the DAX and the interest rates were provided by Bloomberg. Unlike Collin-Dufresne and Goldstein (2001), Aunon-Nerin et al. (2002) and Benkert (2004) we do not explicitly use the firm's leverage as an explanatory variable for the CDS premia, since we expect this information to be already captured by the stock price returns.

[10]We also explored implied volatility as an indicator of investors' perceptions about the uncertainty of future earnings. We used call–option implied volatility with the shortest time to expiration, as long as this time is more than 20 days, derived from the Black and Scholes (1973) model. However, this factor was only significant in a single–factor regression and even then its explanatory power, measured by the adjusted R^2, was relatively low (3–10%).

Stock returns provide information how the future performance of the firm is perceived by investors. Increasing stock prices are associated with improving market expectations and, therefore, with lower expected default risk. As a consequence, higher stock returns are associated with decreasing CDS premia. To separate firm–specific stock returns R^i from the market returns R^{DAX} we estimate **abnormal stock returns** from the following market model:[11]

$$R_t^i - R_t^f = a_t^i + b_t^i (R_t^{\mathrm{DAX}} - R_t^f), \tag{6}$$

where R is the one–period log return of the asset price and R^f is the risk–free one–year interest rate. The residuals from equation (6) serve as a proxy for the abnormal stock returns.

An increase in the **DAX** over a certain time period is often perceived as a signal of improving macroeconomic conditions. When the state of the economy improves, expected profits of banks in general also increase since fewer borrowers default on their loans. Therefore we expect a positive relation between the DAX returns and the log CDS premia changes.

Fluctuations in **credit risk-free interest rates** measured by the **level of the term structure** affect the performance of banking institutions and therefore their default risk in various ways. One reason is the maturity mismatch between their assets and liabilities, usually called term–transformation risk. Banks typically refinance short–term and grant loans long–term. Therefore, higher levels of interest rates immediately increase the refinancing cost but do not immediately increase their earnings. For this reason higher interest rates are not favorable to the profitability of a bank and its credit quality. From a micro perspective one would expect CDS premia to increase with rising interest rates.

Previous empirical research on CDS, with Duffee (1998) among others, links the impact of the yield curve on corporate bond spreads to the business cycle. As documented in Fama and French (1989), credit spreads widen when economic conditions deteriorate. Indeed, the short–term risk–free interest rate is usually being raised by macroeconomic policy when the economic activity is high and approaches the peak of non–inflationary growth. With a delay, also middle– and long–term interest rates rise, so that the level of the term structure increases.[12] This suggests to associate increasing risk-free interest rates (and a flattening slope of the term structure) with better economic prospects for firms and with falling CDS premia. A corresponding negative relation of the CDS premia and the risk–free

[11] The estimation in the sample returned a beta coefficient, denoted here by b, of 1.6 for HypoVereinsbank, 1.2 for Commerzbank and 1.1 for Deutsche Bank, while the intercept was insignificant. The risk in investing in the stocks of the three banks was greater than the risk of the market index portfolio.

[12] At the same time, rising interest rates are perceived as a signal of a *future* economic activity slowdown. Empirical results confirm that the risk-free yield curve has predictive power of real economic activity, as shown for the EU countries in Davis and Fagan (1997) and confirmed recently for the US and Germany by Estrella et al. (2003).

interest rate has been documented by several empirical studies, among others by Duffee (1998), who observes higher interest rate levels to be associated with falling bond spreads regardless of the maturity and credit rating, based on a sample of quarterly observations for US corporations between 1985 and 1995. Neither of the studies examines the relation of the risk–free interest rate to the CDS premia of financial institutions explicitly. Since these arguments initially suggest contradictory signs of the relation between interest rates and credit spreads, the sign of the corresponding regression coefficient is indeterminate.

As a proxy for the level of credit risk–free interest rates we consider the 10–year European swap rate. We choose the European interest rate swap market since it provides sufficiently liquid yields for the whole range of maturities from one to 30 years.[13]

As a proxy for liquidity risk in the CDS market we choose the **bid–ask spread**. Bid–ask spreads have been found to be negatively correlated with the trading volume and with the transaction frequency in Garbade (1982) which justifies their use as liquidity indicators. Since investors demand an additional premium for liquidity risk, higher bid–ask spreads are associated with higher CDS premia. Less liquid securities have higher expected rates of return, for example they contain liquidity premia which has been documented in numerous studies for different asset types.[14]

Figure 1 shows the time series of the proposed risk factors during the whole observation period. The subperiod of high CDS premia from August 2002 to June 2003 was accompanied by depressed stock prices of the analysed banks (panels A–B). The DAX and the 10–year risk–free interest rate (panel C) overall decreased in this time period, which may reflect the deteriorating economic situation. Therefore, in this time interval different sectors of the capital market (equity and CDS) signal higher uncertainty about the prospects of the whole economy and particular banks in our sample. Also the CDS bid–ask spreads (panel D) widened from the previous level of 5–10bp to 20–40bp in the time interval from September 2002 to June 2003.

5 Explaining the dynamics of CDS premia

5.1 Model selection

We estimate a linear regression model with the risk factors discussed in section 4, based on weekly observations sampled on Wednesdays. The sample period extends from 13 March

[13] According to the Bank of International Settlements the turnover in the Euro-denominated interest rate swaps almost doubled since January 2002, approaching USD 45tr of the outstanding notional amount at the end of 2003. See BIS Quarterly Review (2004).

[14] See for example Amihud and Mendelson (1986) for spot equities, Amihud and Mendelson (1991) for government bonds, Collin-Dufresne and Goldstein (2001) for US corporate bonds and Houweling et al. (2004) for Euro bonds.

2002 to 16 February 2005, with 152 observations, and is restricted by the data availability for CDS premia, since the trading in the CDS of Commerzbank and HypoVereinsbank was not sufficiently frequent before March 2002 to allow a meaningful analysis. If CDS prices are not available on Wednesday then the closest trading day with non–missing observations is selected.

