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Seminar paper

Price Discovery and Dynamic Relation between CDS Markets and Bond Markets

based on

Blanco, Brennan, Marsh (2005):
An Empirical Analysis of the Dynamic Relation
between Investment-Grade Bonds and Credit Default Swaps

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1 Introduction: Motivating the use of the Hasbrouck (1995) methodology for bond spreads and credit default swaps (CDS)

Why is understanding the procedures of price discovery and arbitrage links in financial markets so important?

Price discovery describes the incorporation of new information into the price. Thus, it is of high interest to traders where new information enters the price in order to optimize their trading strategies. Besides, arbitrage relations can be used to increase yields.

In 1995 Hasbrouck outlined the predominance of the NYSE in the price discovery mechanism of stocks. In his article "One Security, Many Markets: Determining the Contributions to Price Discovery" he defined information shares associated with the contribution to price discovery of the different stock markets. These information shares are defined as the proportional contribution of a particular market's innovations to the innovations in the common efficient price. The Hasbrouck methodology is not limited to stocks, nor is it just applicable to identical securities traded on different markets. It can be used for all securities that share a common factor and are linked by arbitrage relations. Accordingly, the price relationship between spot and derivative rates, bonds and corresponding futures are analyzed using Hasbrouck's methodology.

Therefore, Blanco et al. published a paper on "An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps" (2005). They test the theoretical equivalence of credit default swap prices and credit spreads implementing the Hasbrouck methodology. Triggered by their research Doetz repeats and amplifies the analysis for a European data set. Thus, the methodology that was initially used for determining price discovery on the stock market is now applied to the markets of credit default swaps (CDS) and bonds. In the credit market the driving question is whether there are useful signals about potential risk at an early stage. Therefore, it is of interest to figure out whether CDS premia or bond spreads are better signals and how the arbitrage relation between these two indicators is empirically. I analyze the empirical relation of five bond spreads and the corresponding CDSs in the following. I seek to test the empirical validity of the theoretical arbitrage relation equating CDS prices to credit spreads.

The subsequent seminar paper is structured as follows. I will define and explain what credit default swaps and credit spreads are in section two. In a third section I will explain the theoretical model and the Hasbrouck weights that are used to attribute price discovery effects to the two different credit risk instruments. Fourth, the treated data is presented. Then, in a fifth part the analysis is conducted and I finally conclude in section six with a brief summary and concluding comments.

2 Definition of bond spreads and CDS

What does a credit default swap, abbreviated CDS stand for? A CDS is an easy way to trade credit risk as it transfers the credit exposure between parties. It is the most widely used credit derivative and provides protection against the risk of a credit event. Often it is compared with insurances as it is a hedge for the holder of debt. The protection buyer pays a periodic fee in return for a contingent payment by the seller upon a credit default happening in the reference entity. If a credit event does not occur until the maturity date, the protection seller just receives the payments. In the case of credit default there are two types of settlement:

- Physical settlement: repayment at par against physical delivery of a reference asset,
- Cash settlement: notional amount minus the post-default market value of the reference asset.

Most CDS contracts are physically settled, where upon a credit event the protection seller must pay the par amount of the contract against the protection buyer's obligation to deliver the bond against which protection is being sold.
The typical term of a CDS contract is five years, although almost any maturity is possible. CDS contracts also specify the credit events that entail payment obligations by the protection seller:

- Bankruptcy,
- Failure to pay with respect to the bond/loan debt,
- 'Restructuring', which is a source of controversy in the CDS market.

With a CDS one can make profit without having invested anything as it is possible to sell the other investor credit protection and receive the premium as long as the company does not default. Furthermore, it is also possible to buy and sell CDSs that are outstanding.

Like the bonds themselves, the cost to purchase the swap from another party fluctuate as the perceived credit quality of the underlying company changes.

There are two competing theories for the pricing of credit default swaps.

1. 'Probability model'
2. 'No-arbitrage model'

The 'probability model' takes the present value of a series of cashflows weighted by their probability of non-default. This method suggests that CDSs should trade at a considerably lower spread than bonds. The second model, proposed by Duffie, uses a no-arbitrage approach for pricing CDSs. It is assumed that there is no risk free arbitrage. Duffie uses the LIBOR as the risk free rate. In other applications US Treasuries are taken as the risk free rate. The Duffie approach is frequently used by the market to determine theoretical prices. For the subsequent analysis I will stick to the 'no-arbitrage model' proposed by Duffie.

Having defined CDS with Duffie's 'no-arbitrage' model indirectly also explains what bond/ credit spreads are. Bond spreads describe the difference between the yield of a corporate bond and a risk free security of similar time to maturity. As mentioned above in practice US Treasuries are often taken as the risk free rate. But as government bonds can be distorted due to repurchase agreements swap rates are better benchmarks for the risk free rate and used in this analysis. Besides, swap rates display the costs of financing of many market participants.

Finally, the theoretical relation between a CDS price and the corresponding bond spread can be written as: $p_{CDS,t} = p_{CD,t}$, where $p_{CDS,t}$ denotes the CDS premia and $p_{CD,t}$ the bond spread at t. This holds just if CDS and bond spreads price risk equally. If not there is room for arbitrage.

Here I will leave the theory on CDS and bond spreads and go over to the structural model and the econometric approach advocated by Hasbrouck.

3 The model: From a microstructure model to VECM (compare Hasbrouck (1995))

3.1 A simple microstructure model

In his econometric approach Hasbrouck started off with an easily accessible microstructure model and transformed it into a vector-error-correction-model (VECM) that can be estimated.

The simple microstructure model Hasbrouck introduces has the following form:

$$p_{1,t} = p_{1,t-1} + \omega_t$$
$$p_{2,t} = p_{1,t-2} + \varepsilon_t$$

The price variables are indicated with p, the ω_t and the ε_t are zero-mean i.i.d. and uncorrelated disturbances. In the first market the price follows a random walk. The second market incorporates the price from the first market two periods lagged. Both series are integrated and thus nonstationary. But the difference between the prices is stationary. The prices do not move very far from each other. They are cointegrated. This microstructure model can be written in many other valid representations:

- vector moving average form (VMA),
- common trends representation,
- error correction model (ECM).

