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Financial crises and information transfer: An empirical analysis of the lead-lag relationship between equity and CDS iTraxx Indices

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Financial Crises and Information Transfer
–
An Empirical Analysis of the Lead-Lag Relationship between Equity and CDS iTraxx Indices

by

Stefan Ehlers*, Marc Gürtler**, and Sven Olboeter***

Abstract. This study examines the lead-lag-relationship between European equity and CDS markets in the context of the financial crisis. Previous research identified the stock market to lead the CDS market in an ordinary economic environment. Against the background of our study this lead-lag-relationship strengthens when moving from the non-crisis- to the crisis-scenario on a daily as well as on a weekly basis. Hence, we conclude that information transfer from stock to CDS markets widens during the financial crisis. In addition and in contrast to the literature we find an extraordinary day-of-the-week-effect on weekly returns as an anomaly for information processing.

Keywords: Granger-causality, iTraxx Indices, Credit Default Swaps, Day-of-the-Week-Effect, Feedback System

JEL-classification: G14, G15, G17

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1. Motivation and Literature Overview

The credit default swap market historically was a very fast growing market till the end of year 2007. From the second half 2007 to the first half 2008 we find a heavy decrease by 12.16 % from 62.17 trillion dollars to 54.61 trillion dollars which represents the first slump since 2001. From this point on till the first half of 2009 the notional outstanding amount nearly halved to 31.22 trillion dollars.[1] This outstanding growth and today's situation on the financial markets world-wide is motivation enough to analyze the behavior and the relationship between European standardized Credit Default Swap (CDS) indices and the stock market. It is well known that the consequences of the subprime crisis starting in 2007 are the rise of credit spreads and the fall of stock markets. Against this background it is interesting to know if an information transfer between the stock and the CDS markets is observable since this would help to understand information flows between the financial markets. There are a couple of studies analyzing the relationship between CDS and stock markets. But, to our knowledge, no study dedicated to the question if the relationship between these two markets changes from an ante-subprime to the subprime period.[2] The understanding of information flows during the subprime crisis compared to the information transfer in non-crisis scenarios is a valuable complement to the existing literature on the link between stock and CDS markets.

Before getting into the issue in question we give a short overview of the literature including some statistical results in addition to the essential results of the studies. Norden and Weber (2009) implement a vector autoregression (VAR) model on 58 international company names to identify comovements between stock, bonds and CDS markets. They focus on a single-name analysis and a time horizon from January 2000 to December 2002 on a daily and weekly basis. Norden and Weber (2009) split up their data set into two subsets. Subset 1 covers the period from January 2000 to June 2001 and subset 2 comprises the period from July 2001 to December 2002. In contrast to the paper on hand this was not done to examine impacts from a macro-economic downturn movement but to provide a back-testing for the findings between subset 1 and subset 2. Correlations between stock and CDS markets calculated by a Spearman coefficient are observed to be negative and mostly significant at a 1 % level. On a weekly basis they detect a median correlation of -0.25 and on a daily basis of -0.1. Due to autocorrelation tests they find stock, CDS and bond prices to be autocorrelated whereas autocorrelation for returns on these asset classes is negligible up to the fifth lag. The results show a lead of stock markets to the bonds and CDS markets. Furthermore, it can be concluded that CDS markets lead bond markets. In general, the response is stronger on a daily than on a weekly basis.

Fung et al. (2008) investigate the relationship between stock markets and the family CDX of CDS indices. Concretely, they use the CDX.NA.IG, based on investment-grade entities, and the CDX.NA.HY, based on high-yield names, on a daily data history ranging from April 2004 to December 2007. Thus, the analysis approximately covers the first 10 months of the financial crisis. The authors construct a hypothesized index from January 2001 to March 2004

[1] This information is provided by the International Swaps and Derivative Association. For more information see www.isda.org.

[2] The subprime period, in our case, is defined as the time between the starting point of the subprime crisis and the 31st May 2009, the end of our empirical dataset.

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by actual spreads from constituents of these indices. As benchmark stock indices they consider the S&P 500 and two other indices containing the same references like the CDX counterparts. Fung et al. observe a Pearson correlation coefficient of approximately −0.34 for both, IG and HY, with S&P 500 at 1 % level of significance over the whole sample period. In addition, they find a close relationship between CDS indices and stock markets during the credit crunch in mid-February 2007. Using a vector autoregression (VAR) model they conclude the stock market to lead the investment-grade and high-yield CDS market.

An analysis using the family iTraxx of CDS indices is provided by Byström (2008) who examines the relationship of iTraxx CDS and stock prices by several statistical procedures. His study comprises iTraxx sectoral indices such as Industrials, Autos, TMT, Energy, Consumers, Subordinated and Senior Financials as well as the corresponding sectoral stock indices. His research is based on a daily data series from 21st June 2004 to 18th April 2005 which consists of the very first 10 months of trading in iTraxx. On the one hand Byström observes significant positive first order autocorrelation within the CDS indices (except from iTraxx Autos) and no autocorrelation for the stock indices tested by Ljung-Box test and OLS regressions. On the other hand Byström concludes from rank and Pearson's correlation analysis that CDS spreads tend to widen if stock prices fall and vice versa. Moreover, he finds volatility of stock index returns to be significantly negatively correlated with iTraxx CDS spreads and company-specific information embedded in the stock prices before it appears in iTraxx CDS spreads.

In the study on hand we examine the influences of the financial crisis on the relationship between CDS indices and the stock market for European markets. Furthermore, a brief cross-continental analysis is provided as we do not only take into account European stock indices but additionally the Dow Jones Industrial Average from the U.S. market. Our analysis is based on a daily (from 2nd January 2007 until 29th May 2009) and on a weekly basis (26th September 2004 until 29th May 2009) for CDS iTraxx and stock indices. Thus, the impact of a less frequent trading period (weekly level instead of a daily level) and the corresponding information transfer is considered as well. In addition, due to our large data history containing at least 2 years and 5 months for the daily data history we expect that our results sketch a statistically more valid picture than the results from Byström who incorporated only a 10 months data history.

In comparison to Fung et al. (2008) we are able to involve a larger subprime data history of nearly 22 months which contains 12 months more of information. To our knowledge we are the first who investigate the changes in the transfer of risk information between markets within a common financial environment and markets within a financial crisis for the European market. Against this background the question arises, how the relationship between CDS and stock indices changes if economies move into a macro-economic downturn period. In this context we deal with the problem if there is an informational breach between markets before and during the financial crisis. Therefore, we split up our data history into two subsets as will be explained in more detail in the following section. The analysis is performed by using a Granger-causal regression with a separate estimate of maximum lags which have to be considered. We determine the maximum lags for each VAR system separately by the use of the Schwarz-Bayes and the Hannan-Quinn criterion.[3]

[3] For the Schwarz-Bayes and the Hannan-Quinn criterion see e.g. Lütkepohl (1991), p. 132.

Available studies on standardized indices (e.g. Byström (2008)) are focused on the iTraxx sector indices. Compared to Byström our focus is not solely based on sector indices but also on the very important benchmark indices iTraxx Europe, iTraxx Europe Crossover and iTraxx HiVol. Consequently, our analysis uses the main benchmark indices that are traded over futures contracts at the EUREX.

Because we involve standardized indices we focus on the systematic risk information transfer which differs from the contribution of Norden and Weber (2009) who analyze the single-name risk information flow. On the one hand the advantage of an analysis on single-name CDS is that the idiosyncratic factor plays a major role compared to the systematic factor. On the other hand the evaluation of the overall relationship between different markets on a single-name basis is difficult because of the undiversified idiosyncratic risk. Therefore we use market indices since in that case idiosyncratic risk is negligible and systematic risk takes the center stage and interaction of different markets can be analyzed without accounting for firm specific characteristics. Against this background it is not surprising to us that some of our results differ from Norden and Weber (2009). Concretely, we find a day-of-the-week effect in the weekly returns which not occurs in the study of Norden and Weber.

The article is organized as follows: In section 2 we start with a description of our procedural methodology, followed by a presentation of the data basis and a brief statistical analysis in section 3. Section 4 deals with the statistical analysis of Granger-causality over the whole sample period. Section 5 provides a corresponding analysis of the two sub-periods and section 6 deals with anomalies in the weekly returns. Section 7 concludes with a short summary.

