An Assessment of the Relationship between the Credit Default Swap Market and the Stock Market

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Abstract

Following in the footsteps of *Credit Default Swap and Equity Prices: the iTraxx CDS Index Market* (Byström, 2005), this paper investigates the link between the iTraxx credit default swap index market and the stock market. Similar to Byström's (2005) findings, a negative correlation between the iTraxx credit default swap indices and the stock price returns from a sample of companies matched to the credit derivatives indices was found. Furthermore, tendency of causality is found as firm-specific information is being embedded into stock price returns before it is embedded into credit default swap spreads. The existence of positive significant correlation between stock price volatility and credit default swap spreads was also confirmed. Finally, significant positive autocorrelation in the iTraxx credit default swap indices was found.

1. Introduction

In Section 1.1, a brief look at the importance and the changing attitude towards credit risk is addressed. Also, the birth of and increasing popularity around how the financial sector, and businesses in general, are making use of the credit default swap market will be addressed in Section 1.2. Furthermore, in Section 1.3, an explanation of the iTraxx credit default swap indices will be reviewed. In Section 1.4, a brief look at the critiques of the credit default swap market is reviewed. Finally, in Section 1.5, the structure of this paper will be addressed.

1.1 Credit Risk

Credit risk is defined as the probability that a party that takes on credit will not be able to meet their obligations. Due to the possibility of this occurring and depending on the size of the credit, the creditor could be subject to financial losses.

Credit risk can be monitored and measured by the yield on different kinds of bonds, such as sovereign or corporate bonds, because of its strong positive correlation with the size of the underlying credit risk. The higher the perceived credit risk, the higher the rate of interest investors will demand for lending their capital. Credit risk is therefore measured based on the creditors' overall ability to repay its debt.[1]

As attitudes towards credit risk have changed over time, its role in financing societies has rapidly gained importance. As a consequence of the encouragement given by government and financial institutions towards individuals and firms, a much milder approach towards credit risk has been established in the past 40 years.[2]

This relatively liberal attitude towards credit risk has increased the importance of credit valuators, such as Moody's, to give adequate credit valuations and information to investors and other participants in financial activities. Table 1.1 below, demonstrates Moody's Long-Term Corporate Obligation Ratings, which look at the relative credit risk of fixed-income obligations with maturities that are equal to or

[1] Özveren (2009), p. 5.
[2] Caouette, Altman, Narayanan (1998), p. 10.

exceed one year. Also, it addresses the likelihood of default and any financial loss suffered in the event of default.[3]

Table 1.1

Aaa	The highest quality of obligations, with minimal credit risk.
Aa	High quality of obligations and subject to very low credit risk.
A	Upper-medium grade obligations and subject to low credit risk
Baa	Medium-graded obligations that may possess certain speculative characteristics and are subject to moderate credit risk.
Ba	Obligations with speculative elements and are subject to substantial credit risk.
B	Speculative obligations that are subject to high credit risk.
Caa	Poor standing obligations that are subject to very high credit risk.
Ca	Speculative obligations that are likely in, or very near, default, with some prospect of recovery of principal and interest.
C	The lowest rated obligations, which are typically in default and with little prospect for recovery of principal or interest.

1.2 Credit Default Swap

One can identify two types of credit default swap. The first is single-name credit default swap. This is a credit derivative for which the reference entity is a single name. The other is a multi-name credit default swap. This is a credit derivative contract where the reference entity is at least one name. In this kind of derivatives contract, the investor will buy the contract and pay a periodic fee to the seller in order hedge against a potential default event. The higher the likelihood of a default event, the higher are the payments that are required from the investor. The investor will make this periodic payment to the seller until the event of default occurs or until the value of the underlying asset is obsolete. Moreover, the payoff is contingent on default by a single reference entity. This derivatives contract obtains the right to sell a

[3] Moody's Investors Service (2012)

particular bond issued by a company. Which is also known as the reference obligation.[4]

Mitigating and controlling for credit risk is one of the most age-old problems in banking. With the growing importance of credit risk and the changing attitudes towards it, a demand for several financial innovations has evolved through time. One of the financial innovations to mitigate credit risk was to use derivatives contracts.

Traditionally, derivatives were a way of betting on future values of an asset. For hundreds of years, farmers used derivatives to protect themselves from fluctuating crop prices. Through time, commodities traders used this type of derivative in order to mitigate losses from fluctuating oil, gas, gold and other commodity prices. However, implementing derivatives contracts in the credit market was a new concept, a concept that started during the mid-1990's as the innovation was based on reducing the riskiest parts of a loan and selling it to investors that might be willing to take on the riskiest parts in exchange for a high yielded return. The purpose was to address the problem of different kinds of credit risks that might be embedded in the financial activities. With this, a drive to implement a new kind of derivatives contract, namely credit default swap, came to light.[5]

The first trace of a huge credit default swap was engineered in the mid-1990's when JP Morgan granted a huge loan to Exxon after the oil company spilled enormous amount of crude oil near the state of Alaska. In other words, JP Morgan went in as an insurer for Exxon if the oil company were to default on their obligations. However, the problem for JP Morgan was that Exxon needed several billions of US-dollars in credits due to the oil spill and thousands of lawsuits that were filed against them. In order to mitigate the credit exposure and the risk that was embedded in the excessive loan that Exxon required, JP Morgan swapped some parts of the derivatives contract with investors that were willing to take on the riskiest credit exposure.[6] In this way, JP Morgan could take on credit it wanted and swap the riskiest parts of the derivatives contract that it did not want to be exposed to.

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4 Özveren (2009), p. 9.
5 PBS Frontline (2012)
6 Bloomberg Businessweek (2012)

This was made under the banner of mitigating risk and therefore the concept of credit default swap accelerated exponentially. It simply filled into every party's needs. The credit seller wanted to take on favorable credit exposure to make it easier for it to grant more credit to different kinds of credit buyers, such as private sector companies, pension funds and municipalities. Even sovereign states bought these new credit derivatives products. This was done because credit default swap was designed so that credit buyers who wanted easy leverage could do so without breaking any financial regulations. But the need did not stop there, the risk takers fancied these products since they were often valued as high graded products and at the same time, it gave them high yielded returns. According to several estimations, in 1998, the total size of the credit default swap market was roughly US$180 billion. A decade later, estimations and surveys conducted by Bank for International Settlements (BIS) shows that the size of the market at hand has increased to US$41 trillion.[7] This is a clear indication of the popularity for credit default swap during the past two decades.

1.3 iTraxx Credit Default Swap Indices

The popularity and importance of swapping credit derivatives contracts during the past two decades has lead to a demand and need for a credit default swap benchmark.

Credit default swap indices are relatively new financial instruments. It provides investors market-wide credit risk exposure and arbitrary advantages. There are several credit default swap indices. One of them is the iTraxx credit default swap index. It is a credit default swap benchmark that was created when two other credit default swap benchmarks, iBoxx and Trac-x, merged in 2004.[8] It covers the regions of Europe, Japan, Asia (excluding Japan) and Australia.[9]

In this paper, the focus is shifted toward the iTraxx Europe credit default swap index, which is also the most widely traded of all iTraxx credit default swap indices.[10] When it comes to the iTraxx Europe credit default swap index, it is worth mentioning the individual tranches that are embedded within the benchmark. Figure 1.1

[7] Stultz (2009), p. 78.
[8] Byström (2005), p. 2.
[9] Term (2009), p. 3.
[10] Bhar, Colwell and Wang (2008), p. 6.

demonstrates the individual tranches embedded in the iTraxx Europe credit default swap Series 7.[11]

Figure 1.1

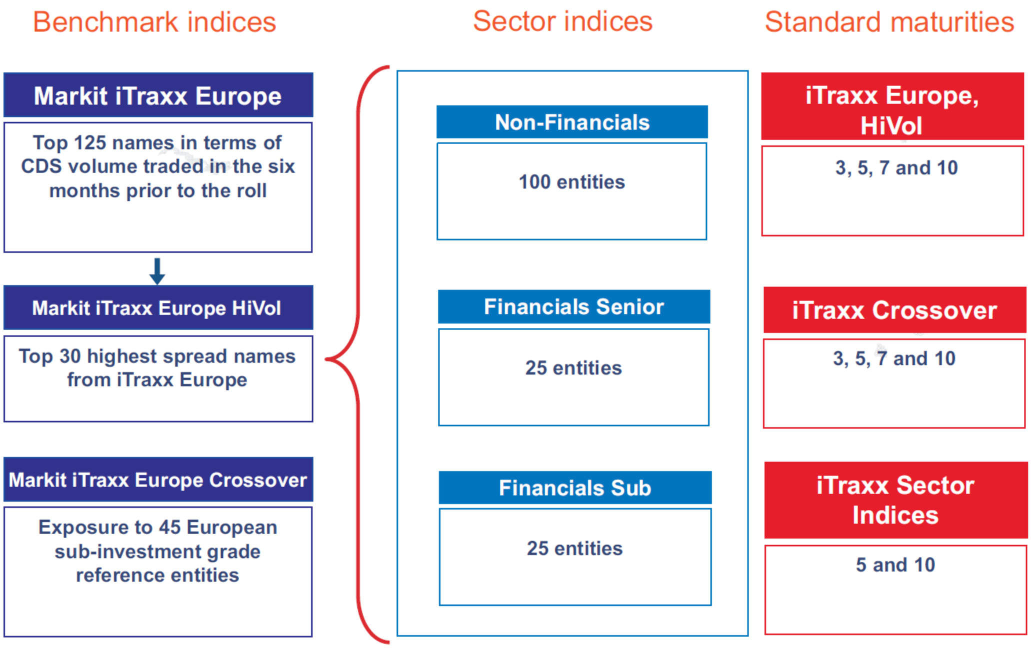

Figure 1.1: iTraxx Europe credit default swap indices. They are classified according to their portfolio composition in terms of sectors and credit spreads. In addition they come with different maturities. Every six months, the index family is rolled into a new series, thereby ensuring that the underlyings are liquidly traded. The figure is reproduced from a presentation by Markit on iTraxx credit default swap Europe Indices Series 7.