The error correction model looks as follows:

$$\Delta p_{1,t} = \omega_t$$
$$\Delta p_{2,t} = (p_{1,t-1} - p_{2,t-1}) - \Delta p_{1,t-1} + \varepsilon_t$$

The ECM can be estimated. There are infinitely many ECM's that can be used for estimation. The ECM can only be set up under the assumption that the prices in the two markets are driven by an underlying common efficient price. That unobservable efficient price follows a random walk.

3.2 Formal summary of cointegration

Next, in a more formal statement the cointegrated microstructure model is outlined: There are n price variables that are closely related due to a common factor. That unobservable, common factor m_t follows a random walk: $m_t = m_{t-1} + u_t$, where u_t is i.i.d. distributed with zero mean and constant variance. The observed price series are integrated of order one. Furthermore, the price changes are covariance stationary. Therefore the price changes can be written in vector moving average representation (VMA):

$$\boldsymbol{\Delta}\mathbf{p}_t = \boldsymbol{\Psi}(\mathbf{L})\mathbf{m}_t,$$

where $\mathbf{m}_t$ is a zero mean vector with uncorrelated disturbances. The corresponding covariance matrix i $\boldsymbol{\Omega}$. $\boldsymbol{\Psi}$ is a polynomial in the lag operator.

The difference between any two prices is stationary although each price is nonstationary. The difference stationarity implies that the price series are cointegrated of order $n-1$. Constructing a $\boldsymbol{\beta}'_{(n-1)\times n} = [\boldsymbol{\iota}_{(n-1)} - \mathbf{I}_{(n-1)}]$ yields $n-1$ variables given by $\boldsymbol{\beta}'\mathbf{p}_t$ that are stationary, where $\boldsymbol{\iota}_{(n-1)}$ is a column unit vector and $\mathbf{I}_{(n-1)}$ is the identity matrix. Stationarity of $\boldsymbol{\beta}'\mathbf{p}_t$ requires that $\boldsymbol{\beta}'\boldsymbol{\Psi}(\mathbf{1}) = 0$ and $\boldsymbol{\Psi}(\mathbf{1})$ is the sum of the VMA coefficients. Furthermore, given the structure of $\boldsymbol{\beta}$ the rows of $\boldsymbol{\Psi}(\mathbf{1})$ are all identical and can be written as $\boldsymbol{\psi}$. The long run impact of a disturbance on the price is $\boldsymbol{\Psi}(\mathbf{1})\mathbf{m}_t$ and the same for all prices. Using these specifications the VMA representation can be transferred to a common trends model:

$$\mathbf{p}_t = \mathbf{p}_0 + \boldsymbol{\psi}\left(\sum_{s=1}^{t}\mathbf{m}_s\right)\boldsymbol{\iota} + \boldsymbol{\Psi}^*(\mathbf{L})\mathbf{m}_t,$$

with $\mathbf{p}_0$ as a vector of initial values. The product $\boldsymbol{\psi}\left(\sum_{s=1}^{t}\mathbf{m}_s\right)\boldsymbol{\iota}$ includes the random walk that is common to all prices. $\boldsymbol{\Psi}^*(\mathbf{L})$ is a matrix polynomial in the lag operator, multiplied by $\mathbf{m}_t$ it is a zero mean covariance stationary process. Under the assumption that there is a nonstationary vector autoregressive representation (VAR) for the price levels the vector error correction model (VECM) can be deduced by the Granger Representation theorem. The VAR representation of the price levels looks as follows:

$$\mathbf{A}(\mathbf{L})\mathbf{p}_t = \boldsymbol{\kappa} + \mathbf{m}_t,$$

with $\mathbf{A}(\mathbf{L}) = \mathbf{I} - \mathbf{A}_1\mathbf{L} - \ldots - \mathbf{A}_K\mathbf{L}_K$. The order of the VAR is K.

With $-\mathbf{A}(\mathbf{1}) = \boldsymbol{\alpha}\boldsymbol{\beta}'$ and $-\sum_{i=j+1}^{K}\mathbf{A}_i = \boldsymbol{\Gamma}_j$ for $j = 1, 2, \ldots, K-1$ the VAR can be written as VECM:

$$\boldsymbol{\Delta}\mathbf{p}_t = \boldsymbol{\alpha}(\boldsymbol{\beta}'\mathbf{p}_{t-1} - E(\boldsymbol{\beta}'\mathbf{p}_t)) + \boldsymbol{\Gamma}_1\boldsymbol{\Delta}\mathbf{p}_{t-1} + \boldsymbol{\Gamma}_2\boldsymbol{\Delta}\mathbf{p}_{t-2} + \ldots + \boldsymbol{\Gamma}_{K-1}\boldsymbol{\Delta}\mathbf{p}_{t-K+1} + \mathbf{m}_t$$

This VECM is just one particular specification but as already stated above in 3.1 there are many other possible representations. Here $\boldsymbol{\beta}$ is constructed in such a way that the cointegrating vector builds up the price discrepancies relative to the first price $p_{1,t}$.
There could have been any other benchmark price. But each choice for cointegrating vectors is only possible by imposing some normalization.

3.3 Deriving the information shares

After having specified the general setting the information share of a market is derived. The random walk term $\mathbf{m}_t$ is common to all prices. The component of the price change that enters the price durable is the increment $\boldsymbol{\psi}\mathbf{m}_t$. It is assumed that the price change is due to new information. The variance of $\boldsymbol{\psi}\mathbf{m}_t$ is $\boldsymbol{\psi}\boldsymbol{\Omega}\boldsymbol{\psi}'$. If market innovations are uncorrelated, the variance-covariance matrix $\boldsymbol{\Omega}$ is diagonal. Assume there are n different markets, then $m_{j,t}$ is the innovation in the jth market. Thus, $\boldsymbol{\psi}\boldsymbol{\Omega}\boldsymbol{\psi}'$ consists of n terms, each of which represents the contribution to innovation from one specific market. Market j's information share can thus be defined as the proportion of market j's contribution to the random walk innovation relative to the total variance:

$$S_j = \frac{\boldsymbol{\psi}_j^2 \boldsymbol{\Omega}_{jj}}{\boldsymbol{\psi}\boldsymbol{\Omega}\boldsymbol{\psi}'}$$