2. Methodology

2.1. The Partitioning of the Data Set

The aim of our study is to analyze if the interaction between credit and stock markets has changed during the financial crisis. As already mentioned our data history covers the time period from 26th September 2004 until 29th May 2009 on a weekly basis (in each case from Friday to Friday) and the period from 2nd January 2007 until 29th May 2009 on a daily basis. Thus, within both periods there is a time interval before and a time interval including the financial crisis. To identify possible changes in the interaction between stock and credit markets we have to find a trigger event that characterizes the beginning of the financial crisis. We used the 14th June 2007 as this cut-off point in time because this date is determined by the Bank for International Settlements to be the first key event that induced the financial crisis in Europe.[4] Therefore we run a Chow-test on the investigated return series to determine if there is evidence for a structural interrupt in the data history at this date. The results show a unique break at a 1 % level of significance in the data history at this point in time.[5] The time period before 14th June 2007 acts as a kind of benchmark period because within this period the economy in Germany and Europe was running at a "normal" level, which in turn means that there were no extraordinary events in the credit and stock markets. The second time period

[4] The Bank for International Settlements (2008) located the initial trigger events between the 14th June and 22nd June 2007 as first rumours occurred that two Bear Stearns-managed hedge funds have been subject to heavy losses from subprime-mortgage securities.

[5] See Chow (1960). Results are available upon request.

therefore characterizes the period where the financial crisis hits Europe and the credit and stock markets began to change their behavior as can be observed in the rapid decrease of the stock markets and the increase of the spreads in the CDS markets. On the basis of these two time periods and the corresponding data sets it is possible to analyze the interaction between the markets and to identify possible changes within this interaction by moving from the non-crisis to the crisis period.

In addition, we examine the behavior of the markets for the whole sample period in order to show the problems arising from the analysis of data when there is an extraordinary event included. The results show that there are significant differences between the analysis of the two subsets and the whole sample.

2.2. Granger-Causality

We analyze the interaction between the credit and stock markets using the concept of Granger-causality. This method was introduced by Granger (1969) to identify possible links and lead-lag relationships between different time series. In this sense a series X is said to Granger-cause a series Y if X values provide statistically significant information about future values of Y. Since it is possible that each of the two variables Granger-causes the second (so called feedback systems), Granger-causality does not necessarily imply actual causality. Against this background we firstly have to justify that there is a reasonable economic link between the considered series. This aspect is given in our analysis, because several studies as Norden/Weber (2009) and Fung et al. (2008) have shown, that there is a lead-lag relationship between stock and CDS markets. Moreover, it is economically plausible to assume a relationship between these two markets because it is well known that a negative change in the creditworthiness of a firm has a direct consequence for the equity value of the firm and vice versa.[6]

Another assumption that has to be fulfilled in the context of Granger-causality is the (trend-) stationarity of the underlying time series. To check the stationarity in each series, we use unit root tests, such as the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski/Philips/ Schmid/Shin (KPSS) test.[7] The null hypothesis of the ADF test is non-stationarity, complementing the KPSS test. The KPSS test is applied since the ADF test has low power against stationarity near unit root processes. If e.g. the null hypothesis of the ADF test is rejected at the 1 % level of significance and the null hypothesis of the corresponding KPSS test is not rejected at the 10 % level we interpret a time series to be stationary. On the other hand, if the tests come to complementary results, we additionally apply a Philipps-Perron test as a third statistical procedure.[8] On this basis we decide by majority whether or not the considered time series is regarded as stationary. The possibility of inconsistent results between the ADF and the KPSS test demonstrate the reasonability to analyze stationarity with two tests that have different null hypothesis. Rejecting the null hypothesis of the ADF test only with a specified level does not automatically mean that the underlying process is

[6] The link between creditworthiness and the equity value of a firm is the fundament of structural models like Merton (1974).

[7] See Greene (2003) for more information about the ADF test and Kwiatkowski et al. (1992) for more information about the KPSS test.

[8] In brief, the Phillips-Perron test checks a time series for the null hypothesis of a unit root against the alternative of no unit root. If the null hypothesis is rejected then a time series is claimed to be stationary.

stationary. Against this background, all of our results are backed by a second or even a third statistical procedure.

The concept of Granger-causality is based on a VAR model. In our analysis the considered data set consists of two time series $(r_t^{(CDS)})_t$ and $(r_t^{(stock)})_t$ of length T, whereby $(r_t^{(CDS)})_t$ represents a time series of CDS index returns and $(r_t^{(stock)})_t$ stands for a time series of stock returns. On this basis, the formulation of the present VAR model is as follows:[9]

$$r_t^{(CDS)} = \alpha_1 + \sum_{j=1}^{m} \beta_{1,j}^{(stock)} \cdot r_{t-j}^{(stock)} + \sum_{j=1}^{m} \gamma_{1,j}^{(CDS)} \cdot r_{t-j}^{(CDS)} + \varepsilon_{1,t}, \tag{1}$$

$$r_t^{(stock)} = \alpha_2 + \sum_{j=1}^{m} \beta_{2,j}^{(stock)} \cdot r_{t-j}^{(stock)} + \sum_{j=1}^{m} \gamma_{2,j}^{(CDS)} \cdot r_{t-j}^{(CDS)} + \varepsilon_{2,t}, \tag{2}$$

where α_i, $\beta_{i,j}^{(stock)}$ and $\gamma_{i,j}^{(CDS)}$ (i = 1, 2) are the coefficients that are estimated by the ordinary least square method. $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ have to fulfill the usual restrictions of uncorrelated error terms. To determine the optimal number m^* of lags that has to be incorporated into the VAR model we use two well accepted procedures: the Schwarz Bayesian Information Criterion (SBC) and the Hannan Quinn Information Criterion (HQC).[10] After applying both criteria we decided to take the maximum of both quantities as the optimal lag length m^* and denote the VAR model by VAR(m^*). Since almost we are confronted with the case $m^* = 1$, in addition, we test fixed lag lengths of m = 2 (on a weekly basis) and m = 5 (on a daily basis) but the results do not change significantly implying both criteria to work well.

After estimating the optimal lag length the Granger-causality test can be performed. The null hypothesis H_0 "the time series $(r_t^{(stock)})_t$ does not Granger-cause the time series $(r_t^{(CDS)})_t$" is not rejected if all regression coefficients $\beta_{1,\cdot}^{(stock)}$ of equation (1) are zero, i.e. the null hypothesis can also be represented as follows:

$$H_0: \beta_{1,1}^{(stock)} = \ldots = \beta_{1,m^*}^{(stock)} = 0. \tag{3}$$

Analogously, according to equation (2) the null hypothesis H_0 "the time series $(r_t^{(CDS)})_t$ does not Granger-cause the time series $(r_t^{(stock)})_t$" can be transformed into

$$H_0: \gamma_{1,1}^{(CDS)} = \ldots = \gamma_{1,m^*}^{(CDS)} = 0. \tag{4}$$

Both null hypotheses are assessed by a F-statistic using a decomposition of the model into a restricted and an unrestricted model. As the unrestricted model was already described by equation (1) and (2), respectively, the restricted model is obtained by setting all $\beta_{1,j}^{(stock)}$ and $\gamma_{2,j}^{(CDS)}$, respectively, to zero, implying the restricted model to be an autoregressive process of order m^*. The relevant F-statistic is a function of the residual sum of squares of the restricted (RSS_{rm}) and of the unrestricted model (RSS_{urm}) and is further referenced to be the relevant Granger statistic G:

$$G = \frac{(RSS_{rm} - RSS_{urm}) \cdot (T - 2 \cdot m^* - 1)}{m^* \cdot RSS_{urm}} \sim F(m^*, T - 2 \cdot m^* - 1). \tag{5}$$

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[9] We refer to the Granger-causality procedure presented in Greene (2003).

[10] These information criteria avoid an overfitting of the model by adding a penalty term to the residual sum of squares for every additional lag. As long as the reduction of the residual sum of squares is greater than the penalty term a additional lag is beneficial. The aim is to find the minimum of the information criterion by a given number of lags. We decided to use a maximal lag number of five, because this covers for daily data the period of one week.

The basic idea behind this procedure is to analyze if the entry of additional variables into the restricted model improves the explanatory power of the overall relationship significantly. After the tests of the present study have been introduced the next section deals with the considered data series.

3. Data Description and Brief Statistical Analysis

In our analysis we focus on the European markets and, hence, on major iTraxx CDS indices as well as major European equity indices. On the one hand the considered iTraxx CDS indices are in detail iTraxx Europe (Europe), iTraxx Europe HiVol (HiVol), iTraxx Europe Crossover (Crossover), iTraxx Europe Non-Financials (NonFin), iTraxx Europe Financials Senior (FinSen) and iTraxx Europe Financials Subordinated (FinSub). The main iTraxx Europe index consists of 125 reference names. New series are issued every six months. Its high volatility counterpart (HiVol) includes 30 names with the highest spreads whereas the Crossover index consists of 50 names with a sub-investment grade. Non-Financials contains 100 reference entities from various industries such as Automobile, Energy, TMT etc. The Financials' indices are subject to 25 senior subordination financial entities (Financials Senior) and 25 junior subordination financial entities (Financials Subordinated). The iTraxx indices Europe, HiVol and Crossover are issued with 3, 5, 7 and 10 years of maturity. iTraxx Non-Financials, Financials Senior and Financials Subordinated are issued with 5 and 10 years of maturity. iTraxx European CDS indices provide the most liquid market for standardized CDS indices for European CDS counterparties. This rapidly growing market suffered strongly from the price erosion obtained by the impacts of the subprime crisis mid of June 2007.