Figure 1.1 shows how one should depict the iTraxx Europe credit default swap indices. First, the family is classified according to the liquidity of the benchmark itself (that is the iTraxx Europe credit default swap). Second, they are classified in their probability of defaulting (iTraxx Europe HiVol and iTraxx Europe Crossover). Third, the classification continues through the sectors in which one is investing in (Non-financials, Financial Senior, Financial Sub). Finally, the classification ends with the maturity of the indices (three to ten years, depending on the index). [12]

However, the iTraxx credit default swap Europe indices Series 7 is an obsolete series. In March 2012, Series 17 was released after several changes had been made e.g. merging *the autos* and *the industrials* indices into a common index and abolishing two

[11] Term (2009), p. 3.
[12] Term (2009), p. 3.

different financial indices as a new *financial* index was created. This replaced *the senior financials* and *the sub financial* indices. Furthermore, new companies where added to the different sectorial credit default swap benchmarks.[13] Table 1.2 demonstrates the iTraxx Europe credit default swap Series 17 components.

Table 1.2

Sector	Number of companies
Autos and Industrials	30
Consumers	30
Energy	20
Financials	25
TMT	20

Table 1.2 demonstrates the number of companies for individual iTraxx credit default swap indices. *The autos* and industrial sectors consist of companies such as BMW, Siemens and Volkswagen. *The consumers* sectorial index is made up of companies such as Electolux, Danone and Nestle while *the energy* sectorial index is made up of companies such as E.ON, Fortum and Statoil. *The financials* sectorial index is a combination of 25 companies including Banco Santander, Commerzbank and Lloyds Bank. *The TMT* sectorial index, which stands for *telecommunications, media and technology*, has companies such as Pierson, Ericsson and Telecom Italia completing the index.

With the help of the diverse iTraxx credit default swap indices, one can exploit the credit default swap market expectations by executing relative-value trades between sectors, buying single-names versus their sector or even constructing tailored synthetic credit risky portfolios, such as collateralized debt obligations (CDO), using risk-free covered bonds together with a position in a suitable iTraxx credit default swap index. In other words, the introduction of liquid and tradable credit default swap indices has made it possible for a new generation of financial innovations, derived from credit derivatives products, based on the iTraxx credit default swap indices. Moreover, there is a possibility that the index at hand might outperform standard single-name credit default swap in the near future.[14]

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[13] Markit (2012)
[14] Byström (2005), p. 4.

1.4 Critiques of the Credit Default Swap Market

The main critique against using derivatives as a means to mitigate credit risk is that it might paradoxically increase risk. Even though credit default swap were not the epicenter of the current global financial crisis, critics claim that it is not entirely in the periphery of the crisis.

As explained in Section 1.2, one can think of credit default swap as an insurance policy. Under banking regulations, the insurance seller has to set aside a certain amount of capital relative to the size of the actual loan in the event of the loan is not paid in hundred percent as one would expect. However, an aspect of the credit derivative is that the credit default swap seller does not need to set aside some capital reserve. Many believe that credit default swap were designed to take advantage of this regulatory arbitrage. Empirical evidence has shown that when there is a loophole and minimal regulatory oversight in the financial market, capital and activity seem to go into that market, causing it to expand dramatically. In other words, the ambiguity made it possible to treat credit default swap as an over-the-counter derivative, where there is little or no regulatory oversight of the market.[15] Nobody really knows who owes what to whom and sometimes even when the maturity of the underlying asset is set to expire.

With this in mind and the notion that banks and other financial institutions could buy and sell credit default swap to offload credit risk and free up capital, critics believe that this was the main reason why investment banks chose to implement the same idea into the mortgage market. The idea was that house prices in the United States would never go down and using credit default swap in the mortgage market would create a financial holy grail, which is to create an asset with high credit rate with the underlying asset having high yielded returns. Credit default swap fueled the mortgage market that eventually turned into a financial bubble.[16]

[15] PBS Frontline (2012)
[16] Arentsen, Mauer, Rosenlund, Zhang and Zhao (2012), p. 18.

1.5 Structure of the Paper

In Chapter 2, Section 2.1, a brief look at the most popular measurements of the relationship between credit cost and stock returns is addressed. In Section 2.2, the purpose of this paper will be underlined. The explanation of the data set will be addressed in Section 2.2. The estimation inferences of the relationship between the iTraxx credit default swap indices and its compatible stock return indices in general is addressed in Chapter 3.

2. Fundamentals

Since the Merton (1974) model is the most favorable credit risk model based on the movements in the stock markets, the model is briefly reviewed in Section 2.1, along with other credit risk measurers. Section 2.2 addresses the purpose of this paper, where most of the focus will be the relationship between credit default swap spreads and the stock price return movements. The methods used in this paper to estimate this relationship are also addressed. In Section 2.3, a descriptions of the data, as well as the sample quotes components, are addressed.

2.1 Credit Risk Measurements

As implied in Chapter 1, credit risk is associated with the underlying reference entity and quantifying the amount of credit risk is a crucial parameter when measuring credit default swap valuation. An investor can make strategic investments based on credit risk measurements. There are several ways for investors to follow credit risk. Some of them rely on rating agencies and/or traditional scoring models that use accounting information. Also, extracting information from markets that have acknowledged credit risk embedded in the market prices is an alternative way of measuring credit risk.[17]

Hull, Predescu and White (2004) used the assumption that credit risk is embedded in the market to show that the credit default swap spread is approximately equal to the difference between the par yield on a risky bond and the par yield on a riskless bond with the same maturity, $s = y - r$. They argue that this relationship must hold under an assumption of no arbitrage in the market. If $s > y - r$, an actor in the market could make a risk-free profit by going long in a risk-free bond, shorting a corporate bond and selling the credit default swap connected with the bond. Similarly if $s < y - r$, arbitrage can be made by shorting a risk-free bond at the same time as buying a risky bond and the credit default swap connected with the bond. This relationship shows a strong theoretical link between credit default swap spreads and corporate bond spreads.[18]

[17] Byström (2005), p. 4.
[18] Gripsten and Bergström (2007), p. 5.

The most well-known stock market based credit risk model is the Merton (1974) model. Using this model, an assumption has to be made that a company has a certain amount of zero-coupon debt that will become due at a future time T. If the value of its assets is less than the promised debt repayment at time T, the company will default on its obligations. The equity of the company is a European call option on the assets of the company with maturity T and a strike price equal to the face value of the debt.[19] The model can be used to estimate either the risk-neutral probability that the company will default or the credit spread on the debt. The Merton (1974) model has been extended and applied on other assets and markets, such as Black and Cox (1976), Geske (1977), Longstaff and Schwartz (1995), Leland and Toft (1996), and Collin-Dufresne and Goldstein (2001), but none has emerged as clearly superior.[20]

Furthermore, simplified versions of the Merton (1974) model has also been introduced. Byström (2003) used the *Credit Grades*™ model, where the default probability is a simple function of the stock price volatility and the leverage ratio. Simplifications of the default probability expression in the *Credit Grades*™ model can actually be found in the earlier papers made by Hall and Miles (1990) and Clare and Priestley (2002).[21]

To implement the Merton (1974) model, one requires the current value of company's assets, the volatility of the company's assets, the outstanding debt, and the debt maturity as inputs. One popular way of implementing the Merton (1974) model is to estimate the current value of the company's assets and the volatility of the assets from the market value of the company's equity and the equity's instantaneous volatility using an approach suggested by Jones et *al* (1984). A debt maturity date is chosen and debt payments are mapped into a single payment on the debt maturity date in some way.[22]

Making an empirical linkage between the stock market valuations and the credit default swap market is also adequate. This is the case because the most important determinant of the credit default swap prices is the likelihood that a credit event

[19] Merton (1973), p. 22.
[20] Hull, Nelken and White (2004), p. 3.
[21] Byström (2005), p. 4.
[22] Hull, Nelken and White (2004), p. 3.

involving the underlying reference entity occurs. Also, when it comes to the theory of the Merton (1974) model, the model indicates that the probability of a firm defaulting should be linked to the stock market valuation as well as the stock price return volatility of the reference entity.[23]

2.2 Purpose

Following in the footsteps of Byström's (2005) paper: *Credit Default Swap and Equity Prices: the iTraxx CDS Index Market,* this study will investigate the relationship between the iTraxx credit default swap indices and the stock price movements of the underlying entities. Studying this relationship is important because of the predictions made by the Merton (1974) model. One should expect a negative correlation between the credit default swap indices and the stock market valuation. That is, the credit default swap indices spread should appreciate when the stock market valuation is depreciating and vice versa.[24] This negative relationship was found by Byström (2005) and has ever since been an important guideline for studying the iTraxx credit default swap indices.

Applying similar methods as Byström (2005), this paper will implement the method using the list of iTraxx Europe credit default swap Series 17 alongside created stock market price returns indices that match the different credit default swap sectorial indices. Also, three separated historical periods are implemented to find interesting behaviors from the relationship at hand. The methods used by Byström (2005) starts with both ordinary Pearson correlations and Spearman's rank correlations between credit default swap spreads, stock price returns and stock return volatilities. The next step is to estimate the degree of contemporaneous and cross-serial correlations between the iTraxx credit default swap market indices and the created stock price market indices by estimating the following empirical model:

[23] Byström (2005), p. 4.
[24] Byström (2005), p. 5.

$$rCDS_t = \beta_{0,t} + \beta_{1,t}\, rCDS_{t-1} + \beta_{2,t} r_t + \beta_{3,t} r_{t-1} + \varepsilon_t$$

where

- $rCDS_t$ = the percentage change in iTraxx credit default swap indices spread from $t - 1$ to t
- r_t = the percentage stock index return from $t - 1$ to t
- $\beta_{i,t}$ = regression coefficients
- ε_t = normally distributed error term

The exclusion of adding a proxy for a risk-free interest rate, such as the US Treasury bill rate or the British Banking Association London Interbank Offered Rate (BBA LIBOR), into the OLS regression is done on purpose since credit default swap are pure credit exposures without interest rate risk.[25]

One should expect a contemporaneously, but not serial, correlation between stock price returns and the credit default swap indices. This expectation is based on the assumption that information is simultaneously embedded into security prices in both markets. If the information is not simultaneously embedded into stock price and the credit default swap markets, a lead-lag relationship between these two markets can be observed.[26]

If the assumption of simultaneous information in the markets does not hold, a two-dimensional vector autoregression approach to identify causality will be implemented. A Granger-causality test between the iTraxx credit default swap indices and the compatible stock return indices will be studied with the following vector autoregression models:

$$\mathrm{rCDS_t} = \mathrm{a_1} + \sum_{j=1}^{k} \mathrm{b_{1p} rCDS_{t-p}} + \sum_{j=1}^{k} \mathrm{c_{1p} r_{t-p}} + \varepsilon_1$$

$$\mathrm{r_t} = \mathrm{a_2} + \sum_{j=1}^{k} \mathrm{b_{2p} rCDS_{t-p}} + \sum_{j=1}^{k} \mathrm{c_{2p} r_{t-p}} + \varepsilon_2$$

The Wald test is implemented in order to see if the assumptions of parameter restriction $\mathrm{b_{1p}} = \mathrm{b_{2p}} = 0$ and $\mathrm{c_{1p}} = c_{2p} = 0$ hold. If the restriction does not hold,

[25] Byström (2005), p. 5.