The estimation is performed with the ordinary least–squares method (OLS)[15] and afterwards with a seemingly unrelated regression. We estimate the following model:

$$\Delta \ln(\text{CDS premium})_t^i = \alpha^i + \beta_1^i \Delta \ln(\text{bidask})_t^i + \beta_2^i R_t^{*i} + \beta_3^i R_t^{\text{DAX}} + \beta_4^i \Delta r_t^{10\text{Yr}} + \varepsilon_t^i, \tag{7}$$

in which ε_t^i denotes the disturbance term of bank i in time period t. Whereas previous studies on the dynamics of CDS premia, like Aunon-Nerin et al. (2002) and Benkert (2004) have focused on an analysis in levels, we consider first differences as more appropriate. The reason is that in our sample CDS premia are autocorrelated in levels and non–stationary. Furthermore, an estimation in first differences accounts for potential (near) collinearity that may be present in levels. Our approach is therefore closer related to Collin-Dufresne and Goldstein (2001) and Boss and Scheicher (2002) who explain the dynamics of credit spreads for corporate bonds in the US and the Euro area also with variables in first differences. A comparison with studies based on credit spreads of bonds seems to be justified, since a range of suggestive empirical evidence, for example by Blanco et al. (2003) and Zhu (2004), supports a co–movement of CDS premia and bond spreads, at least in the long run.

To check for potential autocorrelation in the CDS premia, we use the Portmanteau $Q-$test. The test does not reject the white noise hypothesis for log–changes of the CDS premia at the 10% significance level, indicating no substantial autocorrelation. The series in levels, however, are found to be highly autocorrelated (see Table 1, panels A–B). Since the weekly changes of the CDS premia are not autocorrelated, including autoregressive terms as explanatory variables is not necessary. Furthermore, we did not find significant autocorrelation in the explanatory variables, based on the Portmanteau statistics. Therefore, changes in the variables can be viewed as a 'pure surprise' which justifies not including lagged variables in the model.

We find the time series in levels for CDS premia non–stationary for weekly time intervals, based on the augmented Dickey–Fuller test. The hypothesis of a unit root in the first differences, however, must be rejected (Table 1). This observation is similar to Pedrosa and Roll (1998) and Bierens et al. (2003) who find no empirical evidence of stationarity in credit spreads of corporate bonds, albeit on a daily basis. We also checked that the

[15]The OLS model is estimated using Huber–White correction for possibly non-normally distributed or homoscedastic disturbance terms as well as for observations that exhibit large residuals, leverage or influence. The Huber-White estimator corrects the standard errors while the coefficient estimates do not significantly change compared to the OLS. See Huber (1967) and White (1980).

series in levels for the bid–ask spreads, stock prices and the DAX are also non–stationary, whereas the stationarity of the first differences is not rejected. Therefore, the estimation should be performed for the differenced series, since otherwise it would return invalid P-values, spurious regression results.[16]

Furthermore, a model in first differences solves a potential problem of (near) collinearity that may be present in levels.[17] To check for collinearity Belsley et al. (1980) propose scaled condition indices for the n-th variable, $\kappa_n(X^TX) = (\frac{\lambda_{max}}{\lambda_n})^{-\frac{1}{2}}$, for each eigenvalue λ_n of X^TX, where X is the regressor matrix. Values of κ_n below 100 indicate no significant collinearity. Table 2 provides collinearity diagnostics for the explanatory variables in first differences. We obtain scaled condition indexes of $\kappa_n \leq 3$ that indicate no collinearity.

In order to chose the appropriate estimation method, we first run separate OLS regressions for the three banks and examine the residuals. The results for the OLS estimation are provided for reference in Table 3. The residuals are found to be highly correlated, with correlation coefficients of above 50% (see Table 4, panel A). The Breusch–Pagan test rejects at the 1% significance level the null hypothesis of no joint correlation of the error terms. The high cross–correlation of the residuals may indicate the presence of missing factors in the model.

Since there exists contemporaneous correlation in the disturbance terms obtained from the separate least–square estimation, the OLS estimator is inefficient though still consistent. A more efficient method is to estimate all equations jointly rather than separately, performing the **seemingly unrelated regression estimation (SURE)** of Zellner (1962).[18] The SUR estimator is more efficient than the OLS, since it uses the information in the variance–covariance matrix of the residuals Σ and on the explanatory variables that are included in the system, but otherwise excluded from the i-th separate equation. We estimate a system of three equations in (7) that are related by the disturbances ε^i. The latter are assumed to be independent and identically distributed with a zero mean and a non–diagonal covariance matrix Σ.[19]

[16] A typical feature of a spurious regression is that it returns implausibly high adjusted R^2 coefficients. When we estimated the model described by equation 7 but replacing first differences by levels we observed very high R^2 statistics, for example 97.4% for Commerzbank, 85.5% for Deutsche Bank, and 96.2% for HypoVereinsbank.

[17] Multi–collinearity is present when at least one explanatory variable can be expressed as a linear combination of several others. Broadly speaking, near collinearity exists in a regression with several regressors if there is a high multiple correlation when one of the variates is regressed on the others. As a consequence parameter estimates are typically imprecise with large standard errors.

[18] To estimate the SUR, we first obtain a consistent estimate of the matrix Σ from the OLS estimation of separate equations. Then an estimated generalized least squares estimator is applied to the stacked model of the related equations, conditional on the estimated matrix $\hat{\Sigma}$. We iterate the procedure using the newly obtained estimator to estimate the new variance–covariance matrix of the residuals and to form a new estimator, until convergence (obtained in 7 steps).

[19] While the estimated OLS residuals have a zero mean, the assumption of the identical independent

5.2 Results from a seemingly unrelated regression (SUR)

A comparison of the results from the SUR estimation (Table 5) with the OLS results shows an improvement in the estimation efficiency, indicated by lower standard errors of the SUR estimates for all significant factors. The only exception is the risk–free interest rate for Commerzbank, but there is still a gain in efficiency, since the corresponding P-value becomes lower.[20] SUR provides more restrictive estimates and attributes less explanatory power to the risk factors, while more of the CDS premia variation is associated with a common unobservable variable that is driving the highly correlated errors. Therefore, SUR returns somewhat lower adjusted R^2 for the model with the specified risk factors and higher correlation coefficients of the estimated error terms.