Table 1 about here

For our statistical analysis we use weekly and daily iTraxx Credit Default Swap Index data for all six above mentioned indices with 10 years maturity whereby all indices are considered with closing spreads.[11] As already mentioned the considered time periods of the weekly data (from 26th September 2004 to 29th May 2009) and the daily data (from 2nd January 2007 to 29th May 2009) differ. However, to our knowledge this data basis is the largest one investigated within the standardized index trading context which in turn makes it possible to divide the data history in a non-crisis and a crisis period.

On the other hand, we consider 9 major European equity indices and also the Dow Jones Industrial Average in order to additionally consider cross-continental relationships. We investigate the main equity indices from the largest economies in Europe which are FTSE 100 (United Kingdom, FTSE), DAX 30 (Germany, DAX), CAC 40 (France, CAC), IBEX 35 (Spain, IBEX) and the STOXX50 (STO). To measure sector effects we use the following four Dow Jones Stoxx Supersector indices: Banks (DJBanks), Financial Services (DJFinS), Automobiles & Parts (DJAuto) and Industrial Goods & Services (DJInd). In these supersector indices companies have been classified by their primary revenue source.[12]

[11] The data was made available by Thomson Reuters.
[12] For further information see www.stoxx.com.

We start our study with a first brief statistical analysis of index returns. In addition to the determination of different moments of the return distributions we test the returns for autocorrelation by a Ljung-Box (LB) test (H_0: log-returns are autocorrelated) up to a maximum lag length of $l_{max} = int(12 \cdot (T/100)^{0.25})$.[13] As can be seen in Table 2, iTraxx Crossover and iTraxx Non-Financials are the only two indices that show no significant autocorrelation on a weekly basis and iTraxx Crossover on a daily basis, respectively. Thus, on weekly and on daily basis CDS data we observe clear indications for autocorrelated returns. Taking a quick look at the descriptive statistics we find the return distributions to be leptokurtic and most of them right-skewed. According to Table 3 we find (except from Dow Jones Industrial Goods & Services) all indices to be autocorrelated up to lag 15 or 19, respectively. Stock index returns also show a leptokurtic behavior that is impressively demonstrated by the Dow Jones Automobile & Parts index.

Table 2 about here

Table 3 about here

In the next section we investigate the time series with respect to Granger-causality.

4. Analysis of Granger-causality for the Complete Sample Period

Since the application of Granger-causality is based on the assumption of trend-stationarity of the considered time series we additionally have to check this property. The results of the two tests of stationarity of the weekly returns are homogeneous. According to Table 4 the ADF test rejects the null hypothesis of non-stationarity at a significance level of 1 % for all indices. In comparison the null hypothesis of stationarity cannot be rejected at a significance level of 10 % according to the KPSS test.[14]

For daily returns the results are slightly different. The null hypothesis of non-stationarity is rejected for all returns at a 1 % level of significance according to the ADF test. Furthermore, the null hypothesis of stationarity is not rejected according to the KPSS test for almost all returns except the iTraxx HiVol index for which stationarity is rejected at a significance level of 10 %. To analyze this inconsistent result regarding the iTraxx HiVol index we additionally apply the Philipps-Perron test as a third statistical procedure. The null hypothesis of Philipps-Perron is rejected at a 1 % level of significance. Against this background we treat iTraxx HiVol returns as stationary as well.[15]

[13] The choice of this specific maximum lag was suggested by Schwert (1989). The maximum lag to be tested has been rounded to the next integer so that we tested 15 lags on a weekly basis and 19 lags on daily basis.

[14] The application of the ADF test also requires the residuals of the ADF-regression not to be autocorrelated. The autocorrelation of residuals is checked by the Durbin-Watson test for a lag of order 1 and with the Ljung-Box test for higher order of autocorrelation. According to the Durbin-Watson test the null hypothesis of no autocorrelation can not be rejected. In addition, the Ljung-Box test does not reject the null hypothesis of no autocorrelation until a lag of 15 which is chosen by the criterion of Schwert (1989). More detailed information is available from the authors upon request.

[15] In accordance with the “weekly case” we also do not detect any autocorrelation of the “ADF-residuals” in the “daily case” for all indices (here until lag 19). More detailed results are available upon request.

Table 4 about here

After analyzing the stationarity characteristics we now come to the analysis of Granger-causality between the iTraxx CDS indices and the equity indices. Since we examine all possible combinations of equity and CDS indices with regard to Granger-causality the selection of 10 equity and 6 iTraxx CDS indices on a weekly and a daily basis obviously lead to 240 equations according to (1) and (2). Since the presentation of all 240 results would exceed the dimension of this article we only show the results with significant relationships in the sense of Granger-causality up to a 10 % level of significance. Results from the Schwarz Bayesian Information Criterion and the Hannan Quinn Information Criterion imply an optimal lag length $m^* = 1$ or $m^* = 2$ for all vector autoregression models. Thus, we have to consider both, VAR(1) and VAR(2) models.

First of all, we analyze all equations according to (1), i.e. we examine uni-directional[16] Granger-causality in the sense of "Equity Granger-causes CDS".

Table 5 about here

As can be seen in Table 5 there are some relationships in which equity indices Granger-cause iTraxx CDS indices in the cases of VAR(1) models, i.e. in which the coefficients $\beta_{1,1}^{(stock)}$ are significantly different from zero. Particularly concerning the daily returns there are a lot of relationships in the sense of Granger-causality. The returns of the iTraxx indices Crossover, Non-Financials, Financials Subordinated and Financials Senior are Granger-caused by almost all considered equity indices. The coefficients $\beta_{1,1}^{(stock)}$ and $\gamma_{1,1}^{(CDS)}$ are nearly all significant at a 1 % level of significance. This is also true for the significance of the Granger-statistic G.

In contrast, there are only three relationships on the weekly basis and the corresponding results are somewhat surprising because two of the coefficients $\beta_{1,1}^{(stock)}$ are positive. This would mean that with increasing stock markets the credit spreads expand. This can also be observed by consideration of the correlation matrix when the correlation between the equity returns of t−1 and the CDS index returns of t is calculated which is almost positive.[17] These results will also be obtained for the post-subprime period as will be shown later. Since, at first sight, these results are surprising, we decided to take a closer look at the weekly returns in section 6. Furthermore, it should not go unnoticed that there are also two one-sided systems of type VAR(2) on the daily basis. These relationships can be detected for the HiVol and DJAuto index and for the Europe and DJAuto index as well.[18]

In a next step we analyze all equations according to (2), i.e. we analyze Granger-causality in the sense of "CDS Granger-causes Equity". As can be seen in Table 6 there are just a few relationships in this sense of Granger-causality. This result is in line with the studies of

[16] In the following the uni-directional cases of Granger-causality "(1)" or "(2)", respectively, are presented separately from the bi-directional cases "(1) and (2)", the above mentioned feedback systems. I.e. if an equity index Granger-causes a CDS index and the CDS index in turn Granger-causes the equity index we treat this case as a feedback system and not as a Granger-causality in the sense of (1) or (2).

[17] It should be mentioned that most of the positive correlations are not significant. Results are available upon request.

[18] More detailed information concerning this system is available from the authors upon request.

Byström (2008) and Fung et al. (2008) which have shown that information is firstly embedded in the stock markets and then transported into the CDS market.

Table 6 about here

The last case to examine corresponds with the presence of feedback systems in the data that occur several times according to Table 7. The most interesting feedback system is given by the weekly returns of the STOXX50 index (STO) and the iTraxx Financial Subordinated index (FinSub). A cross-continental feedback system can be found between weekly returns of the Dow Jones Industrial Average index (DJA) and the iTraxx Non-Financial index (NonFin). In the case "DJA Granger-causes NonFin" the coefficient $\beta_{1,1}^{(\text{stock})}$ is significant at the 1 % level while the coefficient $\gamma_{1,1}^{(\text{CDS})}$ is not significant. The other way round the coefficient $\gamma_{2,1}^{(\text{CDS})}$ is significant at the 1 % level whereas the coefficient $\beta_{2,1}^{(\text{stock})}$ is not significant.[19]

Table 7 about here

As a first intermediate result we obtain Granger-causalities between stock and CDS markets. These relationships are considerably stronger for daily returns than for weekly returns. The iTraxx indices with financial underlyings are often Granger-caused by the equity indices. We keep this in mind because the sample period includes the time before the beginning of the financial crisis and also the time during the financial crisis. In a next step we analyze the relationship between stock and CDS markets for the two sub-periods to identify changes within the relationship before and during the financial crises.