[26] Byström (2005), p. 6.

one cannot reject the possibility that Granger causality between the variables at hand occurs.

After using a Granger causality test, the problem of serial correlation in the residuals becomes very real. To tackle this problem, one needs to add adequate number of lags to the vector autoregression model. The Akaike information criterion is used to determine the number of lags (up to ten lags) so that the risk for serial-correlation in the residuals can be dealt with efficiently. Finally, the Lagrange-Multiplier multivariate test for autocorrelation is used to see if there is any serial-correlation in the residuals in the vector autoregression models.

2.3 Data

To adequately study the relationship between the iTraxx credit default swap indices and the stock market price returns, indices are created based on the individual sectors in the Series 17 credit default swap indices.[27] Table 1.2 demonstrates the components of the Series 17 final company groups. The credit default swap returns and stock price return quotes are available at Thomson Reuters Datastream program. However, some companies were found to be unsuitable candidates for the sample. The reasons for their exclusion vary e.g it could be because some companies in the iTraxx credit default swap Series 17 indices are not traded in the stock market and therefore it is impossible to use those companies when creating stock market sectorial indices that should match the iTraxx credit default swap indices. Another reason is the problem of data sampling, where it can be difficult to find adequate credit default swap or stock price quotes for some companies. Other problems such as historical duration, premature expiration dates of the companies' sampling period etc., making it inadequate for a minority of companies to be included in this paper. Table 2.1 lists the companies that are excluded from the different iTraxx credit default swap indices and the compatible stock market sectorial indices.

[27] Markit (2012)

Table 2.1

Sector	Excluded companies
Autos and Industrials	• Atlantia S.p.A • Daimler AG • Glencore International AG • Lanxess AG • PostNL • Sanofi S.A. • Vinci S.A.
Consumers	• Next Plc • SABMiller Plc • Safeway Inc. • Sodexo S.A.
Energy	• BP Plc • Centrica Plc • EnBW Energie Baden-Württemberg AG • GDF Suez S.A. • Royal Dutch Shell Plc • Vattenkraft AB
Financials	• Münchener Rückversicherungs-Gesellschaft AG • Swiss reinsurance Rückversicherungs-Gesellschaft AG
TMT	• British Sky Broadcasting Group Plc • British Telecommunications Plc • Telefonica S.A.

Table 2.1 lists the excluded companies from the different sectors that will add up to the iTraxx credit default swap sectorial indices and the compatible stock market indices. Out of 125 companies in the iTraxx credit default swap Europe Indices Series 17, only 22 companies were found to be not suitable for the sample, due to various reasons.

When it comes to the credit default swap quotes, they are based on five-year maturities for the underlying assets. The iTraxx credit default swap indices are equally weighted in their underlying single-name credit default swap contracts. This makes it reasonable to construct stock price return indices as equally weighted indices. Furthermore the sample credit default swap and/or stock price return quotes are based on the Euro currency. If not, they where converted into Euro. Both the credit default indices and the created stock price return indices are in a daily frequency, where the historical data starts from June 1, 2004 (when the first iTraxx credit default swap indices quotes were available) to June 30, 2012.

Moreover, three sub-periodic time spectrums are implemented. The first period, named *alpha*, has a historical time spectrum stretching from the sample periods beginning (June 1, 2004) to December 31, 2007. The second period, named *beta*, starts at January 1, 2008 to December 31, 2010. This period is a very turbulent one as it contains the event when the oldest investment bank on Wall Street, Lehman Brothers, filed for Chapter 11 bankruptcy protection on September 15, 2008. It was the event that shaped the financial crisis that many regions of the world, especially in Europe, are facing today. Another major event during *the beta* sample period was the election of Barack Obama as the President of the United States. During the transition time, his first days at office were not an easy one as many major stock markets were experiencing devastating weeks and months. This led up to the credit crunch that Europe is exposed to even today. Therefore, estimation results during *the beta* period are expected to be relatively extreme compared to the other sub sample periods. The third and last sample period is named *omega*, were it starts from January 1, 2011 to June 30, 2012. Overall, one should expect negative correlation between stock price returns and credit default swap spreads.

3. Empirical Inferences

Section 3.1 describes the sample data and provides an explanation for the patterns identified in the iTraxx credit default swap indices and stock indices. This is done in terms of both level and logarithmic change. Also, some important events that might explain the behavior of the indices can be found in this section. In Section 3.2, ordinary Pearson correlation and Spearman rank correlation is implemented to find the general relationship between the indices at hand. Furthermore, finding correlations between the indices using lags and volatilities will be explained in this section. Finally, building on the findings of Section 3.2, an OLS-regression will be examined in Section 3.3. The inferences found in the OLS-regression and Section 3.2 in general will be strengthened by adding vector-autoregression models to check for causality between and amongst the credit derivatives and the equities markets.

3.1 Descriptive Statistics

Again, following the footsteps of the Byström's (2005) *Credit Default Swap and Equity Prices: the iTraxx CDS Index Market* this study applies the Phillips Perron test for stationarity in order to assess the data. The empirical results for the iTraxx credit default swap indices, matched stock price return indices and the stock indices volatilities are can be found in the Appendix. The Phillips Perron test indicates that most of the indices are non-stationary when looking at credit default swap and stock price indices levels (Tables X.1 and X.3). While in terms of returns, the indices are stationary (Tables X.2, X.4 and X.5).

Looking purely at the quotes of the credit default swap indices, it is clear that there different behavior is exhibited by the spreads, depending on which time horizons and sectorial indices are being analysed. Chart X.1 depicts *the financial* index, showing that the credit default swap spreads are somewhat stable during the sample time period of *alpha*. However, during the final months of the sample period, there are some volatile activities as the spread starts to widen. This can be explained by the fact that reports about house prices in the United States where unexpectedly starting to depreciate.[28] Since the financial markets of the United States and Europe are very intertwined, the reports of deteriorating house prices in the United States where very

[28] CNN Money (2007)

unpleasant for the named financial markets, leading to accelerated credit default swap spreads in both the United States and in Europe. In the sample period of *beta*, the volatile behavior in the credit default swap spread for *the financial* index is continuing and widening. The numerical evidence of the increasing volatility can be observed in Table X.1. The crash of Lehmann Brothers and the euro crisis in countries such as Greece are major events that define the large volatility and high spread quotes for *the beta* period. This highly volatile period is seen in other iTraxx credit default swap sectorial indices. A continuation of widening credit default swap spreads is taking place in *the omega* time period sample. As contagion risk of the financial crisis took part in many countries in Europe, the cost of borrowing was still very high throughout the financial sector. However, looking at the logarithmic return in Table X.2, it is clear that the volatile behavior of *the financial* index has declined. This is an indication that an adaption of high credit default swap prices was taking place throughout *the omega* sampling period. Also, many banks became subject to many stabilization programs such as the European Financial Stability Facility where big institutions such as International Monetary Fund, the European Union and the European Central Bank went in as guarantor to mitigate the volatile financial markets, including the credit default swap markets.[29] Furthermore, the decreasing logarithmic return volatility in *the omega* period seems to be the case in other sectorial iTraxx credit default swap indices.

Comparing the credit default swap indices with the corresponding stock return indices on a daily basis, found in Table X.4, the prior indices seem to be more volatile. This is the case since the credit default swap indices seem to have relatively extreme changes from one day to the next. In all sub sample periods, except for *the autos and industrials* index in *the beta* period, the largest recorded logarithmic daily changes are found in the credit default swap indices, when compared to the compatible stock return indices. Again, this is a sign of a rapid credit cost increases that were taking place during the financial crisis in Europe, especially during *the beta* period. The reason why *the autos and industrials* stock return index were more volatile compared to same sectorial credit default swap index is a result of the precarious situation that the auto sector, as well as the industrial sector, had in both the United States and Europe. The United States lost its position as the number one car making nation as the

[29] The New York Times (2011)

government where forced to be the major shareholder of General Motors when the company filed for Chapter 11 bankruptcy on June 1, 2009.[30] It is logical that such an event creates major uncertainty in the stock markets. In Europe, the United States government backed reconstruction of General Motors, meant that several European car making companies were on the hook as they needed to find new investors. During *the beta* period, and up to date for several companies, this resulted in massive stock selloffs and/or even bankruptcy. However, in the general sample period, the credit default swap spread changes and the stock returns seem to have identical extreme changes through all sectorial indices. In other words, in the long term, the changes seem to converge.

Finally, an assessment of possible serial correlation in both iTraxx credit default swap indices and the compatible stock return indices are made. Similar inferences found by Byström (2005) can be underlined in almost all sectorial indices, as well through the different time periods. In Table X.4, small Ljung-Box test statistics are found when looking at the stock return indices in *the alpha* period, indicating that there are no autocorrelation in the sample. However, during the most volatile period of the current financial crisis, *the beta* period, there seems to be some form of autocorrelation. The positive significant autocorrelation during *the beta* period indicates that there might be some inefficiency in the stock market, giving those investors that predicted index changes the best chance to make substantial profits.[31] In other words, stocks where traded in the cheap and therefore could lead to major profits for those investors that dared to invest in a volatile stock market. This can be seen when looking at the stock price of *the consumers* sectorial index in Chart X.6 of the Appendix. This pattern is found in all stock price sectorial indices. Looking at the iTraxx credit default swap indices, finding small Ljung-Box test statistics is an anomaly. In Table X.2, very large positive autocorrelation throughout time periods and sectorial indices seems to be the case. This inference underlines the case that was explained in Section 1.4, that critiques of the credit default swap believes that the then new financial innovative market was designed to take advantage of the regulatory arbitrage. That is, the strong positive autocorrelation can explain the exponential growth of the new credit

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[30] Bloomberg (2009)
[31] Byström (2006), p. 7.

derivatives market. Investors were looking for safe graded investments that gave high yielded returns. This was explained in Section 1.2. From a longer sample period perspective, both credit default swap and stock return indices have a significant positive autocorrelation throughout all sectorial indices. With this in mind, along with the inferences made by Byström (2005), the result of positive autocorrelation defines the long-run opportunity investors have in the stock market and the credit default swap market.