The SUR estimation identifies the **DAX** as the most important factor in explaining the dynamics of the CDS premia. This judgement is based on the magnitude of the estimated coefficients and on the marginal contribution of this variable to the total explained variation of the CDS premia (Table 7). A one–percent increase in the DAX results in an approximately one–percent decrease in the CDS price of Deutsche Bank and in an even stronger decrease for the remaining banks. The coefficients are highly significant, at the 1% significance level, indicating that the CDS premia are very sensitive to the changes of the DAX. This signals a potential sensitivity to the state of the economy. For the higher rated Deutsche Bank the DAX accounts for about 87% of the total explained variation, that is by over 30% more than for the riskier banks.[21] This observation is in line with previous studies which notice that better rated firms sometimes appear to be even more sensitive to economy–wide systematic risk than more risky companies. Such a converse relation is, for example, embedded in the asset correlation assumptions of the risk weight functions for corporate exposures in the internal ratings based approach of Basel II.[22]

Our results show that the sensitivity of the CDS premia to the market factor, proxied here by the DAX, is somewhat lower than the sensitivity of the US bond spreads. Collin-Dufresne and Goldstein (2001) find that a monthly return of one percent for the S&P 500 index is associated with an average credit spread decrease of about 1.6bp in absolute terms.[23]

distribution is not met in practice, since the disturbance terms are heteroscedastic. However, in this case the SUR estimator remains consistent, since the disturbances are not correlated with the explanatory variables and therefore the OLS estimator of the matrix Σ is consistent.

[20] The coefficient estimate increases more strongly than the standard error.

[21] In June 2004 Deutsche Bank was better rated by the S&P as AA-, compared to Commerzbank and HypoVereinsbank which were rated A-. Also the KMV perceived Deutsche Bank as less default risky, with an expected default frequency score (EDF) of 0.09%, while Commerzbank came out at 0.4% and HypoVereinsbank at 0.7%.

[22] See Basel Committee on Banking Supervision (2004).

[23] In contrast to Collin-Dufresne and Goldstein (2001) our coefficient is computed in percentage terms. To compare the coefficients, one can convert the change in the CDS premium from percentage into absolute terms. Thus, a one–percent return in the DAX is associated with an average decrease of the CDS premium

The **bid–ask spread** is as expected positively related to the CDS premia and significant for all three banks. The CDS premia of Commerzbank and HypoVereinsbank increase by about 0.13–0.15% when the bid–ask spread widens by one percent. The liquidity effect accounts for 23–33% of the explained CDS price variation. The high sensitivity to bid–ask spreads for the two banks could be a sign that there is not yet deep liquidity in the CDS market for these obligors, for which less trading in CDS takes place. Indeed, we have observed still some indications of stale CDS prices for the two banks in the period before March 2002. For Deutsche Bank the liquidity proxy remains statistically significant, but practically has no impact on the CDS price, judging by an almost zero contribution to the percentage of the explained variance.

The **abnormal stock returns** have the expected negative sign of the coefficient. They remain significant for Commerzbank and HypoVereinsbank and according to Table 5 account for about 17% of the total explained variation. For Deutsche Bank this factor is not statistically significant. The idiosyncratic credit risk proxied by the abnormal stock returns is priced by the CDS market for the two lower–rated obligors, but its impact on the CDS price is not large. The relatively low contribution of the abnormal stock returns to the total explained variance is similar to the results for corporate bond spreads of Collin-Dufresne and Goldstein (2001) for the US market and Boss and Scheicher (2002) for the European market that find only week explanatory power of individual stock returns.

The credit risk–free **interest rate** has a positive sign for all three banks. While its impact on the CDS price is lower than for the other factors (with a contribution to the total adjusted R^2 of 3–5%), it remains significant for Commerzbank and Deutsche Bank. The positive coefficient of the interest–rate in our sample differs from the result of Duffee (1998) and of Collin-Dufresne and Goldstein (2001). The authors find a negative relation of risk–free interest rates and credit spreads and argue that interest rates rise when the economy prospers and therefore the corporate default risk and credit spreads decline. However, these studies focus only on non–financial companies. Our results suggest rather that for financial institutions such as banks the impact of the interest rate can be fundamentally different. This could be explained by a dominating effect of an increase in term–transformation risk. Regarding the impact of the macroeconomic environment, we perceive DAX returns to be a better indicator than interest rates.

Our model estimated by the seemingly unrelated regression is able to explain between 27% (Deutsche Bank) and 40% (Commerzbank) of the total CDS premia variation measured by the adjusted R^2. This is more than for US corporate spreads in the study of Collin-Dufresne and Goldstein (2001) who are able to explain only about 25%, and slightly less than in Boss and Scheicher (2002) with 34–41%. Still a large part of the CDS premia variation remains unexplained by our model. It is possible that other variables omitted

of 1.56%·60bp≃0.94bp for Commerzbank, where 60bp is the average CDS premium (see Table 1, panel A). For HypoVereinsbank it is 1.3%·60bp≃0.78bp and for Deutsche Bank 1.02%·26bp≃0.27bp.

in our model have a substantial impact on the CDS premia. Another explanation could be that the remaining CDS premia variation is driven by an unobservable systematic factor that may be common to the banking sector or even common to the whole market. Such a factor may be responsible for driving the observed correlation of the estimated residuals. We investigate this hypothesis by looking at the correlation matrix of the residuals obtained from the SURE and perform a principal component analysis on the error terms.

The correlations of the residuals from the SUR estimation, together with the results of the Breusch and Pagan (1979) test of independence are displayed in Table 6, panel A. The residuals are highly positively correlated, with correlation coefficients of about 60%.

To explain the directions of the co–movement of the residuals, we perform a **principal component analysis (PCA)** (panel B). The PCA decomposition is equivalent to the eigensystem decomposition of the correlation matrix of the residuals, with the eigenvalues and associated eigenvectors ordered from the largest to the smallest eigenvalue. The first principal component explains about 75% of the total CDS premia variation that remains unexplained by the SURE. The weights of the first eigenvector are all positive and have approximately the same magnitude of 0.567–0.584. Therefore, the first principal component can be interpreted as corresponding to changes in the level of the CDS premia. An exogenous shock to the first principal component would result in an almost parallel shift in the CDS prices of all three banks. The first principal component can be attributed to the unobserved common systematic factor that may be interpreted as as banking–sector specific or market–specific. It is possible that this factor is related to the overall condition of the economy that may not be sufficiently captured by the DAX or because of market segmentation between the equity and the CDS market. It is however difficult to find an adequate proxy for this factor, since alternative indicators of economic activity like the GDP or indicators of the business optimism are provided only on a low–frequency basis that is not sufficient for our study. The impact of a common systematic risk factor has also been found by Collin-Dufresne and Goldstein (2001). They identify the first principal component being responsible for about 76% of the variation in the US credit spreads that remained unexplained by the OLS estimation. This result is very similar to ours. However, the authors propose a different interpretation of the underlying unobservable factor. They attribute the common factor to demand and supply shocks driving the corporate spreads. These demand and supply shocks are independent from the equity market, which may be caused by the segmentation of the bond and the equity market. However, the demand and supply shocks may originate in information coming from the banking sector, from the economy or from other sources representing common systematic risk. Therefore, the interpretation of Collin-Dufresne and Goldstein may not be fundamentally different from ours. The study of Boss and Scheicher (2002) for Euro credit spreads also documents high residual correlation of 67–81% indicating substantial impact of a common component, not captured by the explanatory variables.