5. Granger-causality Analysis for the Split-up Periods

Analogously to the analysis of the overall period under consideration we also have to test stationarity of the time series for the separated sub-periods. The results are presented in Table 8.[20] According to the ADF test for all indices and both sub-periods we identify a rejection of the null hypothesis of non-stationary returns at a 1 % level of significance. The results from the KPSS test show no rejection of the null hypothesis of stationary returns at a 10 % level of significance. Consequently, we detect the return series to show stationary behavior for both sub-periods which allows us to apply the Granger regression method.

Table 8 about here

To analyze Granger-causality we firstly deal with the non-subprime period. As shown in Table 9 we observe a higher frequency of equity indices which Granger-cause CDS indices in the daily data set than on the basis of weekly data. On the weekly basis the stock indices Granger-cause iTraxx Financials Senior and iTraxx Financials Subordinated whereas on the

[19] Furthermore, we detect a VAR(2) feedback system on the daily basis between Crossover and DJAuto. Details are again available upon request.
[20] Again, according to the Durbin-Watson test the null hypothesis of no autocorrelation of the "ADF-residuals" can not be rejected.

daily data basis the Granger-causalities cover the complete investigated iTraxx family from iTraxx Europe to iTraxx Financials Subordinated. Note that we displayed all Granger-causalities with a significant Granger-statistic G up to 10 % level of significance. Most of the Granger-causalities are significant at 1 % and 5 % level.

Table 9 about here

The number of non-subprime Granger-causalities from CDS to stock indices is reduced to four in total on a weekly and on a daily basis. On weekly basis IBEX is Granger-caused by Crossover, HiVol and NonFin and on daily basis DJA is Granger-caused by FinSen. Since, in addition, two out of four regressions provide only a 10 % level of significance for the G-statistic, we can conclude that mainly the one-sided information transfer from equity markets to the CDS market is identifiable over the non-subprime period.[21]

Furthermore, we observe feedback systems with special participation of the financial sector as can be seen in Table 10. On the weekly basis, we identify feedback systems between the iTraxx Financials Senior and Subordinated Sector and the stock index Dow Jones Automobile & Parts at a 10 % level of significance. The feedback systems on the daily basis in particular involve iTraxx HiVol, iTraxx Financials Senior and Subordinated. The Granger-statistics G of most feedback systems are significant at a 1 % or 5 % level. These systems are typical examples of Granger-causalities that do not correspond with an economic meaningful link of cause and effect.

Table 10 about here

After dealing with the non subprime-period now we come to the corresponding analysis of the subprime period. Firstly, the fact is shown that, compared to the non-subprime period, there are less equity indices that Granger-cause CDS indices in the subprime period on a weekly basis (see Table 11). The related Granger-statistics are mostly only significant at a 10 % level except of one with a 5 % level of significance. On the daily basis subprime Granger-causalities from equity to the CDS market can be observed for all equity indices and for all CDS indices with no special focus on both sides. Daily cross border relationships between Dow Jones Industrial Average to all iTraxx indices exist and are strong.[22] Hence, the number of significant Granger-causalities from equity indices towards CDS indices increased on a daily basis from 35 in the non-subprime period to 42 in the subprime period.

Table 11 about here

According to Table 12 it is easy to see that on a weekly basis all potential impacts from CDS on equity indices would have been rejected if one would apply a 5 % level of significance. This, in general, is also true for Granger-causalities from equity to CDS markets where only

[21] Again, detailed information is available upon request.

[22] For the sake of completeness we would like to mention that we observed two regressions, i.e. one feedback system, with a maximum lag length of $m^* = 2$ estimated by the Schwarz-Bayesian Information and the Hannan-Quinn Criterion. The results of the related VAR(2) model are not displayed but available from the authors upon request.

the relationship "IBEX Granger-causes iTraxx Crossover" passes the 5 % level of significance. This fact leads us to the conclusion that weekly Granger-causalities do not play an important role in the subprime period. However, as presented above this is not true for the non-subprime period as there are relevant Granger-causalities within a 5 % level of significance regarding the Granger-statistic.

Table 12 about here

Furthermore, in the subprime period we also observe a disappearance of a lot of feedback systems (see Table 13) in comparison with the non-subprime period.[23]

Table 13 about here

Three out of four feedback systems are obtained at 1 % or 5 % level of significance where on the equity side the STOXX50 and the Dow Jones Automobile & Parts are involved and on the iTraxx side we find the iTraxx Crossover, iTraxx Financials Senior and Subordinated. Since no financial equity index is picked up by feedback systems the picture has strongly changed compared to the non-subprime situation. Thus, in the subprime period financial equity indices only occur when they Granger-cause CDS indices and not vice versa and not within the framework of feedback systems. Weekly feedback systems did not occur in the subprime period.

To summarize the results we give an overview in Table 14 in which the number of Granger-causalities is presented for the complete as well as for the two sub-periods.

Table 14 about here

With regard to Granger-causality in the sense of "Equity Granger-causes CDS" we firstly realized that weekly data does not play an important role since we only detect a few Granger-causalities for the non-subprime period. Against this background the more interesting case relates to daily data. Beneath many Granger-causalities of the European equity indices to the iTraxx CDS indices we observe a lot of cross-continental causalities of the Dow Jones Industrial Average to European iTraxx CDS indices in the daily data. Although this fact holds for the complete period, for the non-subprime, as well as for the subprime period, the majority of Granger-causalities tends to emerge from the subprime period.

In contrast, the analysis of the case "CDS Granger-causes Equity" shows only a few relationships. Briefly summarized, 6 relationships are found in the complete sample, 4 relationships in the non-subprime and 3 relationships are detected in the subprime samples. Compared to 216 possible Granger-causalities the impact of CDS leading equity indices is negligibly small.

Nearly the same result follows with respect to Feedback systems containing benchmark iTraxx indices. For the iTraxx Crossover index there were 2 systems on a daily basis in the subprime period. The iTraxx HiVol contains 1 system in the complete and another 2 in the

[23] For an additional feedback system we estimated a maximum lag length of $m^* = 2$. The results are again available from the authors.

non-subprime period on a daily level as well. But for both financial indices (FinSen, FinSub) we observed 10 feedback systems (5 each) on a daily level in the non-subprime period which vanished in the subprime period.

6. A More Detailed Analysis of Weekly Causalities

The analysis of the previous sections shows significant differences between the results determined on the basis of daily and on the basis of weekly data. On the one hand the number of Granger-causalities detected on a daily basis is considerably higher than on a weekly basis. On the other hand and quite remarkable the coefficients $\beta_{i,j}^{(stock)}$ prove to be positive on a weekly basis, whereas the daily basis leads to comprehensible negative beta-coefficients. A possible explanation for the latter result is the day-of-the-week effect. As previously stated the weekly returns of the previous sections refer to a Friday-to-Friday examination interval. To verify the robustness of the results we rerun the analysis for the other four possible weekly return intervals Monday-to-Monday, Tuesday-to-Tuesday, Wednesday-to-Wednesday, and Thursday-to-Thursday for the complete, the non-subprime and the subprime period. In Figure 1 the results are presented for all cases that comprise significant Granger-causalities of the direction "Equity index return Granger-causes CDS index return".[24] We only consider this direction because there are just a few uni-directional systems for the opposite direction.

Figure 1 about here

The boxplots in Figure 1 present the lower and the upper quartile as well as the median of the beta coefficients. As a first result we find the betas of the first four days of the week to be completely different distributed compared to those of the Friday-to-Friday interval. Hence, we find a day-of the-week effect within our information transfer processes implying the need to interpret the results regarding the Friday-to-Friday return interval with care. Consequently, it is very important for weekly returns to analyze the relationship between different time series for all five possible return intervals and not only for one as this would have led to other conclusions.

Furthermore, the results for the non-subprime period are different to those of the other periods. Primarily, we find more bi-directional systems (27) than for the complete (6) and subprime (11) periods. To our mind, this fact is due to the different sizes of the data histories of the different periods. In addition, results for the complete and for the subprime periods behave nearly identical for the different Day-to-Day return intervals except for Monday when investigating the boxplots. In this context the non-subprime period seems to have a separate day-of-the-week effect on a Monday-to-Monday basis. Nevertheless the Friday day-of-the-week effect is a strong indicator for an information inefficiency of the markets. This Friday-to-Friday effect represents an anomaly in information processing of capital markets.

Another interesting aspect has to be mentioned when considering the detected feedback systems for weekly returns. All significant feedback systems that have been identified in the

[24] To analyze Granger-causality, again, we firstly perform the ADF and KPSS test to check the data for stationarity. All weekly returns satisfy this condition, whereby the results are available upon request.

complete and in the subprime period are no longer existent on daily returns. This effect has been investigated by McCrorie and Chambers (2006). They showed that less frequent data can lead to feedback systems even if there are only uni-directional causalities on a finer time grid. Against this background they conclude that less frequent data can generate spurious Granger-causalities. Our results confirm their findings in the sense that the relationship "CDS index return Granger-causes the Equity index return" of bi-directional systems for weekly returns obviously is a spurious lead-lag-relationship which is also inconsistent on different day-to-day intervals.