This definition of market j's information share holds only if price innovations are uncorrelated across markets and the variance-covariance matrix $\boldsymbol{\Omega}$ is diagonal. In most practical applications, however, correlation plays a role. As part of the contemporaneous correlation is due to time aggregation, correlation is minimized by shortening the interval of observation. But note, that shortening the observation interval only lessens contemporaneous correlation. The remedy to the problem is triangularization of the variance-covariance matrix $\boldsymbol{\Omega}$. Triangularization yields upper and lower bounds for the information shares and is done as follows:
The factor structure $\mathbf{m}_t = \mathbf{F}\mathbf{z}_t$ gives the innovations in the n market prices. The vector $\mathbf{z}_t$ is a $(n \times 1)-$vector of random variables with mean zero and $Var(\mathbf{z}_t) = \mathbf{I}$. $\mathbf{F}$ is the Cholesky factorization of $\boldsymbol{\Omega}$. This factorization allows us to interpret $z_{i,t}$ as the normalized component of $m_{i,t}$ that is orthogonal to the innovations that precede it in the ordering. Thus, the information share of the innovation variance attributable to z_j is:

$$S_j = \frac{\left([\boldsymbol{\psi}\mathbf{F}]_j\right)^2}{\boldsymbol{\psi}\boldsymbol{\Omega}\boldsymbol{\psi}'},$$

where $[\boldsymbol{\psi}\mathbf{F}]_j$ denotes the jth element of the row matrix $\boldsymbol{\psi}\mathbf{F}$. By factorization a hierarchy is imposed. The hierarchy is such that the information share on the last price is minimized and that on the first price is maximized. Thus, an upper and a lower bound for the information share of market j can be computed. For the upper bound $\boldsymbol{\psi}$ and $\boldsymbol{\Omega}$ are permuted to place that market's price first. For the lower bound that markets price is placed last. An intuitive explanation of the information share states that it determines the market that is the first mover in the process of price adjustment.
But note that information shares can only be computed for cointegrated data. Therefore, some technique is needed to determine the leader in the process of price discovery for those series that lack cointegration.

3.4 Granger causality test

Granger causality is a technique for determining whether one time series is useful in forecasting another. Here it is of use for those series that are not cointegrated.
A time series X is said to Granger-cause Y if it can be shown, that the X values provide statistically significant information about future values of Y. Usually the testing is done by a series of F-tests on lagged values of X with lagged values of Y also known. The test works by first doing a regression of ΔY on lagged values of ΔY. Once the appropriate lag interval for Y is proven significant, subsequent regressions for lagged levels of ΔX are performed and added to the regression. But they are only added provided that they are significant and add explanatory power to the model. Therefore in this context the VECM is written and estimated as VAR and the coefficients are tested for Granger causality.
Although Granger causality can be found it does not imply true causality. If both X and Y are driven by a common third process it is also positively tested for Granger causality.

4 Data and descriptive statistics

For the current analysis a sub-sample of the data set used by Doetz is treated. I take five out of the 125 enterprises noted in the iTraxx-Europe. The iTraxx is a CDS index composed of the two most important suppliers of CDS indices Trac-x and Dow Jones iBoxx. According to market observers the liquidity of CDS contracts mapped in the iTraxx index is fairly high. Exactly that high liquidity in the market increases the explanatory power of the CDS quotes used here.

The current data set ranges from January 1, 2003 till October 31, 2006. As most CDS contracts usually expire after five years prices from five year CDSs were taken. The bonds were chosen as follows:

- Only Euro bonds quoted in the stock exchange were taken.
- The coupon of these bonds has to be risk free,
- the maturity finite.
- Synthesized five-year bonds were computed by the means of linear interpolation. Therefore, two bonds where chosen with one bond that has a time to maturity below five years and the other one above five years.

From the so derived synthesized bonds the spread was determined. Swap rates were selected as the fixed interest rate.

For more general information on CDS and the construction of the bond spread see section 2. In table 1 some basic descriptive information on the bonds, the corresponding firms, the country they are settled, the sector, and the number of observations in the CDS and credit spread series are given. Furthermore, mean and standard deviation of bond spread and CDS are presented. The table attaches to the five bond symbols (DAI, DET, ENB, FRAT, VW) the relevant firms.

As can be seen, I use five European bonds, where four companies are settled in Germany. Almost all series have the full rank of observations with only two exceptions but the missing values do not matter for the analysis. Missing values are only at the beginning of the sample. As the sample period is almost four years and I have just 1000 observations at hand it is clear that the data is not high frequency data. Besides, over some periods the prices are not updated, instead it is just continued with one value.

All CDS means are substantially bigger than the equivalent bond spread means. The same holds for the median and the minimum value of the series (see appendix/section 8).

Besides, it is obvious from the large standard deviations relative to the means that bond spreads and CDSs are rather volatile. The fact that the mayor characteristics from descriptive statistics (mean, median, minimum) allocate a higher value to the CDS indicates

Symbol	Company Name	Country	Sector	# of observ. CDS	# of observ. bond spread	mean bond spreads/standard deviation in ()	mean CDS/ standard deviation in ()
DAI	DaimlerChrysler	Germany	Automobile	1000	1000	62.3884 (20.5107)	**85.7250** (27.0518)
DET	Deutsche Telekom	Germany	Telecommunications	1000	1000	54.6584 (42.1956)	**62.5003** (45.1834)
ENB	Energie Baden Württemberg	Germany	Electric Utility	1000	1000	27.7615 (14.6323)	**32.0132** (14.5795)
FRAT	France Télécom	France	Telecommunications	1000	989	48.9519 (38.17767)	**65.8608** (51.9451)
VW	Volkswagen	Germany	Automobile	1000	954	41.0321 (16.2085)	**53.4755** (15.4112)