3.2 Correlation and Rank Correlation

Drawing assessments of correlation between credit default swap sectorial indices and the compatible stock indices, as well as three month stock volatilities in both level and return terms is an adequate step to take. Also cross-serial correlation in the return terms is developed. These are computed under the (ordinary) Pearson correlations and the Spearman rank correlations. The Spearman rank correlation looks at the similarity of rankings in two data series and the rank correlation coefficients are computed due to the fact that the various data comes from very different non-normal distributions.[32]

As expected, both the Pearson correlation and the Spearman rank correlation coefficients show that there is a significantly negative correlation between the credit default swap indices and its compatible stock indices in both prices and return perspectives. In fact, the cross-serial correlation is similarly significant for the relationship between the credit default swap spread and (one day) lagged stock returns. This one-way cross-serial correlation corresponds to the notion that information is flowing from the stock market to the credit default swap market and not vice versa. Also, the correlation between credit default swap indices and the stock return volatility is in general significantly positive. Except for *the financial* index, it is only in *the alpha* sub period that there seems to be non-significant correlation, indicating that trading credit default swap with equities as the underlying asset was not fully established in the stock market. This was briefly explained in Section 1.2. These correlation inferences are in line with the theory of the Merton (1974) model.[33]

32 Byström (2005), p. 9.
33 Byström (2005), p. 8.

3.3 OLS-Regressions and Granger Causality

Continuing with the correlation estimates, credit default swap spreads are regressed on their one-day lags, the stock return indices and the one-day lagged stock return indices. The results can be found in Table X.9. In general, the coefficients of the stock return indices are significantly negative. This is also the case when it comes to the coefficient of the lagged stock returns. These findings correspond to the inferences made in Section 3.2 where it is clear that there is a negative relationship between the cost of credit and the stock price valuation. Furthermore, the $F_{[3,d,f]}$ statistics are significant throughout the long-term indices and the sub-periodic indices. Explanatory power of the models (according to R^2) varies from 0.09 to 0.60, with most falling in the range of 0.25 to 0.40. This indicates that the explanation of the coefficients is relatively strong. Moreover, the OLS-regression supports the positive (6 and 12 lagged) autocorrelation found in Section 3.1 when looking at the size of the Ljung-Box statistics. In the OLS-regression, significant positive first-order autocorrelation is basically found in every iTraxx credit default swap sectorial indices, both in the long-run and in the sub-sample periods.

As explained in Section 3.2, it seems that the flow of information is going from the stock market to the credit default swap market and not vice versa. This raises an adequate question as to whether or not there might be some causality in the relationship between the iTraxx credit default swap indices and the compatible stock return indices. Using a two-dimensional vector autoregression approach in an attempt to identify possible causality is appropriate since it captures the lead-lag relationships within and between stationary variables. Also, it represents a simultaneous equation estimate where it captures the inter-temporal relationships simultaneously. In other words, because of the presence of lag-variables, the inclusion of lead-variables is not necessary for the vector autoregression model.[34]

As demonstrated in Table X.10, it is difficult to find a Granger causality test between the credit default swap indices and stock return indices in the long run. The same inferences can be made about *the beta* sub-period found in Table X.12. However, in *the alpha* sub-period (found in Table X.11), all of the sectorial indices seem to

[34] Norden and Weber (2004), p. 15.

suggest that the stock market is Granger causing the credit default swap market. Thus, this corresponds well to the findings in Section 3.2 that information is embedded first in the equities market and thereafter flows into the credit derivatives market. Seen in the empirical inferences presented in the Appendix section, the credit default swap and stock sectorial indices in *the alpha* period are relatively stable compared to the indices in the long-run sample period and *the beta* sub-period. Once there is high volatility and uncertainty in the markets, information hierarchy might be disturbed and thus causality in the markets is temporarily abolished.

This Granger causality between the credit default swap market and the stock market can be seen in three out of five sectorial indices in *the omega* sub period, Table X.13. The two sectors that do not follow this notion are *the financial* and *the TMT* industries. Again, the suggestion of uncertain periods can be a good explanation as to why *the financial* sub-periodic index does not have any Granger causality in *the omega* sub-period.

Similar results regarding the link between the credit default swap market and the stock market can be found in other papers such as Norden and Weber (2004) where one of the results of their paper was that the relationship between credit default swap spread changes and lagged stock returns in Europe, the United States and Asia were relatively more sensitive for low-graded firms than for high-graded firms.[35] Another paper made by Longstaff, Mithal and Neis (2003) discovered that there is significant, but different, information in the credit default swap and stock markets that can be used to forecast changes in the corporate bond markets. This means that information tends to flow first into the credit derivatives and equity markets and then into the corporate bond market.

Blanco, Brennan and Marsh (2004) found that firm-specific factors such as the entity's stock price and implied volatility have more of an impact on the credit default swap price than what they have on the corporate bond price.[36] These findings are similar to the ones found by Collin-Dufresne, Goldstein and Martin (2001). Using the Chicago Board Options Exchange VIX index, they argue that other aggregate factors

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[35] Norden and Weber (2004), p. 27.
[36] Blanco, Brennan and Marsh (2004), p. 34.

tend to be a more important determinant of the credit spread changes in the bond market than firm-specific factors.[37] Berndt, Douglas, Duffie, Ferguson and Schranz (2008) found that the Moody's KMV expected default frequency is an adequate explanation of the movements of the credit default swap spreads.[38] Before credit default swap were popular, or to some extent even known, Kwan (1996) made an investigation of the relationship between corporate bonds and stocks.[39] The relationship between them seems to be very similar to the relationship of credit default swap and stock market pricing. Campbell and Taksler (2002) identified an empirical link between rising idiosyncratic equity risk and increasing yields on corporate bonds relative to Treasury bonds. In the findings of their paper, firm-level volatility explains much of the variation in bond yields.[40] This is similar to the inferences found in Section 3.2.

Furthermore, using the Akaike information criterion to determine the number of lags to be included in the vector-autoregression models seems to be adequate. This can be said after using Lagrange-Multiplier multivariate, because every index in both long-term and all sub-periods does not have serial-correlation in their residuals.

[37] Collin-Dufresne, Goldstein and Martin (2001), p. 2204.
[38] Berndt, Douglas, Duffie, Ferguson and Schranz (2008), p. 44.
[39] Kwan (1996), p. 1.
[40] Campbell and Taksler (2002), p. 9.

4. Conclusion

Drawing assessments of the relationship between the iTraxx credit default swap sectorial indices and matched stock market sectorial indices in the long-term and different sub-time periods is the corner stone of this paper. Following the footsteps of Byström's (2005) paper: *Credit Default Swap and Equity Prices: the iTraxx CDS Index Market,* similar empirical inferences on this relationship are also found in this paper.

The conclusion that there is a significantly negatively correlation between the credit default swap indices and the stock market indices tends to show that investors should interpret appreciating (or depreciating) stock price valuation as a signal to be bearish (or bullish) about the credit costs of a company or a specific sector. Also, investors might make a wise choice by investing in the credit default swap market since there seems to be a strong positively significant autocorrelation in the market at hand. This concept is very much adequate in the stock market as well. Even though these markets are experiencing relatively volatile periods, the significant autocorrelation in these markets found in this paper underlines the Chinese word *pinyin*, which is the word for danger (or crisis) *and* opportunity.

The empirical inferences found when regressing credit default swap indices on their own one-day lags, the stock return indices and one-day lagged stock return indices can explain the firm-specific information embedded in stock prices before it is embedded into credit default swap spreads. This notion is strengthened with a Granger causality test. Moreover, a three-month stock volatility seems to be strongly positively correlated with the credit cost spread. All in all, these inferences are in line with the theory of the Merton (1974) model.

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Appendix

Table X.1

The five-year iTraxx credit default swap indices spreads in basis points over the time periods June 1, 2004 to December 31, 2007 for the α sub-periodic table, January 1, 2008 to December 31, 2010 for the β sub-periodic table and January 1, 2011 to June 30, 2012 for the ω sub-periodic table. This completes the time period for the general periodic table that starts at June 1, 2004 to June 30, 2012. The mean of the variable is indicated by μ, while σ is the standard deviation. *PP* indicates the Phillips Perron test for stationarity. 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

Credit Default Swap Indices Spreads
(basis points)

General Periodic Table

	μ	σ	Max	Min	PP (no trend)
Financials	70.62	52.95	217.73	8.61	-2,20
Autos & Industrials	106.76	71.29	371.06	31.80	-1.92
Consumers	93.70	46.05	252.93	33.65	-2.10
Energy	75.37	45.53	223.35	21.25	-2.24
TMT	95.06	37.76	218.74	42.00	-2.37

Sub Periodic Table

		μ	σ	Max	Min	PP (no trend)
	Financials	18.76	9.45	59.37	8.61	-1.58
	Autos & Industrials	50.69	10.37	87.06	32.70	-1.41
α	Consumers	51.44	9.90	75.83	34.13	-2.12
	Energy	34.13	7.98	67.36	21.92	-1.52
	TMT	60.52	7.75	80.12	41.77	-1.92
	Financials	112.60	31.39	218.14	46.09	-2.76*
	Autos & Industrials	144.12	59.67	371.06	66.39	-1.81
β	Consumers	121.51	31.18	253.29	76.44	-2.41
	Energy	107.71	31.97	223.11	60.89	-2.29
	TMT	119.11	25.33	219.01	69.40	-2.86**
	Financials	225.59	61.30	356.81	132.04	-1.22
	Autos & Industrials	153.32	34.10	239.07	109.91	-1.30
ω	Consumers	123.80	18.39	174.66	98.01	-1.59
	Energy	170.10	33.16	248.72	118.00	-0.72
	TMT	150.43	28.54	205.42	108.64	-1.10

Table X.2

The daily logarithmic change of the five-year iTraxx credit default swap indices spreads over the time periods June 1, 2004 to December 31, 2007 for the α sub-periodic table, January 1, 2008 to December 31, 2010 for the β sub-periodic table and January 1, 2011 to June 30, 2012 for the ω sub-periodic table. This completes the time period for the general periodic table that starts at June 1, 2004 to June 30, 2012. The mean of the variable is indicated by μ, while σ is the standard deviation. *Skew* indicates skewness, while *Kurt* indicates excess kurtosis. *PP* indicates the Phillips Perron test for stationarity. Also, *Q(6)* and *Q(12)* is the six-day lagged and twelve-day lagged Ljung-Box test for autocorrelation. Furthermore, 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

Credit Default Swap Indices Spread Changes
(daily log-returns)