In an environment with no clear leadership the interaction between the returns is difficult to interpret. In consideration of the definition of Granger-causality a situation in which a CDS index return Granger-causes an Equity index return the forecast of the Equity index return can be significantly improved by taking into account the information embedded in the lagged values of the CDS index return. But this may not be interpreted in the sense that the CDS index return is leading the Equity index return by a pure cause-and-effect chain. Feedback system can have various causes. One explanation lies in the possible existence of a third unknown factor which leads both types of indices (see Granger (1969)). With respect to the results for the complete and subprime period there is evidence for a real leadership of the Equity index returns to the CDS index returns because these findings are confirmed on the finer daily time grid.

Summarizing all results, we conclude that our data of weekly returns is not appropriate for the analysis of lead-lag-relationships because of the day-of-the-week effect. Nevertheless, our findings provide an interesting insight into the relationship between the Equity and the CDS markets and the detected day-of-the-week effect can be used to generate additional profits.

7. Conclusion

We examined the behavior of the lead-lag-relationship between stock and CDS markets in Europe in the context of the subprime crisis. The results suggest that the information transfer from the stock to the CDS market shows a slightly increasing trend when changing from the non-subprime to the subprime period with, furthermore, a considerable higher number of detected significant Granger-causalities on a daily basis than on a weekly basis.

In most cases the leadership of CDS markets towards equity markets does not play an important role. In a lot of cases these systems would not have been selected if we would have applied a 1 % or a 5 % level of significance to the Granger-statistic. In general, we observe that daily data leads to more Granger-causalities than weekly data independent of a subprime or a non-subprime scenario.

The disappearance of all weekly feedback systems from the non-subprime to the subprime period is another interesting matter of fact and, according to the explanations above, provides a relevant breach of information transfer. In contrast, on a daily basis non-subprime feedback systems are reduced during the subprime crisis and their remains become manifest in one-sided systems in the subprime period where in most cases the equity index embeds information before the CDS index does.

Taking the complete sample into account we find negative stock return betas in all cases in the vector autoregression models when analyzing the daily data basis. The opposite is true for weekly data where nearly all stock return betas can be assumed to be positive such that we claim the weekly data behavior to be different in comparison to daily data. The latter result, however, should be interpreted with care since the weekly return series is biased by a day-of-the-week effect which leads to inconsistent results when assuming various Day-to-Day intervals. The day-of-the-week effect is an indication for information inefficiency of the considered markets which can be used for of development of portfolio management recommendations.

The cross continental impact is identified to be strong as well. There is an one-sided information transfer on a daily basis between Dow Jones Industrial Average and all iTraxx CDS benchmark indices and most iTraxx sector indices. Consequently, we conclude that there is no decoupling of European CDS indices and North-American economy. Concretely, the supersector equity indices (DJBanks, DJFinS, DJAuto, DJInd) provide most relationships on a daily basis and there are only a few relationships on a weekly basis.

Furthermore, the very important phenomenon of financial driven indices should be mentioned. If we consider equity or CDS indices, both types incorporating financials can be suggested to have a high interaction with other indices. Especially, in the subprime period financial equity and CDS indices cover a lot of relationships. These results imply the transfer of systematic risk information from one market to the other for financial indices to be sufficient. Finally, we detect statistical evidence for a strong leadership of equity markets towards CDS markets. Hence, we conclude that systematic risk information is carried from equity into the CDS market. This is the main finding (almost) regardless of the presence of a subprime period or a non-subprime period.

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Tables

Table 1

Overview of iTraxx European index series.

iTraxx	description		number of entities
Benchmark Indices	iTraxx Europe	European corporates	125
	iTraxx HiVol	Europe widest spread	30
	iTraxx Europe Crossover	Europe sub-investment grade	50
Sector Indices	Non-Financials	European Non-Financials	100
	Financials Senior	European Senior Financials	25
	Financials Subordinated	European Subordinated Financials	25

Table 2

Statistics for weekly and daily CDS index returns.

	Europe	Crossover	HiVol	Non-Financials	Financials Senior	Financials Subordinated
weekly data						
mean (in %)	0.61	0.49	0.69	0.60	1.37	1.25
st. dev.	0.07	0.06	0.08	0.07	0.13	0.11
skewness	0.35	1.27	0.56	0.70	4.88	0.92
kurtosis	4.91	7.19	5.03	6.74	50.40	6.87
$Q_{LB}(15)$	36.07^{***}	19.58	25.99^{**}	18.06	24.86^{**}	33.99^{***}
daily data						
mean (in %)	0.25	0.17	0.24	0.22	0.51	0.49
st. dev.	0.04	0.03	0.04	0.04	0.06	0.06
skewness	0.06	-0.18	-0.06	0.95	0.53	0.28
kurtosis	6.71	9.07	4.88	10.10	10.64	7.86
$Q_{LB}(19)$	31.18^{**}	10.95	34.96^{**}	49.37^{***}	36.86^{***}	41.92^{***}

Notes: The table contains moments and autocorrelation statistics for weekly and daily iTraxx CDS Index returns. Three asterisks stand for a rejection of the null hypothesis at 1% level of significance, two asterisks at 5% level of significance, and one asterisk at 10% level of significance. This notation holds for all statistical tests performed in this analysis.

Table 3

Statistics for weekly and daily Stock Index returns.

	IBEX	FTSE	STO	DJA	DAX	CAC	DJBanks	DJFinS	DJAuto	DJInd
weekly data										
mean (in %)	0.12	0.03	-0.05	-0.03	0.16	0.01	-0.12	0.05	0.19	0.08
st. dev.	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.04	0.06	0.04
skewness	-1.61	-1.14	-1.57	-0.79	-0.87	-1.36	-0.76	-0.69	4.48	-0.34
kurtosis	12.72	16.37	17.24	11.96	12.24	13.02	10.71	8.81	57.52	8.59
$Q_{LB}(15)$	61.53***	59.97***	67.65***	32.29***	43.36***	55.40***	44.00***	46.44***	35.33***	31.01***
daily data										
mean (in %)	-0.05	-0.04	-0.07	-0.05	-0.03	-0.07	-0.13	-0.11	0.01	-0.06
st. dev.	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.04	0.02
skewness	0.29	0.23	1.04	0.35	0.55	0.53	0.72	0.49	6.26	0.35
kurtosis	8.44	8.29	13.60	9.11	10.24	9.46	8.65	8.06	97.09	8.05
$Q_{LB}(19)$	41.66***	47.94***	36.89***	60.31***	34.44**	45.77***	34.46**	38.83***	56.99***	24.46

Notes: The table contains moments and autocorrelation statistics for weekly and daily Stock Index returns

Table 4

Results of the ADF and the KPSS test for weekly and daily returns for the whole sample period.

	weekly returns		daily returns	
index	ADF	KPSS	ADF	KPSS
iTraxx				
Europe	-1.048***	0.066	-0.873***	0.059
Crossover	-0.989***	0.040	-1.026***	0.052
HiVol	-1.039***	0.076	-0.812***	0.121*
NonFin	-1.024***	0.075	-0.790***	0.090
FinSen	-1.044***	0.086	-0.837***	0.066
FinSub	-0.945***	0.074	-0.813***	0.059
Equity				
IBEX	-1.239***	0.041	-1.055***	0.064
FTSE	-1.172***	0.026	-1.083***	0.042
STO	-1.259***	0.033	-1.071***	0.055
DJA	-1.102***	0.049	-1.149***	0.047
DAX	-1.148***	0.04	-1.041***	0.079
CAC	-1.185***	0.035	-1.106***	0.054
DJBanks	-1.107***	0.057	-0.936***	0.116
DJFinS	-1.143***	0.060	-0.990***	0.086
DJAuto	-1.261***	0.023	-0.917***	0.030
DJInd	-1.081***	0.053	-0.976***	0.081

Notes: The results for weekly and daily returns of ADF and KPSS test for the whole sample period are shown in this table with ADF and KPSS representing the particular statistics.