Table 1: Descriptive statistics

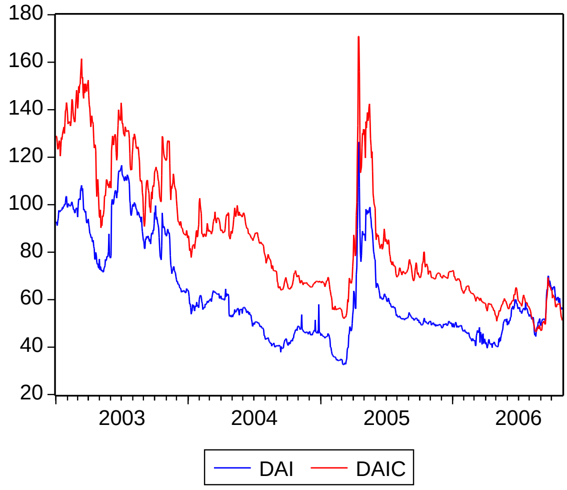


Figure 1: Time series of DaimlerChrysler's bond spread and CDS

that the CDS premia is bigger than the bond spread over large parts of the series. To show that I present a figure that displays a time series over the sampling period. In the figure DAI stands for the bond spread and DAIC refers to the CDS of the DaimlerChrysler bond. From figure 1 it is obvious that the bond spread and the CDS of an identical bond move parallel but over long periods the CDS series is above the bond spread series. The figures of the bonds left can be found in the appendix (section 8). The DET, FRAT and VW series have a similar pattern, even though the distance is narrower in the case of DET and FRAT and there are more crossings. The ENB figure differs the most but the general picture of co-movement is kept.

It is quite straightforward now to analyze whether the series exhibit cointegration and in which market price discovery takes place. That analysis is done in the following section.

5 Results and interpretation

In this section the analysis is undertaken. The data described in section 4 is exploited. For the analysis I use the software package EVIEWS.

5.1 Tests for integration and cointegration

In order to perform time series analysis according to the theory explained in section 3 I have to test my data series for integration first. Blanco et al. and Doetz make use of the KPSS test for stationarity. The KPSS test differs from other unit root tests in that the series is assumed to be stationary under the null. I test the series first under the assumption that it has an intercept and second under the assumption that it has an intercept and a trend. In the first case the null of stationarity can be rejected for all series at the 1 percent significance level. Under the second setting the null can not be rejected for one series (for detailed results see section 8.3).

As the KPSS test is criticized of having low power and as some authors argue that it has to be complemented by an ADF test, I implement the ADF test as main testing instrument. The null is: 'bond spreads and CDSs are $I(0)$'. Three cases are looked at: First there are no additional assumptions imposed on the series, second I allow for an intercept, and third a trend is added to the intercept. I conduct the ADF test in that manner that EVIEWS chooses the optimal lag-length automatically and then tests for unit root. As I aim for non-rejection the results from the ADF test are not very strong either. Furthermore, there is one troubling point, namely that the unit root is rejected under all settings for the FRAT series. The ADF test with intercept and trend yields the most appealing results although it is questionable from a theoretical perspective whether the data has a trend. But even the ADF test with intercept and trend does not reject the null for all but the FRAT series.

	'simple' ADF-test H_0 : unit root		ADF-test with intercept H_0 : unit root		ADF-test with intercept and trend H_0 : unit root	
	bond spread	CDS	bond spread	CDS	bond spread	CDS
DAI	***	***	***	***	***	*
DET	-	-	-	*	***	***
ENB	***	**	***	***	**	**
FRAT	-	-	-	-	-	-
VW	***	***	***	***	***	***

Table 2: Results from the ADF test for non-rejection of H_0: */**/*** indicate significance at a 1/5/10 percent significance level, - indicates a result where H_0 could not be kept

Although I could not keep H_0 for the FRAT series I will assume those to be non-stationary as the KPSS test rejcets stationarity for the FRAT data as well.

Thus, in the next step all the equivalent series can be tested for cointegration as cointegration tests the correlation between non-stationary time series variables. The series are said to be cointegrated if two or more series are themselves non-stationary, but a linear combination of them is stationary. I test the series of the bond spread and the CDS prices for cointegration using the Johansen test. The results can be seen in table 3. Again I use first the test with no imposed assumptions, second I allow for an intercept, and third the test with intercept and trend is conducted.

	Johansen's cointegration test		
	no assumptions	with intercept	with intercept and trend
DAI	not unambiguously allocable	at most one ***	not unambiguously allocable
DET	None *	None *	None *
ENB	None *	None *	None **
FRAT	None *	None *	None *
VW	not unambiguously allocable	None **	None *

Table 3: Results from the cointegration test: */**/*** indicate rejection at a significance level of 1/5/10 percent.

The fact that the hypothesis of no cointegration can be rejected for 4 series - using the test with intercept and the one allowing for intercept and trend - suggests that the CDS market and the bond market price credit risk equally in the long run. The intercept that is included should not bother us too much as it is probably due to mismeasurement of the risk free rate.

Having detected the cointegration relationship I found empirical evidence for one of my core questions, namely that there is an underlying common price to CDSs and bond spreads. Thus, in the long run risk is priced equally in both markets except for some disturbances.

5.2 The VECM specification

As the conducted tests suggest that in four out of the five series the both markets price risk equally in the long run, I concentrate on the dynamic behavior of the CDS prices and the credit spreads now. Therefore, I use the econometric technique of a VECM to figure out which market provides more information for price discovery.