General Periodic Table

	$\mu \cdot 10^2$	$\sigma \cdot 10^2$	Kurt	Skew	Max$\cdot 10^2$	Min$\cdot 10^2$	PP (no trend)	Q(6)	Q(12)
Financials	0.03	1.90	0.00	0.00	13.12	-53.96	-33.15***	200.30***	211.99***
Autos & Industrials	0.02	1.28	0.00	0.00	13.36	-23.66	-36.56***	126.85***	139.42***
Consumers	0.01	1.21	0.00	0.00	7.39	-6.69	-37.21***	93.94***	114.51***
Energy	-0.02	1.58	0.00	0.00	36.09	-11.62	-39.20***	51.46***	54.50***
TMT	0.01	1.25	0.00	0.00	8.86	-23.31	-38.58***	68.25***	74.82***

Sub Periodic Table

		$\mu \cdot 10^2$	$\sigma \cdot 10^2$	Kurt	Skew	Max$\cdot 10^2$	Min$\cdot 10^2$	PP (no trend)	Q(6)	Q(12)
	Financials	0.03	1.21	0.00	0.00	12.71	-5.10	-23.02***	45.76***	51.47***
	Autos & Industrials	0.01	1.00	0.00	0.00	13.36	-3.68	-25.87***	17.57***	29.06***
α	Consumers	0.00	0.91	0.00	0.00	6.84	-4.42	-25.18***	27.51***	45.25***
	Energy	0.02	0.94	0.00	0.00	7.40	-5.77	-27.09***	27.04***	28.45***
	TMT	0.00	0.85	0.00	0.00	6.41	-5.55	-20.90***	94.16***	111.27***
	Financials	0.07	1.57	0.00	0.03	13.12	-8.21	-14.97***	229.75***	237.20***
	Autos & Industrials	0.03	1.21	0.00	0.00	9.16	-6.18	-19.88***	95.09***	101.34***
β	Consumers	0.02	1.29	0.00	0.00	7.39	-6.69	-22.29***	43.90***	53.27***
	Energy	0.05	1.55	0.00	0.00	11.62	-10.71	-22.69***	38.05***	39.56***
	TMT	0.03	1.24	0.00	0.77	8.86	-8.70	-22.43***	44.04***	42.04***
	Financials	0.08	1.17	0.05	0.67	3.68	-4.09	-11.08***	93.07***	99.18***
	Autos & Industrials	0.05	0.88	0.01	0.00	2.95	-4.13	-15.81***	17.00***	25.73**
ω	Consumers	0.03	0.81	0.00	0.01	2.97	-3.92	-17.58***	7.61	13.28
	Energy	0.06	1.01	0.01	0.56	3.29	-3.16	-14.99***	24.54***	29.40***
	TMT	0.05	0.74	0.35	0.00	3.22	-2.39	-16.01***	14.58**	17.85

Table X.3

The stock price indices in level terms, normalized to start at one, over the time periods June 1, 2004 to December 31, 2007 for the α sub-periodic table, January 1, 2008 to December 31, 2010 for the β sub-periodic table and January 1, 2011 to June 30, 2012 for the ω sub-periodic table. This completes the time period for the general periodic table that starts at June 1, 2004 to June 30, 2012. The mean of the variable is indicated by μ, while σ is the standard deviation. *PP* indicates the Phillips Perron test for stationarity (with or without a trend and with four lags). 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

Stock Indices Levels (normalized to start at one)

General Periodic Table

	μ	σ	Max	Min	PP (no trend)	PP (trend)
Financials	0.97	0.39	1.75	0.25	-1.11	-2.03
Autos & Industrials	1.36	0.37	2.37	0.54	-1.52	-1.59
Consumers	1.10	0.25	1.64	0.67	-0.98	-1.49
Energy	1.45	0.33	2.16	0.95	-2.17	-2.26
TMT	1.04	0.17	1.41	0.74	-1.17	-2.00

Sub Periodic Table

		μ	σ	Max	Min	PP (no trend)	PP (trend)
	Financials	1.33	0.23	0.95	1.75	-0.42	-3.30*
	Autos & Industrials	1.45	0.35	2.17	0.96	1.59	-0.86
α	Consumers	1.27	0.23	1.64	0.95	0.44	-2.92
	Energy	1.55	0.34	2.16	1.00	0.02	-3.07
	TMT	1.18	0.12	1.41	0.93	-0.36	-2.56
	Financials	0.53	0.16	1.00	0.20	-2.87**	-2.40
	Autos & Industrials	0.77	0.94	1.20	0.54	-3.16**	-2.94
β	Consumers	0.71	0.12	1.00	0.48	-2.00	-3.07
	Energy	0.63	0.13	1.02	0.45	-2.94**	-2.31
	TMT	0.74	0.09	1.00	0.58	-2.90**	-2.79
	Financials	0.79	0.24	1.25	0.48	-0.72	-0.72
	Autos & Industrials	0.94	0.09	110	0.73	-1.68	-1.87
ω	Consumers	0.96	0.05	1.05	0.85	-1.88	-1.86
	Energy	0.86	0.11	1.07	0.68	-0.92	-1.80
	TMT	0.91	0.07	1.04	0.78	-1.48	-1.96

Table X.4

The daily logarithmic change of the stock indices over the time periods June 1, 2004 to December 31, 2007 for the α sub-periodic table, January 1, 2008 to December 31, 2010 for the β sub-periodic table and January 1, 2011 to June 30, 2012 for the ω sub-periodic table. This completes the time period for the general periodic table that starts at June 1, 2004 to June 30, 2012. The mean of the variable is indicated by μ, while σ is the standard deviation. *Skew* indicates skewness, while *Kurt* indicates excess kurtosis. *PP* indicates the Phillips Perron test for stationarity. Also, *Q(6)* and *Q(12)* is the six-day lagged and twelve-day lagged Ljung-Box test for autocorrelation. Furthermore, 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

Stock Indices Returns (daily log-returns)

General Periodic Table

	$\mu \cdot 10^2$	$\sigma \cdot 10^2$	Kurt	Skew	Max$\cdot 10^2$	Min$\cdot 10^2$	PP (no trend)	Q(6)	Q(12)
Financials	-0.01	1.39	0.00	0.00	36.46	-5.45	-44.31***	10.78*	25.97**
Autos & Industrials	0.01	0.99	0.00	0.00	16.67	-12.12	-46.93***	90.86***	107.75***
Consumers	0.00	0.58	0.00	0.00	5.65	-4.25	-44.54***	54.65***	66.17***
Energy	0.00	0.86	0.00	0.00	24.87	-3.40	-45.53***	26.46***	34.97***
TMT	-0.01	0.56	0.00	0.00	8.06	-3.22	-45.77***	61.47***	97.25***

Sub Periodic Table

		$\mu \cdot 10^2$	$\sigma \cdot 10^2$	Kurt	Skew	Max$\cdot 10^2$	Min$\cdot 10^2$	PP (no trend)	Q(6)	Q(12)
	Financials	0.01	0.48	0.00	0.03	1.82	-1.70	-29.65***	5.73	12.58
	Autos & Industrials	0.03	0.38	0.00	0.00	1.41	-1.75	-26.34***	9.18	27.73**
α	Consumers	0.02	0.30	0.00	0.00	1.32	-1.27	-27.13***	5.26	12.04
	Energy	0.03	0.35	0.00	0.00	1.14	-1.51	-27.01***	5.57	8.22
	TMT	0.01	0.33	0.00	0.00	0.99	-1.38	-26.58***	5.54	10.28
	Financials	-0.05	1.36	0.00	0.00	7.87	-5.45	-26.44***	8.60	16.94
	Autos & Industrials	-0.01	1.14	0.00	0.00	16.67	-12.12	-28.35***	34.03***	39.38***
β	Consumers	-0.01	0.65	0.00	0.00	2.56	-4.25	-26.95***	22.86***	30.01***
	Energy	-0.03	0.75	0.00	0.00	5.28	-3.40	-27.52***	22.34***	35.00***
	TMT	-0.01	0.59	0.00	0.26	3.98	-3.22	-27.53***	26.01***	50.45***
	Financials	-0.07	1.34	0.00	0.49	6.15	-5.34	-17.52***	13.80**	20.03*
	Autos & Industrials	-0.02	0.74	0.00	0.03	2.31	-3.19	-17.32***	11.46*	19.36*
ω	Consumers	-0.01	0.43	0.00	0.01	1.28	-1.67	-17.55***	9.57	13.97
	Energy	-0.04	0.64	0.00	0.19	2.27	-2.27	-17.40***	8.06	13.72
	TMT	-0.02	0.49	0.00	0.35	1.50	-1.83	-17.24***	10.49	13.64

Table X.5

The three-month stock indices return volatility over the time periods June 1, 2004 to December 31, 2007 for the α sub-periodic table, January 1, 2008 to December 31, 2010 for the β sub-periodic table and January 1, 2011 to June 30, 2012 for the ω sub-periodic table. This completes the time period for the general periodic table that starts at June 1, 2004 to June 30, 2012. The mean of the variable is indicated by μ, while σ is the standard deviation. *Skew* indicates skewness, while *Kurt* indicates excess kurtosis. *PP* indicates the Phillips Perron test for stationarity. 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

Stock Indices Return Volatility (3-month, on a daily basis)

General Periodic Table

	$\mu \cdot 10^2$	$\sigma \cdot 10^2$	Kurt	Skew	Max$\cdot 10^2$	Min$\cdot 10^2$	PP (no trend)
Financials	0.71	1.11	0.00	0.00	34.60	0.00	-41.71***
Autos & Industrials	0.46	0.82	0.00	0.00	15.81	0.00	-24.22***
Consumers	0.36	0.42	0.00	0.00	5.33	0.00	-40.38***
Energy	0.41	0.70	0.00	0.00	25.59	0.00	-42.20***
TMT	0.35	0.39	0.00	0.00	7.64	0.00	-38.78***