Table 5

Granger-causality tests (VAR(1)) for the whole sample period with "Equity returns Granger-cause CDS returns" according to equation (1)

Dependent Variable	Independent Variable	α_1	$\beta_{1,1}^{(stock)}$	$\gamma_{1,1}^{(CDS)}$	G-stat.
weekly data					
Crossover	IBEX	0.00	0.27^{***}	0.08	3.24^{*}
FinSub	FTSE	0.01	0.47^{***}	0.11	3.53^{*}
NonFin	DJAuto	0.01	-0.17^{**}	-0.08	4.33^{**}
daily data					
Crossover	IBEX	0.00	-0.27^{***}	-0.11^{***}	12.04^{***}
HiVol	IBEX	0.00	-0.21^{***}	0.13^{***}	5.24^{**}
NonFin	IBEX	0.00	-0.33^{***}	0.16^{***}	19.29^{***}
FinSen	IBEX	0.00	-0.39^{***}	0.12^{**}	9.43^{***}
FinSub	IBEX	0.00	-0.26^{***}	0.15^{***}	4.41^{**}
Crossover	FTSE	0.00	-0.24^{***}	-0.09^{***}	8.33^{***}
HiVol	FTSE	0.00	-0.17^{***}	0.15^{***}	3.26^{*}
NonFin	FTSE	0.00	-0.30^{***}	0.17^{***}	14.95^{***}
FinSen	FTSE	0.00	-0.33^{***}	0.13^{**}	6.16^{**}
FinSub	FTSE	0.00	-0.22^{***}	0.16^{***}	2.97^{*}
NonFin	STO	0.00	-0.24^{***}	0.18^{***}	10.29^{***}
Europe	DJA	0.00	-0.72^{***}	0.04	60.88^{***}
Crossover	DJA	0.00	-0.62^{***}	-0.12^{***}	80.96^{***}
HiVol	DJA	0.00	-0.64^{***}	0.10^{***}	58.43^{***}
NonFin	DJA	0.00	-0.50^{***}	0.18^{***}	46.61^{***}
FinSen	DJA	0.00	-0.70^{***}	0.12^{**}	31.01^{***}
Crossover	DAX	0.00	-0.31^{***}	-0.12^{***}	15.26^{***}
HiVol	DAX	0.00	-0.23^{***}	0.13^{***}	6.22^{**}
NonFin	DAX	0.00	-0.35^{***}	0.16^{***}	22.04^{***}
FinSen	DAX	0.00	-0.41^{***}	0.12^{**}	10.24^{***}
FinSub	DAX	0.00	-0.38^{***}	0.14^{**}	9.03^{***}
Crossover	CAC	0.00	-0.27^{***}	-0.11^{***}	12.47^{***}
NonFin	CAC	0.00	-0.31^{***}	0.16^{***}	19.00^{***}
FinSen	CAC	0.00	-0.37^{***}	0.12^{**}	9.22^{***}
FinSub	CAC	0.00	-0.28^{***}	0.15^{***}	5.31^{**}
Europe	DJBanks	0.00	-0.13^{***}	0.08^{**}	3.41^{*}
Crossover	DJBanks	0.00	-0.20^{***}	-0.11^{***}	14.17^{***}
HiVol	DJBanks	0.00	-0.16^{***}	0.13^{***}	6.72^{***}
NonFin	DJBanks	0.00	-0.24^{***}	0.16^{***}	22.03^{***}
FinSen	DJBanks	0.00	-0.27^{***}	0.12^{**}	9.58^{***}
FinSub	DJBanks	0.00	-0.26^{***}	0.13^{**}	9.49^{***}
Crossover	DJFinS	0.00	-0.25^{***}	-0.12^{***}	14.28^{***}
HiVol	DJFinS	0.00	-0.15^{***}	0.14^{***}	3.62^{*}
NonFin	DJFinS	0.00	-0.27^{***}	0.16^{***}	18.89^{***}
FinSen	DJFinS	0.00	-0.29^{***}	0.12^{**}	7.50^{***}
FinSub	DJFinS	0.00	-0.28^{***}	0.14^{**}	7.57^{***}
NonFin	DJAuto	0.00	-0.13^{***}	0.19^{***}	12.18^{***}
Crossover	DJInd	0.00	-0.25^{***}	-0.11^{***}	12.01^{***}
HiVol	DJInd	0.00	-0.18^{***}	0.14^{***}	4.40^{**}
NonFin	DJInd	0.00	-0.26^{***}	0.17^{***}	14.37^{***}
FinSen	DJInd	0.00	-0.33^{***}	0.12^{**}	8.05^{***}
FinSub	DJInd	0.00	-0.23^{***}	0.15^{***}	4.14^{**}

Table 6

Granger-causality tests (VAR(1)) for the whole sample period with "CDS returns Granger-cause Equity returns" according to equation (2)

Dependent Variable	Independent Variable	α_2	$\beta_{2,1}^{(stock)}$	$\gamma_{2,1}^{(cds)}$	G-stat.
weekly data					
DJA	HiVol	-0.00	0.01	0.06**	5.75**
DJBanks	HiVol	-0.00	-0.01	0.10***	4.12**
DJBanks	NonFin	-0.00	-0.04	0.09*	3.05
DJInd	NonFin	0.00	-0.01	0.07*	3.29*
daily data					
STO	Europe	-0.00	-0.12***	-0.05**	5.05**
STO	HiVol	-0.00	-0.13***	-0.06***	6.28**

Table 7

Granger-causality tests (VAR(1)) for the whole sample period with "Feedback systems" according to the equations (1) and (2).

Dependent Variable	Independent Variable	$\alpha_{1/2}$	$\beta_{1/2,1}^{(stock)}$	$\gamma_{1/2,1}^{(CDS)}$	G-stat.
weekly data					
FinSub	STO	0.01	0.45***	0.12	3.56*
STO	FinSub	0.00	-0.30***	-0.04	3.65*
NonFin	DJA	0.01	-0.33***	-0.08	3.37*
DJA	NonFin	-0.00	-0.03	0.06**	4.90**
HiVol	DJAuto	0.01	-0.21***	-0.11	4.68**
DJAuto	HiVol	0.00	-0.20***	0.10*	3.23*
daily data					
Crossover	STO	0.00	-0.18***	-0.08**	5.43***
STO	Crossover	-0.00	-0.12***	-0.05***	3.79*
HiVol	CAC	0.00	-0.20***	0.14***	5.04**
CAC	HiVol	-0.00	-0.15***	-0.04**	2.73*
FinSen	STO	0.00	-0.22***	0.14**	3.03*
STO	FinSen	-0.00	-0.10***	-0.03	3.87**
FinSub	DJA	0.00	-0.69***	0.14**	33.07***
DJA	FinSub	-0.00	-0.13***	0.02	2.96*
FinSen	DJAuto	0.00	-0.21***	0.15**	11.70***
DJAuto	FinSen	0.00	0.10***	0.08**	9.07***
FinSub	DJAuto	0.00	-0.23***	0.15***	15.22***
DJAuto	FinSub	0.00	0.11***	0.08**	7.89***

Table 8

Results of the ADF and the KPSS test for weekly and daily returns for separated time periods.

	non-subprime period				subprime period			
	weekly returns		daily returns		weekly returns		daily returns	
index	ADF	KPSS	ADF	KPSS	ADF	KPSS	ADF	KPSS
iTraxx								
Europe	-0.939^{***}	0.184	-0.863^{***}	0.260	-1.075^{***}	0.187	-0.876^{***}	0.199
Crossover	-0.956^{***}	0.070	-0.862^{***}	0.198	-1.012^{***}	0.147	-1.043^{***}	0.127
HiVol	-0.845^{***}	0.198	-0.946^{***}	0.206	-1.091^{***}	0.153	-0.812^{***}	0.218
NonFin	-0.840^{***}	0.322	-1.033^{***}	0.179	-1.052^{***}	0.180	-0.783^{***}	0.253
FinSen	-1.067^{***}	0.226	-0.912^{***}	0.139	-1.059^{***}	0.306	-0.837^{***}	0.366
FinSub	-0.889^{***}	0.267	-0.942^{***}	0.187	-0.969^{***}	0.181	-0.813^{***}	0.251
Equity								
IBEX	-1.055^{***}	0.051	-1.052^{***}	0.287	-1.275^{***}	0.065	-1.061^{***}	0.065
FTSE	-1.106^{***}	0.032	-1.077^{**}	0.384	-1.179^{***}	0.049	-1.088^{***}	0.043
STO	-1.154^{***}	0.036	-1.081^{***}	0.359	-1.279^{***}	0.052	-1.075^{***}	0.051
DJA	-1.119^{***}	0.092	-1.109^{***}	0.441	-1.102^{***}	0.059	-1.153^{***}	0.046
DAX	-1.125^{***}	0.037	-1.057^{***}	0.290	-1.153^{***}	0.058	-1.050^{***}	0.067
CAC	-1.186^{***}	0.025	-1.083^{***}	0.313	-1.187^{***}	0.056	-1.112^{***}	0.051
DJBanks	-1.112^{***}	0.058	-1.077^{***}	0.284	-1.113^{***}	0.113	-0.935^{***}	0.139
DJFinS	-1.152^{***}	0.087	-0.986^{***}	0.197	-1.143^{***}	0.097	-0.997^{***}	0.099
DJAuto	-1.022^{***}	0.178	-1.102^{***}	0.101	-1.287^{***}	0.032	-0.916^{***}	0.030
DJInd	-1.059^{***}	0.049	-1.074^{***}	0.236	-1.089^{***}	0.074	-0.979^{***}	0.071

Notes: The results for weekly and daily returns of ADF and KPSS test for the non-subprime and the subprime period are shown in this table with ADF and KPSS representing the particular statistics.