In order to choose the best VECM specification I compare the AIC and the SIC criterion. I check VECM's for up to 20 lags. Often the smallest AIC and the smallest SIC differ greatly in position. I select the optimal lag length for the analysis by picking the specification with one of the lowest values of the AIC. Doetz who works on the same sample allows for eight lags maximally. He just considers the Akaike criterion. As I could not find significant cointegration results for a lag length up to eight for the DET series, I combine the AIC with the SIC criterion. Moreover, I also consider the SIC as it prefers thinner models compared to the AIC. Besides, I do not just want to fix a lag length exogenously without any reason from the estimating point of view or any theoretical reason. Further explanation

on my choice can be found in the appendix (see section 8.4). Note, that for the Johansen cointegration test, done in section 5.1, I have already implemented the lags corresponding to the smallest AIC/SIC resulting from the different VECM's I estimated.
Hence, for all series the best VECM according to the AIC/SIC criterion is estimated. Here in my specific case the VECM I estimate looks as follows:

$$\Delta p_{CDS,t} = \psi_1 \left(p_{CDS,t-1} - \alpha_0 - \alpha_1 p_{CS,t-1}\right) + \sum_{j=1}^{p} \delta_{1j} \Delta p_{CDS,t-j} + \sum_{j=1}^{p} \gamma_{1j} \Delta p_{CS,t-j} + \varepsilon_{1t}$$

$$\Delta p_{CS,t} = \psi_2 \left(p_{CDS,t-1} - \alpha_0 - \alpha_1 p_{CS,t-1}\right) + \sum_{j=1}^{p} \delta_{2j} \Delta p_{CDS,t-j} + \sum_{j=1}^{p} \gamma_{2j} \Delta p_{CS,t-j} + \varepsilon_{2t},$$

where $\Delta p_{.,t}$ stands for the price lags, the subscript CDS denotes the credit default swap and the subscript CS denotes the bond spread. From the estimation of the VECM I get the ψ-coefficients and the variance-covariance matrix of the residuals. Here the results for a VECM with intercept is presented but I also estimated a VECM with intercept and trend and another without any intercept or trend (see appendix/section 8.5). The ψ-coefficients and the variance-covariance matrices are presented in table 4. If the bond market contributes significantly to the discovery of the price of credit risk, then ψ_1 will be negative and statistically significant as the CDS market adjusts to incorporate this information. Thus, negative ψ_1-coefficients point out price leadership of the bond market. If the CDS market is an important place for price discovery, than ψ_2 will be positive and statistically significant. Both markets contribute to price discovery if both coefficients are significant. The ψ-coefficients cautiously point to a dominance of the bond market in the process of price discovery.
But looking only at the ψ-coefficients is a weak measure for price discovery. Therefore, the Hasbrouck information shares are constructed (theory: see section 3.3). The Hasbrouck measures as they are constructed here represent the contribution of the CDS market to price discovery.
As I just analyze the cointegration relationship between two series I do not need a Cholesky decomposition of the variance-covariance matrix. The ψ-coefficients together with the variance-covariance matrix of the error term are selected to construct the information shares for the CDS market. They look as follows:

$$HAS_1 = \frac{\psi_2^2\left(\sigma_1^2 - \frac{\sigma_{12}^2}{\sigma_2^2}\right)}{\psi_2^2\,\sigma_1^2 - 2\psi_1\psi_2\sigma_{12} + \psi_1^2\sigma_2^2}$$

$$HAS_2 = \frac{\left(\psi_2\sigma_1 - \psi_1\frac{\sigma_{12}}{\sigma_1}\right)^2}{\psi_2^2\,\sigma_1^2 - 2\psi_1\psi_2\sigma_{12} + \psi_1^2\sigma_2^2}$$

As theoretically motivated the information share consists of an upper and a lower bound. Some authors argue that the mean of the upper and lower bound is a valid measure for the average information share of a market. Therefore, I also compute the mean, labeled MID.f The results for the Hasbrouck measures are also collected in table 4. According to these measures from almost no price discovery up to 97 percent price discovery takes place at the CDS market.

As it is obvious from the computation, the upper and lower bound of the Hasbrouck measure deliver only useful results if they are not too far apart from each other. Most of my bounds however have a huge spread except for the ENB bond. But they state at least that the CDS market contributes to price discovery even though the amount is vague. Comparing the results from a VECM with intercept with those of other reasonable VECM specifications shows that the estimates can differ tremendously when only small changes in the analysis are made (see appendix/section 8.5).

5.3 Granger causality test for DAI

As the DAI bond is not cointegrated it is actually not correct to define where price discovery takes place using the VECM coefficients. But instead a VAR model is estimated to look for Granger causality between the bond spreads and the CDSs of the DAI bond:

$$\Delta p_{CDS,t} = c_1 + \sum_{i=1}^{p} \delta_{1i}\Delta p_{CDS,t-i} + \sum_{i=1}^{p} \gamma_{1i}\Delta p_{CS,t-i} + \nu_{1t}$$

$$\Delta p_{CS,t} = c_2 + \sum_{i=1}^{p} \delta_{2i}\Delta p_{CDS,t-i} + \sum_{i=1}^{p} \gamma_{2i}\Delta p_{CS,t-i} + \nu_{2t}$$

Next I test the $\gamma_{1.}$ and $\delta_{2.}$ coefficients for Granger causality using an F-test. The result from the Granger causality test rejects the hypothesis that DAI does not Granger cause DAIC at a 1 percent significance level. Thus it can not be ruled out that past values of the bond spread influence up-to-date CDS premia. The opposite hypothesis that DAIC does not Granger cause DAI is also rejected at a 1 percent significance level. Hence, the Granger

VECM coefficients		Variance-covariance matrix			Hasbrouck measures		
ψ_1	ψ_2				lower bound	upper bound	MID
			DAIC	DAI			
-0.00610	0.00012	DAIC	7.55403	4.09585	0.00033	0.48840	0.24437
(0.00322)	(0.00005)	DAI	4.09585	4.72253			
[-1.89170]	[2.38587]						
			DETC	DET			
-0.00202	0.00864	DETC	3.59655	1.92797	0.48573	0.97947	0.73260
(0.00037)	(0.00124)	DET	1.92797	2.77885			
[-5.52438]	[6.94689]						
			ENBC	ENB			
-0.00873	0.05060	ENBC	0.91366	0.19242	0.81734	0.88621	0.85177
(0.00542)	(0.01221)	ENB	0.19242	4.27489			
[-1.61094]	[4.14434]						
			FRATC	FRAT			
-0.01782	-0.00194	FRATC	3.91840	2.07844	0.01203	0.31008	0.16106
(0.00275)	(0.00029)	FRAT	2.07844	2.65330			
[-6.48009]	[-6.73588]						
			VWC	VW			
-0.02371	0.01358	VWC	1.57311	0.85759	0.11562	0.59387	0.35475
(0.00963)	(0.00894)	VW	0.85760	1.81153			
[-2.46135]	[1.51862]						

Table 4: VECM results and Hasbrouck measures: specification with intercept, standard errors in ( ), t-statistics in [ ]

causality test for DAIC on DAI suggests that past values of the CDS prices influence up-to-date values of bond spreads. This supports the theory of an underlying common component and the intuition of co-movement gained from the plot of the two series.