Sub Periodic Table

		$\mu \cdot 10^2$	$\sigma \cdot 10^2$	Kurt	Skew	Max$\cdot 10^2$	Min$\cdot 10^2$	PP (no trend)
	Financials	0.33	0.31	0.00	0.00	1.72	0.00	-18.11***
	Autos & Industrials	0.26	0.25	0.00	0.00	1.69	0.01	-26.37***
α	Consumers	0.51	0.46	0.00	0.00	3.04	0.00	-24.50***
	Energy	0.25	0.21	0.00	0.00	14.72	0.01	-25.82***
	TMT	0.56	0.47	0.00	0.00	3.01	0.01	-27.24***
	Financials	0.90	0.92	0.00	0.00	7.51	0.00	-24.83***
	Autos & Industrials	0.57	0.92	0.00	0.00	15.82	0.00	-14.74***
β	Consumers	0.44	0.44	0.00	0.02	4.03	0.00	-25.11***
	Energy	0.47	0.54	0.00	0.00	5.04	0.00	-23.47***
	TMT	0.39	0.40	0.00	0.00	3.79	0.00	-22.41***
	Financials	0.94	0.86	0.00	0.00	0.59	0.01	-17.00***
	Autos & Industrials	0.51	0.47	0.00	0.00	0.93	0.00	-18.59***
ω	Consumers	0.30	0.27	0.00	0.00	1.58	0.00	-20.90***
	Energy	0.46	0.40	0.00	0.35	2.20	0.00	-17.82***
	TMT	0.35	0.31	0.00	0.43	1.72	0.00	-19.48***

Table X.6

Correlation between the five-year iTraxx credit default swap in levels, stock indices in levels and stock indices return volatilities over the time periods June 1, 2004 to December 31, 2007 for the α sub-periodic table, January 1, 2008 to December 31, 2010 for the β sub-periodic table and January 1, 2011 to June 30, 2012 for the ω sub-periodic table. Correlation indicates ordinary Pearson correlation and Rank Correlation indicates Spearman rank correlation. 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

Correlations (Levels)

General Periodic Table

	Correlation		Rank Correlation	
	CDS-Stock	CDS-3MVol	CDS-Stock	CDS-3MVol
Financials	-0.88***	0.37***	-0.92***	0.46***
Autos & Industrials	-0.17***	0.30***	-0.16***	0.30***
Consumers	-0.74***	0.38***	-0.74***	0.38***
Energy	-0.44***	0.23***	-0.45***	0.26***
TMT	-0.75***	0.30***	-0.75***	0.27***

Sub Periodic Table

		Correlation		Rank Correlation	
		CDS-Stock	CDS-3MVol	CDS-Stock	CDS-3MVol
	Financials	-0.35***	0.31***	-0.68***	0.14***
	Autos & Industrials	-0.59***	-0.05	-0.64***	-0.06*
α	Consumers	-0.60***	0.00	-0.65***	0.25
	Energy	0.08**	0.01	-0.16***	0.00
	TMT	-0.15***	0.02	-0.14***	0.00
	Financials	-0.70***	0.24***	-0.76***	0.18***
	Autos & Industrials	-0.50***	0.24***	-0.59***	0.19***
β	Consumers	-0.67***	0.26***	-0.60***	0.26***
	Energy	-0.57***	0.16***	-0.72***	0.14***
	TMT	-0.48***	0.23***	-0.45***	0.23***
	Financials	-0.95***	0.33***	-0.95***	0.36***
	Autos & Industrials	-0.90***	0.30***	-0.83***	0.26***
ω	Consumers	-0.80***	0.18***	-0.70***	0.12**
	Energy	-0.91***	0.25***	-0.91***	0.29***
	TMT	-0.04***	0.11***	-0.04***	0.07***

Table X.7

Correlation between the five-year iTraxx credit default swap indices in changes, stock indices in changes and stock indices return volatilities over the time periods June 1, 2004 to December 31, 2007 for the α sub-periodic table, January 1, 2008 to December 31, 2010 for the β sub-periodic table and January 1, 2011 to June 30, 2012 for the ω sub-periodic table. Correlation indicates ordinary Pearson correlation and Rank Correlation indicates Spearman rank correlation. 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

Correlation (Changes)

General Periodic Table

	CDS-Stock	CDS-Stock(lagged)	CDS(lagged)-Stock
Financials	-0.62***	-0.08***	-0.14***
Autos & Industrials	-0.28***	-0.17***	0.08***
Consumers	-0.38***	-0.18***	-0.01
Energy	-0.52***	-0.11***	0.00
TMT	-0.43***	-0.13***	-0.01

Sub Periodic Table

		CDS-Stock	CDS-Stock(lagged)	CDS(lagged)-Stock
	Financials	-0.29***	-0.19***	-0.06*
	Autos & Industrials	-0.23***	-0.18***	0.00
α	Consumers	-0.23***	-0.15***	0.06*
	Energy	-0.05	-0.09***	0.00
	TMT	-0.26***	-0.17***	0.01
	Financials	-0.48***	-0.13***	-0.27***
	Autos & Industrials	-0.31***	-0.21***	0.10***
β	Consumers	-0.44***	-0.19***	-0.02
	Energy	-0.37***	-0.18***	-0.02
	TMT	-0.40***	-0.15***	-0.04
	Financials	-0.72***	-0.22***	-0.30***
	Autos & Industrials	-0.67***	-0.37***	0.02
ω	Consumers	-0.61***	-0.16***	-0.01
	Energy	-0.54***	-0.31***	-0.02
	TMT	-0.51***	-0.34***	0.07

Table X.8

Correlation between the five-year iTraxx credit default swap indices in changes, stock indices in changes and stock indices return volatilities over the time periods June 1, 2004 to December 31, 2007 for the α sub-periodic table, January 1, 2008 to December 31, 2010 for the β sub-periodic table and January 1, 2011 to June 30, 2012 for the ω sub-periodic table. Correlation indicates ordinary Pearson correlation and Rank Correlation indicates Spearman rank correlation. 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

Rank Correlation

General Periodic Table

	CDS-Stock	CDS-Stock(lagged)	CDS(lagged)-Stock
Financials	-0.38***	-0.20***	-0.20***
Autos & Industrials	-0.40***	-0.28***	-0.03
Consumers	-0.36***	-0.17***	0.00
Energy	-0.24***	-0.10***	0.02
TMT	-0.37***	-0.16***	-0.01

Sub Periodic Table

		CDS-Stock	CDS-Stock(lagged)	CDS(lagged)-Stock
	Financials	-0.20***	-0.18***	-0.04
	Autos & Industrials	-0.22***	-0.18***	-0.02
α	Consumers	-0.18***	-0.12***	0.05
	Energy	0.03	-0.06*	0.01
	TMT	-0.24***	-0.16***	0.02
	Financials	-0.47***	-0.22***	-0.28***
	Autos & Industrials	-0.49***	-0.33***	-0.03
β	Consumers	-0.45***	-0.21***	-0.02
	Energy	-0.39***	-0.14***	-0.05
	TMT	-0.45***	-0.18***	-0.04
	Financials	-0.68***	-0.23***	-0.27***
	Autos & Industrials	-0.61***	-0.30***	0.02
ω	Consumers	-0.56***	-0.18***	0.01
	Energy	-0.51***	-0.32***	-0.03
	TMT	-0.45***	-0.33***	0.14

TABLE X.9

The OLS-regressions of five-year iTraxx credit default swap indices spread returns regressed on its own one-day lag, the stock return indices and the one-day lagged stock return indices over the time periods June 1, 2004 to December 31, 2007 for the α sub-periodic table, January 1, 2008 to December 31, 2010 for the β sub-periodic table and January 1, 2011 to June 30, 2012 for the ω sub-periodic table. 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

$$rCDS_t = \beta_{0,t} + \beta_{1,t} rCDS_{t-1} + \beta_{2,t} r_t + \beta_{3,t} r_{t-1} + \varepsilon_t$$

OLS-regression

General Periodic Table

	$\beta_{0,t}$	$\beta_{1,t}$	$\beta_{2,t}$	$\beta_{3,t}$	R^2	$F_{[3,d,f]}$
Financials	1.39	0.29***	-0.80***	0.17***	0.44	551.08***
Autos & Industrials	1.87	0.22***	-0.39***	-0.14***	0.15	126.38***
Consumers	0.41	0.15***	-0.88***	-0.25***	0.20	170.73***
Energy	-1.83	0.13***	0.95***	0.08*	0.29	283.20***
TMT	0.31	0.13***	-0.96***	-0.17***	0.21	188.94***

Sub Periodic Table

		$\beta_{0,t}$	$\beta_{1,t}$	$\beta_{2,t}$	$\beta_{3,t}$	R^2	$F_{[3,d,f]}$
	Financials	2.84	0.36***	-0.68***	-0.24***	0.24	97.84***
	Autos & Industrials	3.65	0.10***	-060***	-0.38***	0.09	31.21***
α	Consumers	1.68	0.11***	-0.71***	-0.40***	0.09	29.14***
	Energy	2.59	0.18***	-0.13	-0.20**	0.04	12.70***
	TMT	0.96	0.09***	-0.65***	-0.35***	0.10	34.48***
	Financials	2.32	0.47***	-0.42***	0.14***	0.40	172.97***
	Autos & Industrials	1.71	0.32***	-0.36***	-0.12***	0.23	79.40***
β	Consumers	0.61	0.16***	-0.85***	-0.22***	0.24	83.88***
	Energy	0.73	0.14***	-0.75***	-0.24***	0.18	58.12***
	TMT	1.53	0.17***	-0.82***	-0.16**	0.20	65.69***
	Financials	1.47	0.34***	-0.55***	0.08*	0.60	181.86***
	Autos & Industrials	3.74	0.01**	-0.79***	-0.21***	0.51	130.64***
ω	Consumers	2.52	0.03	-1.13***	-0.17*	0.38	76.05***
	Energy	0.82	0.12**	-0.80***	-0.31***	0.37	70.98***
	TMT	2.43	0.10**	-0.75***	-0.35***	0.35	66.81***

TABLE X.10

The vector-autoregression model for the general periodic time spectrum to identify any causality between the five-year iTraxx credit default swap indices and the compatible stock return indices. The Wald test identifies the Granger causality between the variables at hand. With max ten lags, the Akaike information criterion determines the suitable lags for each vector-autoregression model. Also, the Lagrange multiplier test, which follows a chi-squared distribution, for serial-correlation in the residuals is implemented. The 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