We check the **stability of the SUR estimation results** by constructing a one–step ahead rolling window of 60 weekly observations. Within each window SUR estimation is performed. Figure 2 shows the evolution of the estimated coefficients in 81 steps. The estimated regression coefficients are reported, together with the corresponding t–statistics. The coefficient for the DAX remained highly significantly (at 1%) negative in all periods. The coefficients for the bid–ask spread decreased for Commerzbank and HypoVereinsbank, which indicates increasing liquidity. Abnormal stock returns also remained significant for Commerzbank and HypoVereinsbank throughout the analysed period. The interest rate had a positive coefficient sign and was most of the time significant at 10% for Commerzbank and Deutsche Bank.

These results overall confirm that the systematic market factor is the most important driver of changes in CDS premia throughout the tested period. The bid–ask spread as a liquidity measure was significant only for the two banks with arguably less liquid trading, while the coefficient estimates overall decreased which indicates a maturing market. Factors attributable to the idiosyncratic credit risk (abnormal stock return) remain significant for the lower–rated banks. The interest rate risk is significant only for some banks and not in all periods.

6 Comparison with Default Probabilities of the KMV Model

The results of the regression analysis have important implications for economic models of CDS spreads. The presence of factors unrelated to credit risk, together with the dependence on an economy–wide or a banking sector–specific risk factor, suggest that a model based on foremost idiosyncratic credit risk components, like the firm's leverage, may be insufficient to explain the CDS spreads that are observable in the market. Notwithstanding this problem, such models are frequently used in the industry. Information from these models is readily available for traders in the CDS market and may in this way affect CDS spreads. In order to measure the information content of CDS premia it is therefore promising to compare default probabilities from an equity model with those inferred from CDS spreads. In the following "PD" always refers to a default probability inferred from the reduced–form model in section 2. We compare these PDs with expected default frequencies (EDFs) from the vendor model of Moody's KMV which was selected because of its wide–spread use in the industry.

EDFs are expected to be lower on average than PDs because they have been calibrated to hold under the physical measure, whereas the PDs are determined under the risk–neutral measure. Furthermore, CDS premia may be affected by uncertainty in recovery rates, which does not influence EDFs. These two differences have to be considered when comparing PDs and EDFs. Our analysis, however, focusses not on levels but on the evolution of these two risk indicators.

The risk–neutral PDs are determined from the model defined by (1)–(5) under the assumption of an expected recovery rate of 50%. EDFs and PDs are computed for a time horizon of one year. Since the EDFs are only monthly available, both indicators are compared on a monthly basis. In order to smooth out noise, we determine PDs by monthly averages.

Figure 3 shows the estimated one–year PDs for the banks. Commerzbank and HypoVereinsbank have higher PDs than Deutsche Bank, especially from August 2002 to June 2003. In October 2002 the PD of Commerzbank approached 5% and the PD of HypoVereinsbank 3.4%, while the EDF of Deutsche Bank did not exceed 1.5%. After this more volatile period the PDs of all three banks moved in a range between zero and one percent. The risk–neutral PDs heavily exceed the EDFs, especially in the more volatile period from August 2002 to June 2003. An explanation for this would be that the CDS–implied PDs may more strongly be affected by liquidity constraints. In contrast to them, the KMV EDFs instead use only bank–specific credit risk state variables. Furthermore, the equity market may be more liquid so that even in stress periods liquidity risk has a lower impact on prices. This would explain why the CDS market reacts stronger than the equity market in stress periods since the earlier is more vulnerable to liquidity risk.

It is apparent from Figure 3 that periods of considerable co–movements between CDS–implied PDs and the KMV EDFs occur for Commerzbank and HypoVereinsbank.[24] We further investigate if there is a significant correlation between changes of PDs and EDFs sampled on a monthly basis.

Table 8 lists the correlation coefficients for changes in PD and EDF for the respective banks, $\rho(\Delta PD, \Delta EDF)$. For Commerzbank and HypoVereinsbank we obtain positive correlation of the monthly changes. The correlation is even higher for changes measured over two–month intervals with significant coefficients exceeding 40%. For Deutsche Bank we do not find a significant correlation. The missing significance of correlation for Deutsche Bank may be explained by its strong focus on investment–banking activities which implies a relatively high volume of off–balance sheet activities. As a consequence, the leverage of the firm which is a main driver of the EDF becomes less informative. In contrast, Commerzbank and HypoVereinsbank focus more on the (on–balance activity of)

[24]In the second quarter of 2004 the EDFs for HypoVereinsbank increased above their previous levels. This was caused by a change in the asset volatility, which is one of the two main drivers of the EDFs, together with the leverage. This increase of asset volatility is a spurious result, since was caused by an adjustment of earlier asset volatilities, which in turn should capture a change in the liability structure. However, this change was recognized 6 months after it had occurred and thus provided a spurious signal.

traditional lending business. This argument also suggests that the CDS market may be better suited as an indicator of default risk of Deutsche Bank than the KMV model which depends on the in this case less–informative leverage ratio.

The correlation between PDs and EDFs even increases after February 2003. Since then the EDFs evolve generally more in line with the PDs. An explanation for this can be that the CDS market has become more mature and liquidity has increased whereas before the CDS market lagged the equity market. Such a delayed information processing is typical for less liquid markets. This hypothesis is somewhat confirmed by smaller bid–ask spreads in the later time period after January 2003.[25]

In summary, the informational content of both the CDS–implied PDs and the EDFs from the Moody's KMV model provide useful information about the credit risk of financial institutions. An advantage of using PDs based on a reduced–form model can be that this type of model is unaffected by the limitation of a structural model in situations in which the informational value of the leverage ratio is questionable. However, default probabilities inferred from CDS prices may be more vulnerable to liquidity risk which may dilute their information content for credit risk. Due to their calculation under the risk–neutral measure, the PDs in this paper provide estimates of upper bounds for the "true" default probabilities of the analysed banks.