6 Conclusion

In the preceding paper I conducted an econometric analysis of the long run co-movement and the dynamic relation between bonds and credit default swaps.

I presented evidence that four out of five bond spreads and CDSs are cointegrated. Thus, the parity relation between CDS prices and credit spreads holds on average over time suggesting that the bond and the CDS markets price credit risk equally. But over large periods CDS prices are substantially higher than credit spreads. This might be due to contract specification as CDS prices often contain a CTD option and therefore place an upper bound on the price of credit risk.

Furthermore, the dynamics of price discovery were analyzed. I pointed out the the results greatly depend on the specification of the VECM. Besides, the upper and the lower bound of the information shares have a huge spread. Therefore, the explanatory power of these measures is low compared to information shares computed for stocks.

Although the information shares differ widely and the results are not always significant, it can be deduced from the analysis that both markets contribute to price discovery. From a macroeconomics point of view it can be stated that the CDS market fosters an efficient allocation of credit risk. Furthermore, the CDS premia are helpful indicators of the credit quality of firms to banks and other market participants. Nevertheless, one should not concentrate on CDS premia only when evaluating credit risk.

As I worked on the same data as Doetz I should have confirmed his results. This is not the case, all my numerical results differ. Especially the bounds of the information shares depart in size. One obvious difference is that Doetz allowed for up to eight lags in the VECM maximally. It could be the case that allowing for more than eight lags alters the results to a vast extent. But it rather points to a poor analysis technique for the data at hand. Besides, I estimated three different VECM specifications and got out huge differences in allocating information shares to the different markets. I can just suppose that Doetz imposed some restrictions, which are not known to me.

At the very end of my paper and after having drawn the mayor conclusions from the analysis I will state some critique. Hasbrouck introduced the preceding estimation method and allocation of information shares for identical bonds trading at different markets. Here it is applied to bond spreads and CDS premia. Given the theoretical parity relation between the two markets holds the analysis is valuable. But it seems to be the case that the data has to be manipulated tremendously and one has to fish for econometric tests and VECM specifications that fit the data in order to get out poor results. Besides, the European data is low frequency data which explains why Doetz' and my results are worse than Blanco's et al. results. Furthermore, Blanco et al. figured out that for American bond markets CDS prices lead over credit prices in the price discovery process. I find in accordance with Doetz that bond spreads lead over CDS prices.

I am not sure about the scientific surplus of the analysis as I had to influence and fiddle my data to get out weak results. Doetz gets on average a difference of 0.149 between the upper and the lower bound of the Hasbrouck measure. Whereas Blanco et al. just estimate a difference of 0.08. As stated earlier it may depend on the data and the sampling period as Blanco et al. use mainly US bonds and exclude outliers. Whereas Doetz analyzes European data for a different sample period. Another issue is that both sampling periods are rather short although long run effects are studied.

Further research and possibly improved analysis techniques will give deeper insight into the relation between CDS and bond spreads. Till then we keep that both markets price risk equally up to a certain disturbance, and further both are important for price discovery.

7 References

- Blanco, Roberto, Brennan, Simon and Marsh, Ian W.: "An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps", Journal of Finance 2005, 60(5), 2255-2281.

- Doetz, Nikolaus: "Zeitvariable Beiträge der Märkte für Unternehmensanleihen und Credit Default Swaps zur Preisfindung von Kreditrisiken", Working Paper, 2007.

- Hamilton, James D.: Time Series Analysis, 1994, Princeton University Press.

- Hasbrouck, Joel: "One Security, Many Markets: Determining the Contributions to Price Discovery", Journal of Finance 1995, 1(4), 1175-1199.

- Hayashi, Fumio: Econometrics, 2000, Princeton University Press.

8 Appendix

8.1 Descriptive statistics (continued)

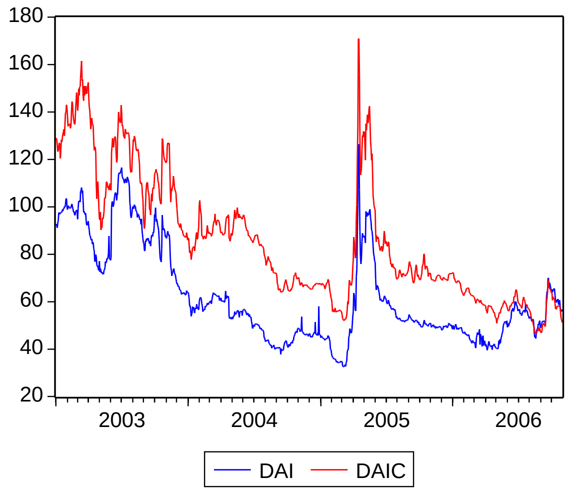
It is obvious that the medians for all CDSs are bigger than for the bond spreads, the same holds for the minimum values of the series. Except for the ENB bond the maximum CDS values are also bigger than the maximum bond spread values. Whenever the CDS values are bigger than the corresponding bond spread value this is indicated in bold.