	Financials		Autos & Industrials		Consumers		Energy		TMT	
	$rCDS_t$	r_t	$rCDS_t$	r_t	$rCDS_t$	r_t	$rCDS_t$	r_t	$rCDS_t$	r_t
Const	2.58***	-1.27***	2.43***	0.96***	0.64***	-0.25***	-1.58***	0.27***	0.91***	-0.70***
$rCDS_{t-1}$	0.42	-0.16	0.15	0.01***	0.15	0.00***	0.13	0.00***	0.14	-0.01***
$rCDS_{t-2}$	-0.04***	0.05*	0.01***	0.09	-0.02***	0.00***	0.01***	0.03**	0.02***	-0.01***
$rCDS_{t-3}$	-0.04***	0.02***	0.00***	-0.02***	-0.05**	0.04	0.00***	-0.02***	-0.02***	0.03
$rCDS_{t-4}$	-0.05**	0.06	-0.06*	-0.00***	-0.06*	-0.01***	-0.04***	-0.02**	-0.02***	0.02*
$rCDS_{t-5}$	0.01***	-0.47*	0.06*	-0.07	0.05*	-0.02*	0.01***	0.00***	0.05*	-0.03*
$rCDS_{t-6}$	0.04***	-0.03***	-0.06*	0.04*	-0.04**	0.01***	-	-	-0.06	0.00***
$rCDS_{t-7}$	-0.04***	-0.01***	0.04**	0.00***	0.01***	0.00***	-	-	-	-
$rCDS_{t-8}$	-	-	-0.03***	0.06	-0.05*	0.00***	-	-	-	-
$rCDS_{t-9}$	-	-	0.03***	0.00***	0.01***	-0.02***	-	-	-	-
$rCDS_{t-10}$	-	-	0.05*	-0.06	0.09	-0.00***	-	-	-	-
r_{t-1}	0.25	-0.10	-0.21	0.00***	-0.27	0.03***	0.06***	0.01***	-0.16	-0.00***
r_{t-2}	-0.02***	0.02***	-0.11	-0.17	-0.06***	-0.04**	-0.10*	-0.06*	0.12	-0.11
r_{t-3}	-0.05***	0.03***	-0.13	0.02***	-0.14	-0.06	-0.08**	0.01***	-0.07***	-0.04**
r_{t-4}	-0.02***	0.06*	-0.09	-0.09	-0.14	0.13	0.08**	0.10	0.05***	0.10
r_{t-5}	0.05***	-0.08	-0.12	-0.11	-0.04***	-0.04**	0.09**	-0.06*	0.01***	-0.10
r_{t-6}	0.08*	-0.04***	-0.11	-0.04**	-0.03***	0.01***	-	-	0.00***	-0.06*
r_{t-7}	-0.03***	-0.05**	-0.07*	-0.09	0.02***	0.06	-	-	-	-
r_{t-8}	-	-	-0.04***	0.01***	-0.10**	-0.00***	-	-	-	-
r_{t-9}	-	-	-0.06**	0.01***	0.04***	-0.05*	-	-	-	-
r_{t-10}	-	-	-0.05**	0.02***	0.04***	0.01***	-	-	-	-
Wald	274.83	90.66	227.02	204.04	171.17	94.43	70.91	35.34	91.61	80.07
R^2	11.63	4.16	9.82	8.91	7.66	4.35	3.28	1.66	4.20	3.69
LM	4.31***		9.60*		1.69***		3.00***		5.67***	

TABLE X.11

The vector-autoregression model for *the alpha* sub-period to identify any causality between the five-year iTraxx credit default swap indices and the compatible stock return indices. The Wald test identifies the Granger causality between the variables at hand. With max ten lags, the Akaike information criterion determines the suitable lags for each vector-autoregression model. Also, the Lagrange multiplier test, which follows a chi-squared distribution, for serial-correlation in the residuals is implemented. The 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

	Financials		Autos & Industrials		Consumers		Energy		TMT	
	$rCDS_t$	r_t	$rCDS_t$	r_t	$rCDS_t$	r_t	$rCDS_t$	r_t	$rCDS_t$	r_t
Const	1.87***	1.47***	1.88***	2.97	0.60***	1.53***	2.15***	3.32	0.29***	1.08***
$rCDS_{t-1}$	0.36	-0.04	0.10	0.01***	0.09	0.02**	0.17	0.00***	0.07*	0.01***
$rCDS_{t-2}$	-0.03***	0.02***	-	-	-	-	-	-	0.03***	-0.02**
$rCDS_{t-3}$	0.06***	0.02***	-	-	-	-	-	-	-	-
$rCDS_{t-4}$	-0.01***	-0.04	-	-	-	-	-	-	-	-
$rCDS_{t-5}$	0.06***	0.01***	-	-	-	-	-	-	-	-
$rCDS_{t-6}$	0.05***	-0.03**	-	-	-	-	-	-	-	-
$rCDS_{t-7}$	-0.08*	0.02***	-	-	-	-	-	-	-	-
$rCDS_{t-8}$	-0.08*	0.01***	-	-	-	-	-	-	-	-
$rCDS_{t-9}$	0.03***	-0.00***	-	-	-	-	-	-	-	-
$rCDS_{t-10}$	0.14	-0.05	-	-	-	-	-	-	-	-
r_{t-1}	-0.22	-0.04***	-0.41	0.05***	-0.41	0.01***	-0.21*	0.04***	-0.39	0.05***
r_{t-2}	-0.07***	-0.02***	-	-	-	-	-	-	-0.06***	-0.07*
r_{t-3}	-0.13***	0.03***	-	-	-	-	-	-	-	-
r_{t-4}	-0.03***	-0.06**	-	-	-	-	-	-	-	-
r_{t-5}	0.16*	-0.04***	-	-	-	-	-	-	-	-
r_{t-6}	0.05***	-0.01***	-	-	-	-	-	-	-	-
r_{t-7}	0.01***	-0.10	-	-	-	-	-	-	-	-
r_{t-8}	-0.19*	0.00***	-	-	-	-	-	-	-	-
r_{t-9}	0.08***	0.01***	-	-	-	-	-	-	-	-
r_{t-10}	0.01***	-0.01***	-	-	-	-	-	-	-	-
Wald	253.81	57.86	39.38	2.62***	30.62	3.76***	35.77	1.82***	36.42	7.93**
R^2(%)	21.55	5.89	4.05	0.28	3.18	0.40	3.69	0.19	3.76	0.84
LM	3.53***		4.04***		4.24***		1.69***		3.28***	

TABLE X.12

The vector-autoregression model for *the beta* sub-period to identify any causality between the five-year iTraxx credit default swap indices and the compatible stock return indices. The Wald test identifies the Granger causality between the variables at hand. With max ten lags, the Akaike information criterion determines the suitable lags for each vector-autoregression model. Also, the Lagrange multiplier test, which follows a chi-squared distribution, for serial-correlation in the residuals is implemented. The 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

	Financials		Autos & Industrials		Consumers		Energy		TMT	
	$rCDS_t$	r_t	$rCDS_t$	r_t	$rCDS_t$	r_t	$rCDS_t$	r_t	$rCDS_t$	r_t
Const	4.27***	-3.67***	1.14***	-0.58***	0.62***	-0.36***	2.79***	-3.61***	1.74***	-1.07***
$rCDS_{t-1}$	0.72	-0.37	0.24	-0.01***	0.15	-0.01***	0.16	0.02***	0.19	-0.02***
$rCDS_{t-2}$	-0.29	0.20	-0.05***	0.16	-0.03***	0.00***	0.00***	-0.10*	0.02***	-0.01***
$rCDS_{t-3}$	-	-	-0.01***	-0.06***	-0.08*	0.05*	-0.03***	-0.03***	-0.05***	0.05*
$rCDS_{t-4}$	-	-	-0.06***	0.02***	-0.08*	-0.18***	-0.08*	0.13	-0.03***	0.02***
$rCDS_{t-5}$	-	-	0.06***	-0.11	0.05***	-0.26***	0.05***	-0.08*	0.06***	-0.03***
$rCDS_{t-6}$	-	-	-0.08**	0.07**	-	-	-	-	-	-
$rCDS_{t-7}$	-	-	0.09*	-0.03***	-	-	-	-	-	-
$rCDS_{t-8}$	-	-	-0.08*	0.13	-	-	-	-	-	-
$rCDS_{t-9}$	-	-	0.05***	0.01***	-	-	-	-	-	-
$rCDS_{t-10}$	-	-	0.05***	-0.10	-	-	-	-	-	-
r_{t-1}	0.17	-0.09*	-0.19	-0.01***	-0.22	0.04***	-0.22	0.02***	-0.14**	0.01***
r_{t-2}	-0.08*	0.05***	-0.11	0.16	-0.10***	-0.06***	0.12***	-0.10*	0.12***	-0.11
r_{t-3}	-	-	-0.13	-0.06***	-0.17*	-0.04***	0.11***	-0.03***	-0.09***	-0.04***
r_{t-4}	-	-	-0.07***	0.02***	-0.15**	0.13	-0.12***	0.13	0.07***	0.11
r_{t-5}	-	-	-0.15	-0.11	-0.10***	-0.05***	-0.16*	-0.08*	-0.06***	-0.10
r_{t-6}	-	-	-0.09*	0.07**	-	-	-	-	-	-
r_{t-7}	-	-	-0.07**	-0.03***	-	-	-	-	-	-
r_{t-8}	-	-	-0.04***	0.13	-	-	-	-	-	-
r_{t-9}	-	-	-0.06***	0.01***	-	-	-	-	-	-
r_{t-10}	-	-	-0.05***	0.10	-	-	-	-	-	-
Wald	382.17	99.29	159.79	99.78	62.81	33.01	63.35	28.16	51.12	35.11
$R^2(\%)$	32.86	11.28	17.13	11.43	7.47	4.07	7.53	3.49	6.17	4.32
LM	1.36***		3.41***		10.49*		1.98***		7.86*	

TABLE X.13

The vector-autoregression model for *the omega* sub-period to identify any causality between the five-year iTraxx credit default swap indices and the compatible stock return indices. The Wald test identifies the Granger causality between the variables at hand. With max ten lags, the Akaike information criterion determines the suitable lags for each vector-autoregression model. Also, the Lagrange multiplier test, which follows a chi-squared distribution, for serial-correlation in the residuals is implemented. The 1%, 5% and 10% significance levels are indicated by ***, ** and *, respectively.