7 Summary and Conclusion

This paper identifies several risk factors that drive changes of the CDS premia of large German banks, based on a sample of the traded contracts for Commerzbank, Deutsche Bank and HypoVereinsbank. Our data sample covers three and a half years and includes 152 weekly observations. We estimate a seemingly unrelated regression that provides more efficient estimates than the OLS, since the SUR estimator accounts for the correlation in the OLS residuals. Depending on the individual bank, our model can explain 27–40% of the total variation of the CDS premia, which is in line with comparable results for US and European corporate–bond spreads.[26] The highest explanatory power has the market systematic risk factor proxied by the DAX, further a liquidity risk factor, measured by the bid–ask spread that is significant for two banks. The factor related to the idiosyncratic credit risk proxied by abnormal stock returns is significant for the lower–rated banks. The interest rate risk is positively related to the CDS premia and is significant for two banks. Overall we find that only 15–25% of the explained variation of CDS premia is caused by firm–specific risk factors whereas the rest is due to systematic factors.

[25]See Figure 1, panel E). Although the bid–ask spreads were also at a low level until September 2002, the trading was not frequent, which is indicated by stale prices.

[26]See, for example, Collin-Dufresne and Goldstein (2001) and Boss and Scheicher (2002).

In terms of this result our findings are similar to previous results for US bond spreads in Collin-Dufresne and Goldstein (2001). They are however different from the results in Boss and Scheicher (2002) for Euro bond spreads which can be explained mainly by interest rate related variables and liquidity proxies. Our finding that changes in the credit risk–free interest rates are positively related to the changes in CDS premia, contrasts with previous results, for example in Duffee (1998) for credit spreads of non–financial companies. The positive coefficient may be attributable to term–transformation risk that is specific for banking institutions.

We confirm the stability of the estimation results in shorter time intervals, in which the significant variables generally maintain their significance and the signs of the coefficients. The remaining part of the variation in CDS premia which is not explained by the SUR estimation can be attributed to an unobservable systematic risk factor that may be common to the banking sector or to the whole market. The principal component analysis of the regression residuals reveals that a shock originating from this common factor results in an approximately parallel shift in the CDS premia of the three banks.

Our results concerning the impact of systematic risk factors raise the question if common structural models that are foremost based on idiosyncratic credit–risk determinants like balance–sheet ratios should be extended to account also for systematic effects. They suggest that this question should be answered in the affirmative. An open question is still the nature of a common unobservable factor, that affects credit spreads of all 3 bonds, but is not captured by the DAX as a proxy of the state of the economy.

We compare the informational content of implied default probabilities (PDs) inferred from a parsimonious reduced–form model to the expected default frequencies (EDFs) of the Moody's KMV model. The PDs substantially exceed the EDFs which is explained by their calculation under the risk–neutral measure, whereas the EDFs are determined under the physical measure. The changes of the PDs are found to be positively correlated with the changes of the EDFs, on a monthly basis. This correlation even increased after January 2003, indicating that the CDS market has matured over the sample period and that the processing of new information has become more efficient.

The correlation between PDs and EDFs becomes, however, insignificant for the more investment–banking oriented Deutsche Bank. A potential reason is that the informational power of the leverage ratio which plays a central role in structural models is lower for banks with large off–balance sheet activities. Whereas this argument favors the use of PDs over EDFs the following argument suggests the opposite. The information content of CDS prices may be diluted by a greater vulnerability against changing market perceptions about liquidity risk. Indicative findings like, for example, decreasing average CDS bid–ask spreads suggest, however, that this argument becomes less important over time.

Therefore, we conclude that structural models based on equity prices as well as reduced–

form models based on prices of credit derivatives are most useful as credit–risk indicators if they are considered together. Both indicators have their specific advantages and drawbacks but together, they can provide a more comprehensive – and arguably more accurate – assessment of the riskiness of the monitored institution.

Further research is warranted on the dynamics of the CDS premia of financial institutions. The current literature has focused so far on the explanation of corporate credit spreads, without considering the specifics of financial institutions. Our finding of a positive relation between changes in interest rates and CDS spreads suggests that results for corporates may not necessarily hold for financial firms. Also, a comparison of implied default probabilities from a dynamic model may provide more efficient estimates of idiosyncratic default risk and possibly also estimates of the market price of risk. A straightforward extension of our static model would allow for a stochastic process of the hazard rate, for example as a mean–reverting jump–diffusion process. Since CDS contracts for maturities other than five years become more frequently traded, one may also consider to include CDS premia for additional maturities in the model estimation.

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Table 1: **Descriptive Statistics for CDS Premia**

Weekly observations sampled on trading Wednesdays. The sample period extends from 13 March 2002 to 16 February 2005, with 152 observations. The Q-statistic is the first-order Portmanteau test for white noise (Panels A–B), with reported P–values in parentheses below. The augmented Dickey-Fuller test statistic was computed for $k = 4$ lags. The double asterisk indicates rejection of the unit–root hypothesis at the 1% significance level.

Panel A. CDS Premia s_t (Basis Points)

	Commerzbank	Deutsche Bank	HypoVereinsbank
No.Obs.	141	141	141
Mean	60.50	26.20	59.29
St.Dev.	47.19	11.57	39.55
Min.	15.15	13.37	18.18
Max.	260	75.5	182
Median	33	20.8	36.2
Skewness	1.34	1.38	1
Kurtosis	4.33	4.63	2.77
Q-Stat.	129.04	131.49	130.85
$(P > \chi_2(1))$	(0.00)	(0.00)	(0.00)
ADF Stat.	-1.823	-1.568	-1.671

Panel B. Changes in Log CDS Premia $\Delta S_t = ln(s_t/s_{t-1})$

	Commerzbank	Deutsche Bank	HypoVereinsbank
No.Obs.	140	140	140
Mean	-0.0032	-0.0027	-0.0018
St.Dev.	0.12	0.07	0.12
Min.	-0.35	-0.26	-0.38
Max.	0.63	0.40	0.60
Median	-0.008	-0.007	-0.01
Skewness	1.88	1.04	1.4
Kurtosis	12.59	10.23	10.8
Q-Stat.	2.77	2.7	0.02
$(P > \chi_2(1))$	(0.14)	(0.13)	(0.89)
ADF Stat.	-10.171^{**}	-10.187^{**}	-11.929^{**}

Panel C. Correlation Matrix of Log CDS Premia Changes ($\Delta S_t = ln(s_t/s_{t-1})$)

	Commerzbank	Deutsche Bank	HypoVereinsbank
Commerzbank	1		
Deutsche Bank	0.7610	1	
HypoVereinsbank	0.7328	0.7161	1

Table 2: **Collinearity Diagnostics**

Scaled index conditions $\kappa_n(X^T X) = (\frac{\lambda_{max}}{\lambda_n})^{-\frac{1}{2}}$ and variance decomposition proportions for $X^T X$, where X is the matrix of the explanatory variables and λ_n are the eigenvalues of $X^T X$. The data sample extends from 13 March 2002 to 16 February 2005, with 152 weekly observations. The abnormal stock return for the i-th bank in excess to the DAX return and above the risk–free rate is computed from the market model as $R_t^{*i} = (R_t^i - R_t^f) - \hat{a}_t^i - \hat{b}_t^i(R_t^{\mathrm{DAX}} - R_t^f)$.