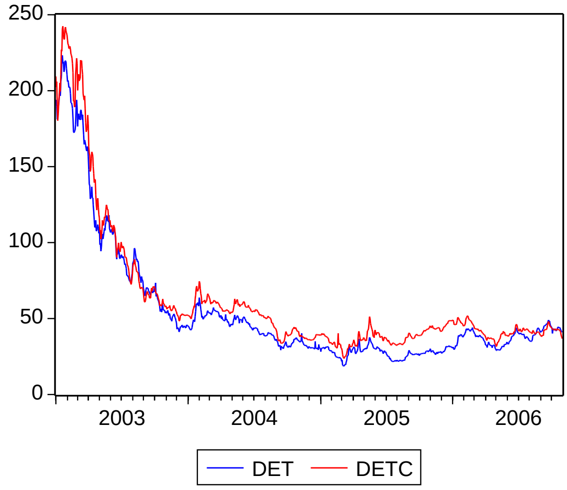
	Median		Minimum value		Maximum value	
	Bond spread	CDS	Bond spread	CDS	Bond spread	CDS
DAI	55.2190	**76.3920**	32.5771	**46.5000**	126.4104	**170.8820**
DET	39.9172	**45.1530**	18.7703	**23.7500**	223.2596	**242.3330**
ENB	22.5205	**25.5265**	8.2383	**12.6880**	87.3074	65.7500
FRAT	37.7639	**48.4720**	17.1086	**25.9640**	258.2770	**295.9170**
VW	43.9784	**55.3155**	6.2378	**22.5190**	75.5268	**93.1760**

Table 5: Descriptive statistics (continued)

8.2 Graphs

Time series for all five bond spreads and CDSs display that the corresponding series move similar. Over large periods the CDS lies above the bond spread. However, there are crossings. The CDS series are indicated with a 'C' at the end of the bond abbreviation and printed in red, the bond spread series are printed in blue.




250
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150
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2003
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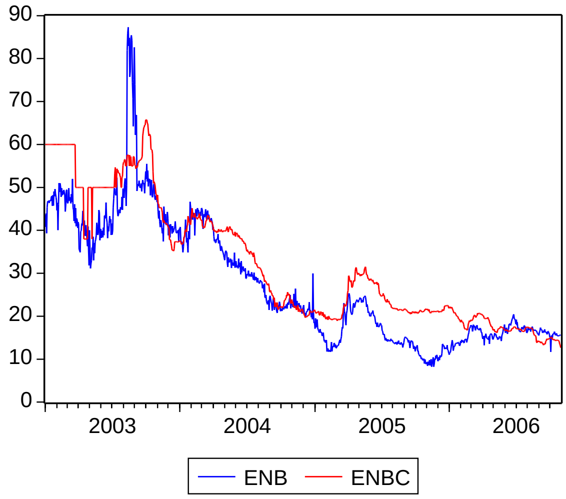
DET
DETC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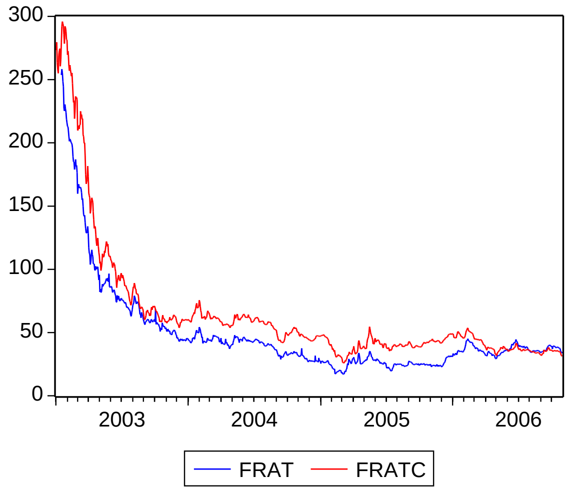
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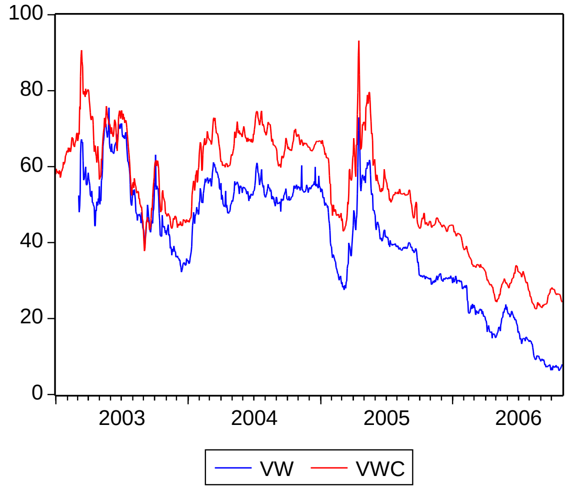

8.3 KPSS test

The KPSS test tests time series for stationarity. The null of stationarity is tested against the alternative hypothesis of integration; */**/*** indicates rejection of the null at a significance of 1/5/10 percent given the critical value of 0.739/0.463/0.347. Therefore, stationarity can be rejected for all series and both types of KPSS tests except for the CDS of the DAI bond in the specification with intercept and trend. I let EVIEWS automatically choose the bandwidth. The default setting, the Newey West Bandwidth, is used.

	KPSS test with intercept H_0 : Stationarity		KPSS test with intercept and trend H_0 : Stationarity	
	Bond spread	CDS	Bond spread	CDS
DAI	2.0094*	2.7278*	0.4815*	0.2731
DET	2.1921*	2.0608*	0.7136**	0.6373**
ENB	3.3378*	3.5677*	0.4129***	0.4987**
FRAT	1.9570*	1.9955*	0.6268**	0.5319**
VW	2.7810*	2.3752*	0.4974**	0.5607**

Table 6: Results from the KPSS test

8.4 The AIC and SIC selection criterion

The table 7 shows the AIC and SIC selection criterion for the best VECM. I estimated the VECMs for 2 up to 20 lags. I derived the smallest distance between the ith smallest AIC and the jth smallest SIC as selection criterion for the VECM specification, which I derived. The AIC of the finally in the analysis estimated specification is indicated in bold. The numbers in brackets indicate the i/j smallest AIC and SIC values, respectively. The smallest values for AIC and SIC where determined up to the 7th smallest entry. I chose that lag length where there is never more than one entry between one of the smallest AIC's and one of the smallest SIC's. I always decided for the lag length with one of the smallest AIC's. The selection is just conducted once for a VECM with intercept. It is obvious that such kind of selection is as arbitrary as just setting a maximum lag length as Doetz does. Thus, looking for the best VECM by choosing the smallest distance between some small AIC and SIC can be seen as an attempt to work scientifically but is corrupted by the data.

8.5 Results for different VECM specifications

As noted in the principal part of the paper the VECM is estimated for three different specifications. The results for the VECM without intercept and trend assumption, and the results for the error-correction model with intercept and trend are presented below in table 8 and 9.