	Financials		Autos & Industrials		Consumers		Energy		TMT	
	$rCDS_t$	r_t	$rCDS_t$	r_t	$rCDS_t$	r_t	$rCDS_t$	r_t	$rCDS_t$	r_t
Const	5.60***	-6.66***	5.36***	-2.72***	3.96***	-3.90***	3.96***	-3.90***	4.19***	-2.34***
$rCDS_{t-1}$	0.80	-0.69	-0.06***	0.14*	0.10**	0.03***	0.98**	0.03***	0.02***	0.12
$rCDS_{t-2}$	-0.29	0.23*	0.00***	0.03***	-	-	-	-	-	-
$rCDS_{t-3}$	-	-	-0.04***	0.07***	-	-	-	-	-	-
$rCDS_{t-4}$	-	-	-0.01***	0.07***	-	-	-	-	-	-
$rCDS_{t-5}$	-	-	-	-	-	-	-	-	-	-
$rCDS_{t-6}$	-	-	-	-	-	-	-	-	-	-
$rCDS_{t-7}$	-	-	-	-	-	-	-	-	-	-
$rCDS_{t-8}$	-	-	-	-	-	-	-	-	-	-
$rCDS_{t-9}$	-	-	-	-	-	-	-	-	-	-
$rCDS_{t-10}$	-	-	-	-	-	-	-	-	-	-
r_{t-1}	0.24	-0.28	-0.44	0.21	-0.04	0.12*	-0.40	0.12*	-0.49	0.20
r_{t-2}	-0.02***	-0.01***	-0.02***	0.05***	-	-	-	-	-	-
r_{t-3}	-	-	-0.06***	-0.06***	-	-	-	-	-	-
r_{t-4}	-	-	-0.20*	0.12**	-	-	-	-	-	-
r_{t-5}	-	-	-	-	-	-	-	-	-	-
r_{t-6}	-	-	-	-	-	-	-	-	-	-
r_{t-7}	-	-	-	-	-	-	-	-	-	-
r_{t-8}	-	-	-	-	-	-	-	-	-	-
r_{t-9}	-	-	-	-	-	-	-	-	-	-
r_{t-10}	-	-	-	-	-	-	-	-	-	-
Wald	165.23	70.16	49.30	19.73*	43.06	4.09***	43.06	4.09***	47.38	13.01
R^2(%)	30.70	70.16	11.73	5.05	10.33	1.08	10.33	1.08	11.24	3.36
LM	7.96**		3.85***		2.46***		2.46***		0.92***	

Charts

The charts below are credit default swap indices (charts X.1, X.3, X.5, X.7 and X.9) and the compatible stock price indices (charts X.2, X.4, X.6, X.8 and X.10) for the five different sectors found in the iTraxx credit default swap indices Series 17. The y-axis on the charts is either credit default swap or stock price levels. The three sub-periodic time spectrums are defined in the x-axis.

Chart X.1

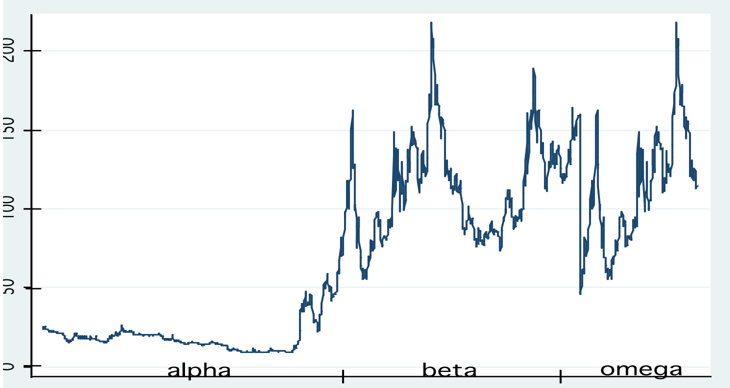

Chart X.2

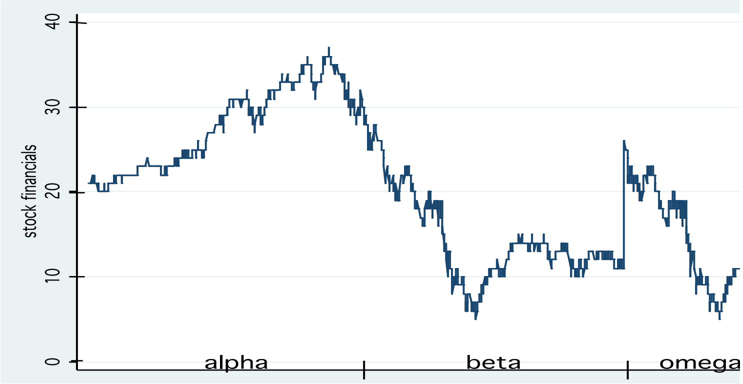

Chart X.3

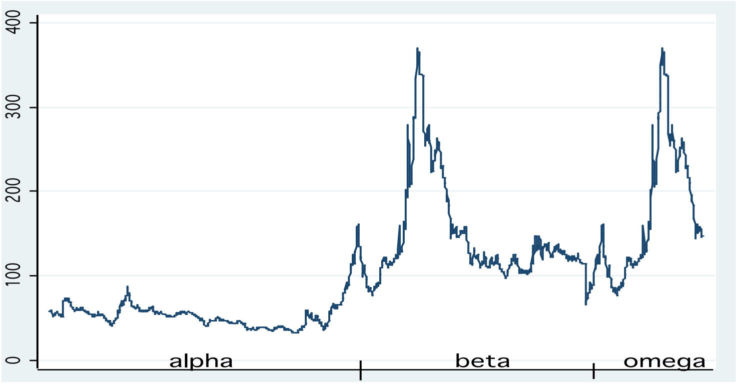

Chart X.4

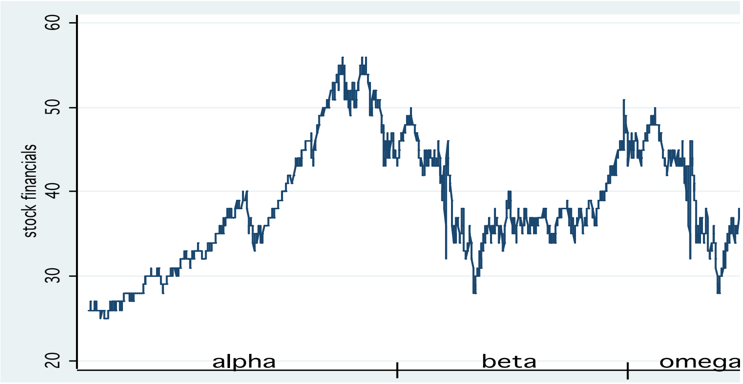

Chart X.5

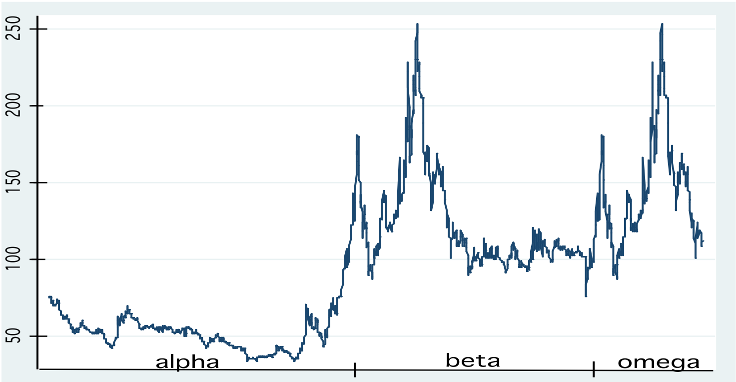

Chart X.6

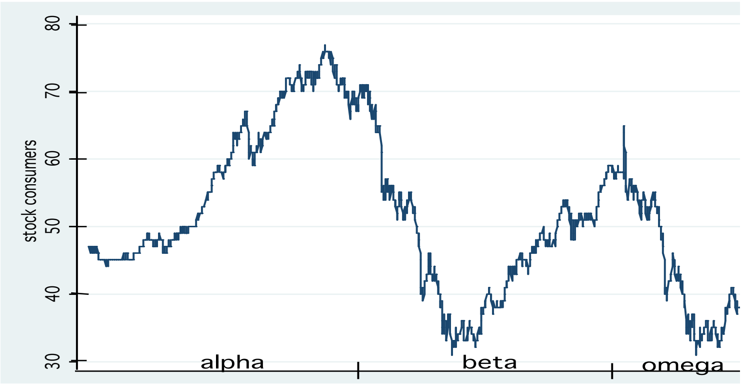

Chart X.7

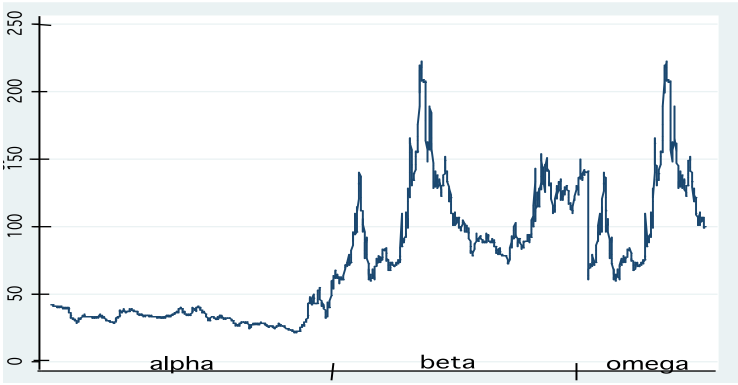

Chart X.8

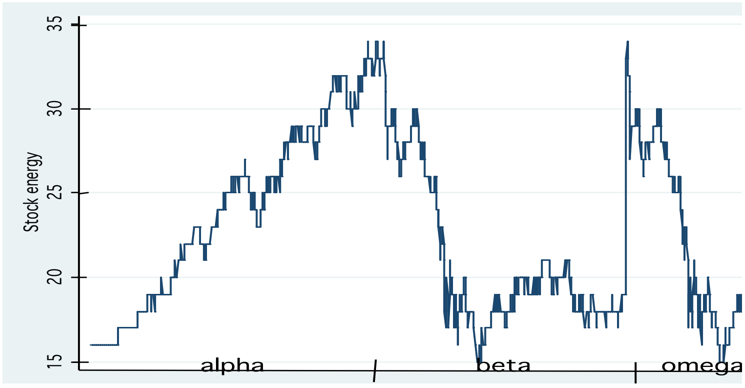

Chart X.9

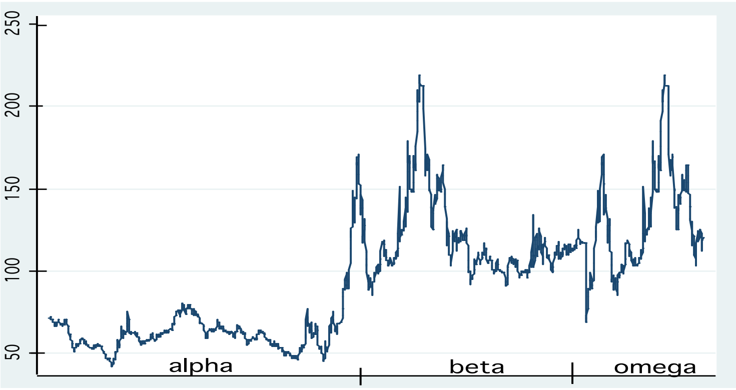

Chart X.10