Commerzbank

Scaled Condition Indexes:					
n	1	2	3	4	5
κ_n	2.18	1.43	1.31	1.26	1.00
Variance–Decomposition Proportions:					
Δln(Bid-ask spread)	0.012	0.631	0.005	0.304	0.047
R^{*i}	0.012	0.631	0.005	0.304	0.047
R^{DAX}	0.797	0.045	0.003	0.009	0.154
$\Delta r^{10\mathrm{Yr}}$	0.805	0.027	0.00	0.01	0.153
Intercept	0.021	0.110	0.756	0.101	0.011

Deutsche Bank

Scaled Condition Indexes:					
κ_n	2.15	1.36	1.29	1.23	1.00
Variance–Decomposition Proportions:					
Δln(Bid-ask spread)	0.026	0.503	0.007	0.458	0.006
R^{*i}	0.034	0.292	0.386	0.281	0.007
R^{DAX}	0.798	0.019	0.000	0.013	0.169
$\Delta r^{10\mathrm{Yr}}$	0.814	0.010	0.000	0.004	0.172
Intercept	0.020	0.252	0.587	0.126	0.015

HypoVereinsbank

Scaled Condition Indexes:					
κ_n	2.23	1.37	1.30	1.27	1.00
Variance–Decomposition Proportions:					
Δ ln(Bid-ask spread)	0.112	0.484	0.002	0.363	0.038
R^{*i}	0.014	0.087	0.772	0.124	0.002
R^{DAX}	0.822	0.015	0.00	0.006	0.158
$\Delta r^{10\mathrm{Yr}}$	0.779	0.048	0.00	0.021	0.151
Intercept	0.016	0.382	0.215	0.375	0.012

Table 3: **Robust OLS Estimation Results For the Multifactor Model**

Separately fitted regressions for the i-th bank. The standard errors are estimated using the Huber–White correction that adjusts for a possible lack of normality and heteroscedasticity in the OLS regression residuals and for observations that exhibit large regression residuals, leverage or influence. The data sample extends from 13 March 2002 to 16 February 2005, with 152 weekly observations. The abnormal stock return in excess to the DAX return and above the risk–free rate is computed from the market model as $R_t^{*i} = (R_t^i - R_t^f) - \hat{a}_t^i - \hat{b}_t^i(R_t^{\mathrm{DAX}} - R_t^f)$. The estimated standard errors are reported in square parentheses and the P–values are in round parentheses. Bold numbers indicate significance at the 10% level. Tested relation:

$$\Delta\ln(\text{CDS prem.})_t^i = \alpha_1^i + \beta_1^i \Delta\ln(\text{bidask})_t^i, + \beta_2^i R_t^{*i} + \beta_3^i R_t^{\mathrm{DAX}} + \beta_4^i \Delta r_t^{10\mathrm{Yr}} + \varepsilon_t^i.$$

	Commerzbank	**Deutsche Bank**	**HypoVereinsbank**
$\hat{\beta}_1$	**0.047**	0.059	**0.189**
$\Delta\ln(\text{bidask})$	[0.068]	[0.047]	[0.070]
	(0.005)	(0.317)	(0.007)
$\hat{\beta}_2$	**-0.853**	**-0.557**	**-0.601**
Abn. Stock Ret. R^*	[0.189]	[0.303]	[0.165]
	(0.000)	(0.068)	(0.000)
$\hat{\beta}_3$	**-1.489**	**-0.995**	**-1.219**
R^{DAX}	[0.325]	[0.178]	[0.262]
	(0.000)	(0.000)	(0.000)
$\hat{\beta}_4$	**0.191**	**0.128**	0.071
$\Delta r^{10\mathrm{Yr}}$	[0.088]	[0.061]	[0.093]
	(0.033)	(0.037)	(0.446)
$\hat{\alpha}$	-0.002	-0.002	-0.001
Constant	[0.007]	[0.061]	[0.007]
	(0.765)	(0.716)	(0.886)
Adj. R^2	0.4247	0.2956	0.3539

Table 4: **Correlation Matrix of Regression Residuals from the OLS Regression**

Calculated for the estimated residuals from equation i in the separate OLS regression. A double asterisk indicates significance at the 1% significance level.

	Commerzbank	Deutsche Bank	HypoVereinsbank
Commerzbank	1		
Deutsche Bank	0.5853^{**}	1	
HypoVereinsbank	0.5388^{**}	0.5231^{**}	1
Breusch-Pagan test of independence: $\chi^2(3) = 122.430$, P-value=0.0000			

Table 5: **Estimation Results for the Seemingly Unrelated Regression (SUR)**

The data sample extends from 13 March 2002 to 16 February 2005, with 152 weekly observations for the i-th bank. The abnormal stock return in excess to the DAX return and above the risk–free rate is computed from the market model as $R_t^{*i} = (R_t^i - R_t^f) - \hat{a}_t^i - \hat{b}_t^i(R_t^{\text{DAX}} - R_t^f)$. The estimated standard errors are reported in square parentheses and the P–values are in round parentheses. Bold numbers indicate significance at the 10% level. The following relation is tested using an iterative procedure (convergence obtained in 7 steps):

$$\Delta\ln(\text{CDS prem.})_t^i = \alpha_1^i + \beta_1^i \Delta\ln(\text{bidask})_t^i, + \beta_2^i R_t^{*i} + \beta_3^i R_t^{\text{DAX}} + \beta_4^i \Delta r_t^{10\text{Yr}} + \varepsilon_t^i,$$

where ε^i are independently identically distributed with zero mean and a covariance matrix Σ.