Table 9

Granger-causality tests (VAR(1)) for the non-subprime period with "Equity returns Granger-cause CDS returns" according to equation (1)

Dependent Variable	Independent Variable	α_1	$\beta_{1,1}^{(stock)}$	$\gamma_{1,1}^{(CDS)}$	G-Stat.
weekly data					
FinSen	IBEX	0.00	-0.76^{***}	-0.08	6.92^{***}
FinSen	FTSE	0.00	-0.73^{***}	-0.09	4.71^{**}
FinSen	STO	0.00	-0.77^{***}	-0.09	5.85^{**}
FinSen	DJA	0.00	-0.66^{***}	-0.10^{*}	3.95^{**}
FinSen	DAX	0.00	-0.68^{***}	-0.09	7.08^{***}
FinSub	DAX	0.00	-0.44^{***}	0.07	4.36^{**}
FinSen	CAC	0.00	-0.57^{***}	-0.08	4.03^{**}
FinSen	DJFinS	0.00	-0.48^{***}	-0.10^{*}	3.71^{*}
FinSen	DJInd	0.00	-0.67^{***}	-0.09	6.98^{***}
FinSub	DJInd	0.00	-0.40^{***}	0.06	3.51^{*}
daily data					
Europe	IBEX	0.00	-0.26^{***}	0.27^{***}	4.92^{***}
Crossover	IBEX	0.00	-0.55^{***}	0.07^{***}	6.43^{**}
HiVol	IBEX	0.00	-0.29^{***}	0.09^{***}	4.51^{**}
FinSen	IBEX	0.00	-0.41^{***}	0.12^{***}	3.45^{*}
FinSub	IBEX	0.00	-0.49^{***}	0.14^{***}	8.55^{***}
Europe	FTSE	0.00	-0.29^{***}	0.27^{***}	3.57^{*}
Crossover	FTSE	0.00	-0.74^{***}	0.04^{**}	6.20^{**}
Europe	STO	0.00	-0.35^{***}	0.24^{***}	6.59^{**}
Crossover	STO	0.00	-0.76^{***}	0.03^{*}	8.64^{***}
HiVol	STO	0.00	-0.37^{***}	0.08^{***}	5.60^{**}
Europe	DJA	0.00	-0.74^{***}	0.28^{***}	28.32^{***}
Crossover	DJA	0.00	-1.82^{***}	0.11^{***}	70.30^{***}
HiVol	DJA	0.00	-1.08^{***}	0.15^{***}	51.73^{***}
NonFin	DJA	0.00	-0.69^{***}	-0.05^{***}	10.42^{***}
Europe	DAX	0.00	-0.35^{***}	0.22^{***}	7.81^{***}
Crossover	DAX	0.00	-0.69^{***}	0.03	8.87^{***}
HiVol	DAX	0.00	-0.37^{***}	0.06^{***}	6.95^{***}
FinSub	DAX	0.00	-0.55^{***}	0.13^{***}	10.20^{***}
Europe	CAC	0.00	-0.37^{***}	0.24^{***}	8.31^{***}
Crossover	CAC	0.00	-0.70^{***}	0.05^{***}	8.75^{***}
HiVol	CAC	0.00	-0.38^{***}	0.08^{***}	6.77^{**}
FinSub	CAC	0.00	-0.56^{***}	0.13^{***}	9.18^{***}
Europe	DJBanks	0.00	-0.28^{***}	0.26^{***}	5.21^{**}
Crossover	DJBanks	0.00	-0.59^{***}	0.05^{***}	6.38^{**}
HiVol	DJBanks	0.00	-0.30^{***}	0.09^{***}	4.73^{**}
Europe	DJFinS	0.00	-0.29^{***}	0.22^{***}	7.47^{***}
Crossover	DJFinS	0.00	-0.72^{***}	-0.03	13.79^{***}
NonFin	DJFinS	0.00	-0.24^{***}	-0.03^{**}	3.19^{*}
Europe	DJAuto	0.00	-0.15^{***}	0.31^{***}	3.23^{*}
Crossover	DJAuto	0.00	-0.28^{***}	0.14^{***}	3.12^{*}
FinSub	DJAuto	0.00	-0.28^{***}	0.12^{***}	4.46^{**}
Europe	DJInd	0.00	-0.23^{***}	0.25^{***}	3.67^{*}
HiVol	DJInd	0.00	-0.59^{***}	0.03^{*}	6.72^{**}
Crossover	DJInd	0.00	-0.30^{***}	0.06^{***}	4.86^{**}
NonFin	DJInd	0.00	-0.27^{***}	-0.05^{***}	3.13^{*}

Table 10

Granger-causality tests (VAR(1)) for the non-subprime period with “Feedback systems” according to the equations (1) and (2).

Dependent Variable	Independent Variable	$\alpha_{1/2}$	$\beta^{(stock)}_{1/2,1}$	$\gamma^{(CDS)}_{1/2,1}$	G-Stat.
weekly data					
FinSen	DJAuto	0.00	-0.38***	-0.09	3.16*
DJAuto	FinSen	0.01	0.00	0.06**	2.81*
FinSub	DJAuto	0.00	-0.31***	0.08*	3.23*
DJAuto	FinSub	0.01	0.01	0.08***	3.63*
HiVol	FTSE	0.00	-0.33***	0.09***	3.52*
FTSE	HiVol	0.00	0.11***	0.11***	2.77*
daily data					
FinSen	FTSE	0.00	-0.47***	0.13***	2.84*
FTSE	FinSen	0.00	0.04***	0.08***	5.56**
FinSub	FTSE	0.00	-0.73***	0.14***	12.06***
FTSE	FinSub	0.00	0.03***	0.09***	5.21**
FinSen	STO	0.00	-0.62***	0.12***	6.05**
STO	FinSen	0.00	0.02*	0.08***	4.92**
FinSub	STO	0.00	-0.68***	0.12***	12.76***
STO	FinSub	0.00	0.00	0.09***	3.68*
FinSen	DAX	0.00	-0.49***	0.12***	4.66**
DAX	FinSen	0.00	0.09***	0.08***	3.73*
FinSen	CAC	0.00	-0.64***	0.12***	7.14***
CAC	FinSen	0.00	0.01	0.09***	5.25**
FinSen	DJBanks	0.00	-0.52***	0.12***	5.46**
DJBanks	FinSen	0.00	-0.00	0.08***	4.27**
FinSub	DJBanks	0.00	-0.62***	0.12***	13.16***
DJBanks	FinSub	0.00	-0.02*	0.09***	3.23***
HiVol	DJFinS	0.00	-0.31***	0.06***	6.65**
DJFinS	HiVol	0.00	0.25***	0.22***	6.33**
FinSub	DJFinS	0.00	-0.37***	0.13***	6.27**
DJFinS	FinSub	0.00	0.14***	0.14***	5.39**
FinSub	DJInd	0.00	-0.43***	0.13***	6.99***
DJInd	FinSub	0.00	0.02*	0.11***	4.46**

Table 11

Granger-causality tests (VAR(1)) for the subprime period with “Equity returns Granger-cause CDS returns” according to equation (1)