	DAI		DET		ENB		FRAT		VW	
included lags	AIC	SIC	AIC	SIC	AIC	SIC	AIC	SIC	AIC	SIC
2	8.6754	8.7443 (2)	8.1527	8.2216	7.1940	7.2629 (1)	7.8406	7.9101	6.6398	6.7112 (2)
3	8.6525	8.7411 (1)	8.1077	8.1964	7.1870	7.2756 (3)	7.8211	7.9105	6.6159	6.7078 (1)
4	**8.6388** (3)	8.7472 (3)	8.0286	8.1371	7.1885	7.2969 (5)	7.7925	7.9018	6.5340	6.6464
5	8.6460	8.7742	7.9900	8.1182	7.1913	7.3195	7.6908	7.8201 (5)	6.5379	6.6710
6	8.6448	8.7929	7.9877	8.1357	7.1983	7.3463	7.6722	7.8215 (6)	6.5404	6.6940
7	8.6389	8.8068	7.9822	8.1502	7.1805	7.3484	7.6023	7.7717 (1)	6.5415	6.7158 (3)
8	8.6442	8.8320	7.9550	8.1428	7.0792	7.2671 (2)	7.6013	7.7908 (3)	6.5407	6.7356
9	8.6423	8.8501	7.9287	8.1365	**7.0727** (5)	7.2805 (4)	7.5804	7.7901 (2)	6.5087	6.7243
10	8.6456	8.8734	7.8972	8.1249	7.0763	7.3040	7.5694	7.7992 (4)	6.4798	6.7162 (4)
11	8.6499	8.8977	7.8152	8.0629	7.0802	7.3280	7.5724	7.8223 (7)	**6.4789** (3)	6.7361
12	8.6527	8.9205	7.7723	8.0401	7.0876	7.3554	7.5551	7.8253	6.4862	6.7641
13	8.6572	8.9451	7.6828	7.9707	7.0925	7.3804	**7.5409** (7)	7.8314	6.4862	6.7850
14	8.6522	8.9601	7.6599	7.9679 (2)	7.0781	7.3861	7.5427	7.8535	6.4811	6.8007
15	8.6536	8.9817	7.6343	7.9624 (1)	7.0837	7.4118	7.5151 (6)	7.8462	6.4793 (4)	6.8198
16	8.6399	8.9881	7.6309	7.9791 (3)	7.0387	7.3869	7.4995 (5)	7.8509	6.4713 (1)	6.8328
17	8.6369	9.0054	7.6271	7.9956	7.0440 (3)	7.4125	7.4923 (4)	7.8641	6.4756 (2)	6.8581
18	8.6353 (1)	9.0240	**7.5927** (1)	7.9814	7.0479 (4)	7.4366	7.4782 (3)	7.8704	6.4825	6.8859
19	8.6364 (2)	9.0453	7.5968 (2)	8.0057	7.0283 (2)	7.4373	7.4707 (1)	7.8833	6.4850	6.9095
20	8.6428	9.0721	7.5973 (3)	8.0266	7.0246 (1)	7.4538	7.4755 (2)	7.9087	6.4809	6.9265

Table 7: The AIC and SIC selection criterion

VECM coefficients		Variance-covariance matrix			Hasbrouck measures		
ψ_1	ψ_2				lower bound	upper bound	MID
			DAIC	DAI			
-0.01186	-0.00338	DAIC	7.55641	4.11571	0.10745	0.16919	0.13832
(0.00713)	(0.00725)	DAI	4.11571	4.74445			
[-1.66436]	[-0.46619]						
			DETC	DET			
0.01274	0.02263	DETC	3.63960	1.96896	0.76040	0.97730	0.86885
(0.00266)	(0.00354)	DET	1.96896	2.81377			
[4.79522]	[6.39999]						
			ENBC	ENB			
-0.00856	0.04852	ENBC	0.91527	0.19363	0.81189	0.88206	0.84698
(0.00500)	(0.01196)	ENB	0.19363	4.27392			
[-1.71291]	[4.05659]						
			FRATC	FRAT			
-0.00486	0.00039	FRATC	4.01508	2.16590	0.00476	0.49673	0.25075
(0.00108)	(0.00009)	FRAT	2.16590	2.73036			
[-4.48571]	[4.24081]						
			VWC	VW			
-0.00236	0.01255	VWC	1.58312	0.85237	0.60029	0.97560	0.78795
(0.00601)	(0.00803)	VW	0.85237	1.81057			
[-0.39349]	[1.56158]						

Table 8: VECM results and Hasbrouck measures: specification with no intercept and no trend, standard errors in ( ), t-statistics in [ ]

VECM coefficients		Variance-covariance matrix			Hasbrouck measures		
ψ_1	ψ_2				lower bound	upper bound	MID
			DAIC	DAI			
-0.03753	-0.01331	DAIC	7.46873	4.05951	0.09608	0.18012	0.13810
(0.00973)	(0.00485)	DAI	4.05951	4.71382			
[-3.85607]	[-2.74277]						
			DETC	DET			
-0.00210	0.00844	DETC	3.59670	1.92801	0.47797	0.97721	0.72759
(0.00038)	(0.00121)	DET	1.92801	2.77877			
[-5.52083]	[6.94907]						
			ENBC	ENB			
-0.01000	0.04962	ENBC	0.91324	0.19335	0.77637	0.85222	0.81429
(0.00574)	(0.01214)	ENB	0.19335	4.27688			
[-1.74388]	[4.08864]						
			FRATC	FRAT			
-0.02368	-0.00488	FRATC	3.90079	2.06801	0.04939	0.20905	0.12922
(0.00347)	(0.00071)	FRAT	2.06801	2.64823			
[-6.81587]	[-6.87567]						
			VWC	VW			
-0.01184	0.04460	VWC	1.58112	0.85835	0.54086	0.95683	0.74884
(0.01009)	(0.01256)	VW	0.85835	1.79151			
[-1.17267]	[3.54981]						

Table 9: VECM results and Hasbrouck measures: specification with intercept and trend, standard errors in ( ), t-statistics in []