	Commerzbank	**Deutsche Bank**	**HypoVereinsbank**
$\hat{\beta}_1$	**0.153**	**0.045**	**0.136**
$\Delta\ln(\text{bidask})$	[0.031]	[0.026]	[0.035]
	(0.000)	(0.083)	(0.000)
$\hat{\beta}_2$	**-0.412**	-0.166	**-0.247**
Abn. Stock Ret. R^*	[0.134]	[0.134]	[0.121]
	(0.002)	(0.216)	(0.041)
$\hat{\beta}_3$	**-1.561**	**-1.025**	**-1.317**
R^{DAX}	[0.221]	[0.149]	[0.236]
	(0.000)	(0.000)	(0.000)
$\hat{\beta}_4$	**0.225**	**0.151**	0.109
$\Delta r^{10\text{Yr}}$	[0.010]	[0.068]	[0.106]
	(0.024)	(0.027)	(0.304)
$\hat{\alpha}$	-0.002	-0.002	-0.001
Constant	[0.007]	[0.005]	[0.008]
	(0.785)	(0.739)	(0.901)
Adj. R^2	0.3956	0.2722	0.3264

Table 6: **Correlation Matrix of Regression Residuals from SUR and Principal Component Analysis (PCA) of the Residuals**

Performed on the estimated residuals from equation i in the seemingly unrelated regression. Double asterisk indicates significance at the 1% level.

Panel A. Correlation Matrix of Residuals from SURE

	Commerzbank	Deutsche Bank	HypoVereinsbank
Commerzbank	1		
Deutsche Bank	0.6501**	1	
HypoVereinsbank	0.6061**	0.5946**	1
Breusch-Pagan test of independence: $\chi^2(3) = 173.8$, P-value=0.0000			

Panel B. Principal Component Analysis of the Residuals

Index Prin. Component	Eigenvalue	Proportion	Cumulative
1	2.234	0.745	0.745
2	0.417	0.139	0.884
3	0.349	0.116	1.000
		Eigenvectors	
	1	2	3
Commerzbank	0.5843	-0.3284	-0.7421
Deutsche Bank	0.5808	-0.4694	0.6651
HypoVereinsbank	0.5668	0.8196	0.0835

Table 7: **Marginal Contributions of Explanatory Variables to the Percentage of Total Explained Variance**

This table shows the marginal contributions mc_{ik} of the k-th variable to the total adjusted R^2, denoted by $\bar{R}_i^2$ for the i-th equation, relative to the contribution of the other explanatory variables. It is defined for the i-th equation as $mc_{ik} = \frac{\bar{R}_i^2 - \bar{R}_{ik}^2}{\sum_{k=1}^{n}(\bar{R}_i^2 - \bar{R}_{ik}^2)}$, $mc_{ik} \geq 0$, where $\bar{R}_{ik}^2$ is computed for the i-th equation with the k-th explanatory variable excluded.

Panel A. Marginal Contributions to Adj. R^2 in the Separately Fitted Regression (OLS)

mc_{ik}	**Commerzbank**	**Deutsche Bank**	**HypoVereinsbank**
Δln(bidask)	0.2244	0.0114	0.2662
Abn. Stock Return R^*	0.2395	0.1493	0.2166
R^{DAX}	0.5074	0.7953	0.5171
$\Delta r^{10\text{Yr}}$	0.0287	0.044	0.00

Panel B. Marginal Contributions to Adj. R^2 in the Seemingly Unrelated Regression

	Commerzbank	**Deutsche Bank**	**HypoVereinsbank**
Δln(bidask)	0.2199	0.0109	0.28
Abn. Stock Return R^*	0.1748	0.0667	0.1711
R^{DAX}	0.5727	0.8732	0.5489
$\Delta r^{10\text{Yr}}$	0.0326	0.0492	0.00

Table 8: **Correlation of Changes in CDS–Implied PDs and KMV EDFs**

The table presents Person correlation coefficients for monthly changes of PD and the EDF values, sampled on the last day end of month for respective banks. The sample extends from September 2001 to January 2005. Panel A presents Pearson correlation coefficients for changes over one month, whereas Panel – for changes over two months. The corresponding P–values are given in parentheses, where $P >\mid r \mid$ is under $\mathrm{H}_0 : \rho = 0$. N is the number of observations.

Panel A. Pearson coefficients for the monthly changes			
	Commerzbank	Deutsche Bank	HypoVereinsbank
whole sample period	0.4937	0.0665	0.4899
$N = 38$	(0.0014)	(0.6914)	(0.0011)
post January 2003	0.6923	0.3140	0.5697
$N = 26$	(< 0.0001)	(0.1547)	(0.0024)
Panel B. Pearson coefficients for two–month changes			
	Commerzbank	Deutsche Bank	HypoVereinsbank
whole sample period	0.5585	0.0785	0.5003
$N = 37$	(0.0003)	(0.6443)	(0.0010)
post January 2003	0.5879	0.3425	0.5003
$N = 22$	(0.0016)	(0.1187)	(0.0039)