Dependent Variable	Independent Variable	α_1	$\beta_{1,1}^{(stock)}$	$\gamma_{1,1}^{(CDS)}$	G-Stat.
weekly data					
Crossover	IBEX	0.01	0.41***	0.15**	3.94**
FinSub	FTSE	0.03	0.66***	0.10	2.82*
Crossover	STO	0.01	0.38***	0.14*	3.07*
FinSub	STO	0.03	0.66***	0.11	2.98*
HiVol	DJAuto	0.02	-0.26**	-0.20*	3.00*
daily data					
Crossover	IBEX	0.00	-0.26***	-0.12***	9.13***
HiVol	IBEX	0.00	-0.21***	0.13***	3.92**
NonFin	IBEX	0.00	-0.33***	0.17***	15.95***
FinSen	IBEX	0.01	-0.39***	0.12**	7.43***
FinSub	IBEX	0.01	-0.25***	0.15**	3.07*
Crossover	FTSE	0.00	-0.22***	-0.11***	6.37**
NonFin	FTSE	0.00	-0.30***	0.18***	12.18***
FinSen	FTSE	0.01	-0.32***	0.13**	4.81**
NonFin	STO	0.00	-0.24***	0.18***	8.15***
Europe	DJA	0.00	-0.71***	0.04	48.58***
Crossover	DJA	0.00	-0.60***	-0.14***	63.22***
HiVol	DJA	0.00	-0.63***	0.10**	45.40***
NonFin	DJA	0.00	-0.50***	0.18***	37.50***
FinSen	DJA	0.01	-0.71***	0.12*	26.25***
FinSub	DJA	0.01	-0.69***	0.14**	27.16***
Crossover	DAX	0.00	-0.30***	-0.13***	11.40***
HiVol	DAX	0.00	-0.22***	0.13***	4.53**
NonFin	DAX	0.00	-0.36***	0.17***	18.35***
FinSen	DAX	0.01	-0.41***	0.12*	7.89***
FinSub	DAX	0.01	-0.37***	0.14**	6.60**
Crossover	CAC	0.00	-0.26***	-0.13***	9.49***
HiVol	CAC	0.00	-0.19***	0.14***	3.65*
NonFin	CAC	0.00	-0.32***	0.17***	15.76***
FinSen	CAC	0.01	-0.36***	0.12*	6.94***
FinSub	CAC	0.01	-0.26***	0.15**	3.77*
Crossover	DJBanks	0.00	-0.20***	-0.13***	11.82***
HiVol	DJBanks	0.00	-0.16***	0.13***	5.20**
NonFin	DJBanks	0.00	-0.24***	0.16***	17.91***
FinSen	DJBanks	0.01	-0.26***	0.12*	7.48***
FinSub	DJBanks	0.01	-0.25***	0.14**	7.12***
Crossover	DJFinS	0.00	-0.23***	-0.13***	10.46***
NonFin	DJFinS	0.00	-0.27***	0.16***	15.24***
FinSen	DJFinS	0.01	-0.29***	0.12*	6.06**
FinSub	DJFinS	0.01	-0.28***	0.14**	5.73**
NonFin	DJAuto	0.00	-0.13***	0.19***	10.03***
Crossover	DJInd	0.00	-0.23***	-0.12***	8.94***
HiVol	DJInd	0.00	-0.17***	0.14***	3.19*
NonFin	DJInd	0.00	-0.26***	0.17***	11.46***
FinSen	DJInd	0.01	-0.33***	0.12*	6.62**
FinSub	DJInd	0.01	-0.22***	0.16***	2.87*

Table 12

Granger-causality tests (VAR(1)) for the subprime period with "CDS returns Granger-cause Equity returns" according to equation (2)

Dependent Variable	Independent Variable	α_2	$\beta_{2,1}^{(stock)}$	$\gamma_{2,1}^{(CDS)}$	G-Stat.
weekly data					
DJA	HiVol	-0.01	0.02	0.07^{*}	3.03^{*}
daily data					
STO	Europe	-0.00	-0.13^{***}	-0.05^{**}	4.27^{**}
STO	HiVol	-0.00	-0.14^{***}	-0.06^{***}	5.71^{**}
STO	FinSen	-0.00	-0.11^{***}	-0.03	3.95^{**}

Table 13

Granger-causality tests (VAR(1)) for the subprime period with "Feedback systems" according to the equations (1) and (2).

Dependent Variable	Independent Variable	$\alpha_{1/2}$	$\beta_{1,1/2}^{(CDS)}$	$\gamma_{1,1/2}^{(stock)}$	G-Stat.
daily data					
Crossover	STO	-0.00	-0.12^{***}	-0.06^{***}	3.37^{*}
STO	Crossover	0.00	-0.17^{***}	-0.09^{***}	3.77^{*}
FinSen	DJAuto	-0.00	0.10^{**}	0.08^{*}	7.50^{***}
DJAuto	FinSen	0.01	-0.20^{***}	0.14^{**}	9.52^{***}
FinSub	DJAuto	-0.00	0.11^{***}	0.08^{*}	6.64^{**}
DJAuto	FinSub	0.01	-0.22^{***}	0.15^{***}	12.12^{***}

Table 14

Comparison of the results for the complete period and the two sub-periods.

Information transfer from	complete period weekly/daily	non-subprime period weekly/daily	subprime period weekly/daily
Equity to CDS market			
IBEX	■/■■■■■	■/■■■■■	■/■■■■■
FTSE	■/■■■■■	■/■■	■/■■■
STO	□/■	■/■■■	■■/■
DJA	□/■■■■■	■/■■■■	□/■■■■■■
DAX	□/■■■■■	■■/■■■■	□/■■■■■
CAC	□/■■■■	■/■■■■	□/■■■■■
DJBanks	/□/■■■■■■	□/■■■	□/■■■■■
DJFinS	□/■■■■■	■/■■■	□/■■■■
DJAuto	■/■■■	□/■■■	■/■■■
DJInd	□/■■■■■	■■/■■■■	□/■■■■■
CDS to Equity market			
Europe	□/■	□/□	□/■
Crossover	□/□	■/□	□/□
HiVol	■■/■	■/□	■/■
NonFin	■■/□	■/□	□/□
FinSen	□/□	□/■	□/■
FinSub	□/□	□/□	□/□
Feedback Systems			
Europe	□/□	□/□	□/□
Crossover	□/■■	□/□	□/■■
HiVol	■/■	■/■	□/□
NonFin	■/□	□/□	□/□
FinSen	□/■■	■/■■■■■	□/■
FinSub	■/■■	■/■■■■■	□/■

Notes: A comparison of relationships in the complete and the split periods is shown in this table. A blank square denotes that no relationships are found containing the specified index. The number of black squares denotes the number of relationships found for the specified index. These results include Granger-causalities of higher lag order.

Figures

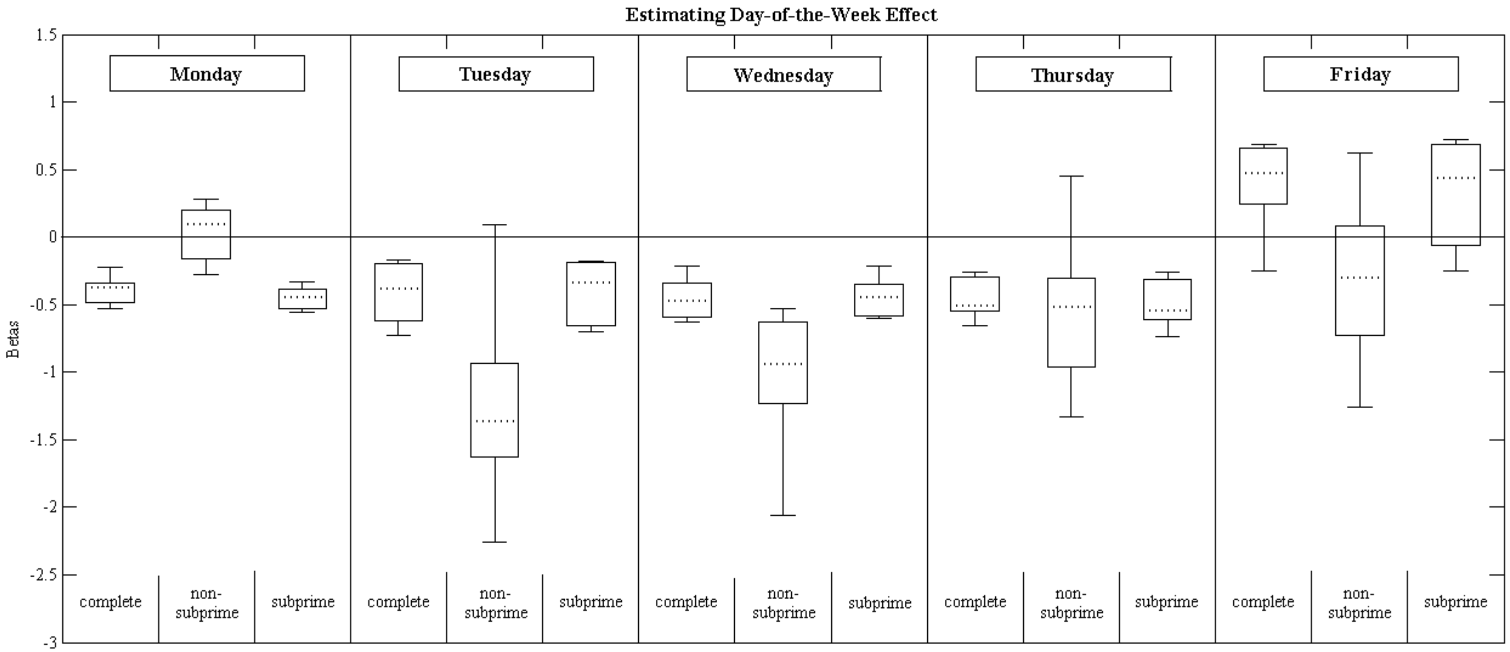

Fig. 1. The boxplots present lower, upper quartile and median (dot line) of the beta coefficients of the significant Granger-causalities. The lines above and below the boxes describe the range of the coefficients.