Figure 1: **Comparison of CDS Premia with the Risk Factors**

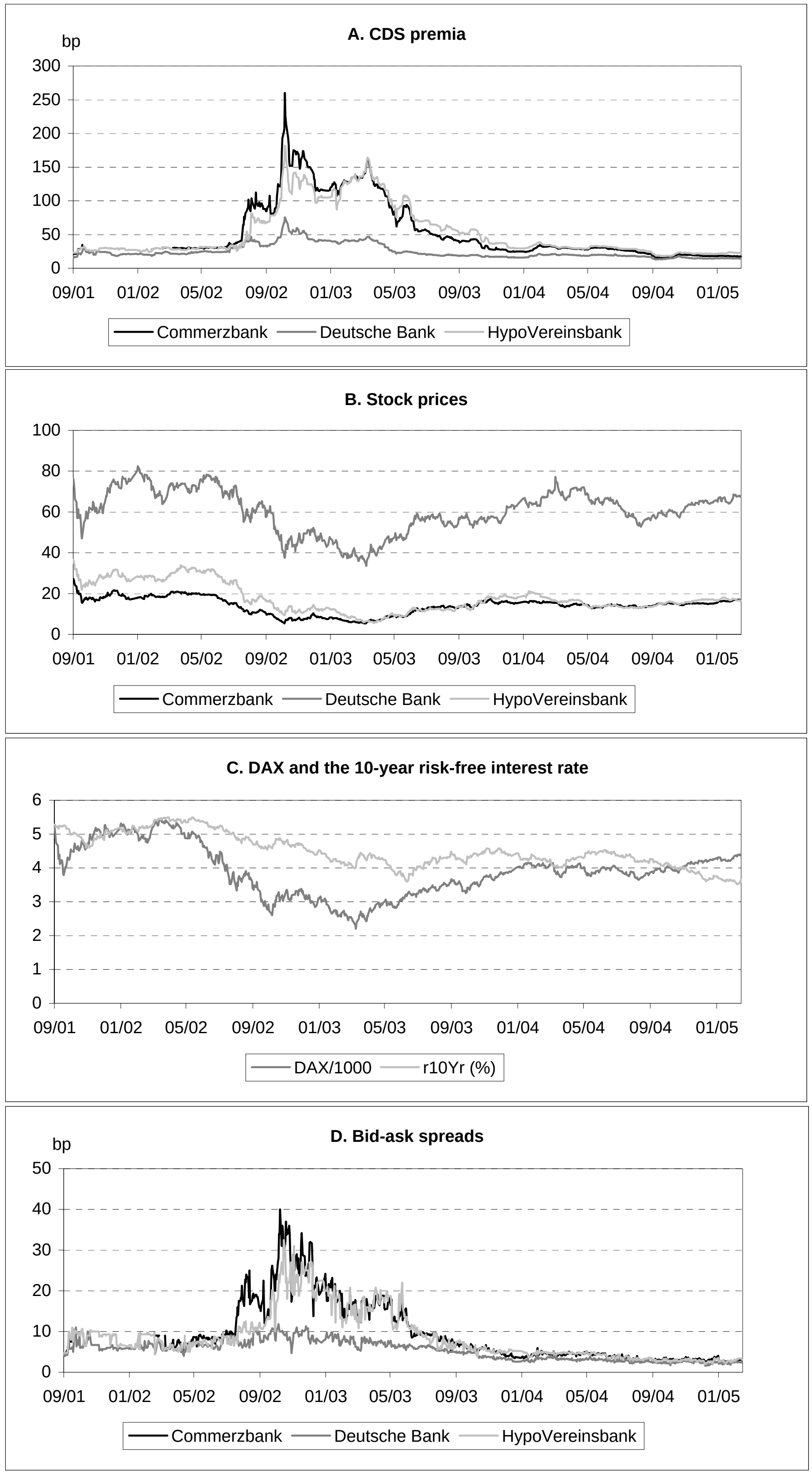

Figure 2: **Stability Check. One-step Ahead Estimation Results for SUR**

The estimation window consists of 60 observations and is moved one step ahead to obtain 81 regression estimates. Displayed are plots of the estimated coefficients $\hat{\beta}$ and the respective sample t-statistics, together with the critical t–values at the 10% significance level.

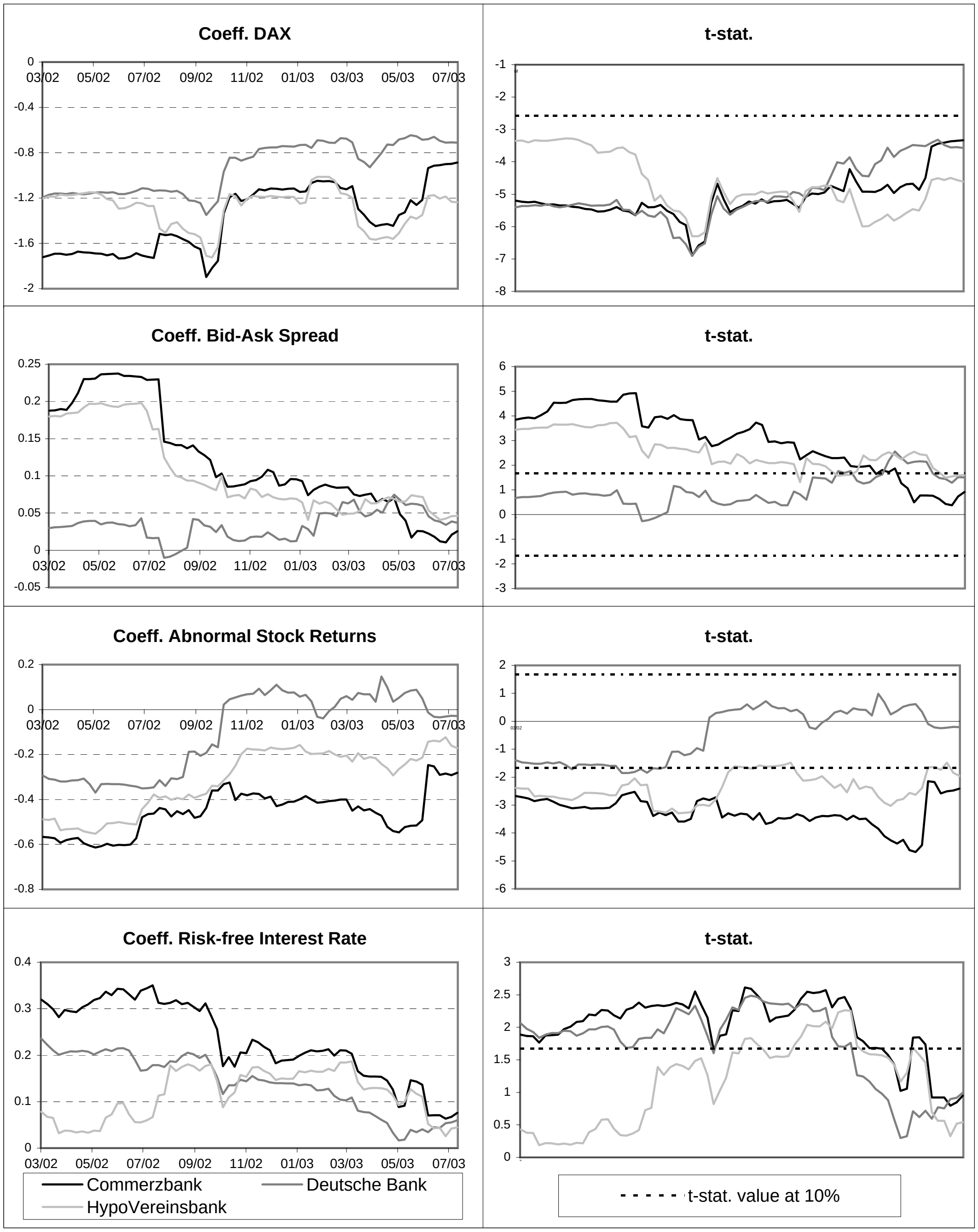

Figure 3: **Comparison of the Estimated Default Probabilities (PDs) with KMV Expected Default Frequencies (EDFs)**