Explaining Credit Default Swap Index Spreads - A Study of the iTraxx Index

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Abstract

In this paper we investigate the relationship between the European iTraxx spreads and the theoretical determinants suggested by the Merton model during the period from June 2004 to September 2006. The Merton model suggests that leverage, volatility and the risk-free rate should influence credit spreads. We use the returns on relevant equity indices, their historical volatility, the European volatility index VSTOXX and the German government 10-year yield as proxies for the respective variables. As predicted by the Merton model, we find the changes in the iTraxx spreads to be negatively related to changes in the equity index returns and the risk-free rate as well as positively related to changes in the volatility on the market. Furthermore, we are able to confirm the validity of the Merton model through a robustness test, including other variables to the regression. Nevertheless, the Merton model provides only limited explanatory power. By including a liquidity measure as well as adding the lag of the iTraxx spreads we are able to increase the explanatory power of the model substantially.

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1 Introduction

Credit risk can be defined as the risk of a bond issuer defaulting on its payments. Financial instruments designed to deal with credit risk, so called credit derivatives make it possible for investors and companies to manage and trade credit risk separated from other sources of risk. Credit derivatives currently constitutes one of the fastest growing areas in the financial markets [Hull *et al.* , 2004b].

The most common credit derivative is the Credit Default Swap (CDS), which allow bondholders to insure themselves against default of a specific bond issuer. The buyer of a CDS pays for the insurance by paying the seller a periodic fee, the so called *CDS spread*[1]. This spread can be seen as the market price of credit risk. CDSs represent almost half of the total trading volume of credit derivatives. Only during 2005 the notional amount of the CDS market grew from $6,4 trillion[2] to $14 trillion[3], more than doubling its size.

A majority of previous reports dealing with credit risk have used corporate bond spreads as a measure of credit risk. The CDS spreads have been found to be closely related to the corporate bond spreads both by theoretical and empirical studies.[4] Furthermore the CDS spreads have been identified in the literature as an interesting alternative measure of credit risk for several reasons; firstly using CDS spreads as an approximation of the price of credit risk does not require any additional assumption about a risk-free benchmark rate [Hull *et al.* , 2004b]. The discount rate used in the pricing of bonds (the bond yield) consists of both the risk-free rate and a spread that compensate the bondholder for the risk connected to the bond. Hence to estimate the credit risk by using the bond yield, the risk-free rate must first be deducted. Finding an appropriate measure of the risk-free rate constitutes a problem[5] that can be avoided by using CDS spreads. Secondly, corporate bond spreads have been found to reflect several factors other than credit risk such as liquidity risk and costs connected with taxes [Longstaff *et al.* , 2004]. Because of the high liquidity in the CDS market, the CDS spreads are considered to reflect liquidity risk to a lower extent than corporate bond spreads. CDS spreads are therefore viewed as a more "pure" measure of credit risk. Thirdly, the pricing of credit risk is more directly reflected using CDS data since the data consist of the actual bid and ask spreads on the market. In contrast, most of the bond data consist of indications from dealers, which the dealer is not actually committed to trade at [Hull *et al.* , 2004b]. Finally, the CDS spreads have been found to both adapt

[1] CDS spreads, corporate bond spreads as well as CDI/iTraxx spreads will jointly be referred to as credit spreads throughout our thesis.

[2] BIS Quarterly review, June 2005.

[3] BIS Quarterly review, June 2006.

[4] See e.g. Hull, Predescu and White(2004) and Blanco, Brennan and Marsh (2003).

[5] See Houweling and Vorst (2005).

faster and more accurately to credit risk changes than corporate bond yields [Blanco *et al.* , 2003]. One of the reasons to this is the higher liquidity and transparency in the market.

During recent years credit default swap indices (CDIs)[6] have been created and these derivatives are very similar to CDSs. However in contrast to the CDS, the CDI insures the creditor against the default of a whole basket of bond issuers. Hence the CDIs provide investors with an attractive alternative to diversify credit risk across industry sectors and has lead to an increase in the efficiency and transparency on the market. The CDIs are completely standardized and hence more liquid than the CDSs. The characteristics of the CDI spreads are very similar to the CDS spreads. However the higher liquidity of the CDI market often leads to slightly lower CDI spreads than CDS spreads [Wang *et al.* , 2006]. A new CDI, the iTraxx, was created in June 2004 and consists of 8 sector indices covering the European and Asian bond markets.[7]

The spreads of the iTraxx could in our view be a very attractive alternative to bond yields when measuring credit risk on the European market. Getting a better understanding of what factors affect the iTraxx spreads might contribute to a better understanding of the sources of credit risk on the European market. However, so far, very little empirical research has been done using iTraxx data. To our knowledge, the only study performed on iTraxx data was Byström (2005), who studied the relationship between the iTraxx spreads and equity prices. Moreover, he takes a first step to investigate the relationship between stock price volatility and the iTraxx spreads through examining the correlations between the two. In this thesis we try to develop Byström's results further, seeking additional factors in the literature of CDS spreads and corporate bond spreads that could help explain the variation in the European iTraxx spreads.

In line with Byström's study, we choose to apply a structural approach. The original structural model was the Merton model that predicts the level of the firm's leverage, the stock price volatility and the risk-free rate to influence credit spreads [Merton, 1974]. The main objective of our thesis is *to examine the relationship between the iTraxx spreads and the theoretical determinants of credit spreads suggested by the Merton model (leverage, stock price volatility and the risk-free rate).*

Our analytical framework is closely related to two previous papers studying credit spreads in the light of the structural framework. The first paper is the one written by Ericsson Jacobs and Oviedo (2004) (EJO)[8], who found that leverage, stock price volatility and the risk-free rate have significant impact on US CDS

[6]We use CDI as an acronym for credit default swap index throughout the thesis.
[7]www.itraxx.com.
[8]Henceforth EJO.

spreads. The second study is the one performed by Collin-Dufresne, Goldstein and Martin (2001) (CGM)[9], who investigated the determinants of changes in corporate bond spreads. They regressed corporate bond spreads on proxies for the spot rate, the slope of the yield curve, leverage, volatility, the magnitude and probability of a downward jump in firm value, and the business climate as explanatory variables.

We find that even though the variables suggested by the Merton model have significant impact on the iTraxx spreads the model only manages to account for at the most one third of the variations of the spreads. This suggests that there are additional factors influencing the iTraxx spreads that are not accounted for by the Merton model. We test our results by performing a robustness regression where our model is found to be substantially improved by adding a measure of liquidity and the lag of the iTraxx spreads.

The paper will be outlined as follows; in section 2 we will provide background information concerning CDSs and CDIs. Next, in section 3 we will introduce the analytical framework and discuss the theoretical determinants of credit spreads according to the Merton model. In section 4 we describe the data we have used. Section 5 will describe the method and the model used in our analysis. Results and discussion from the first regression are presented in section 6. To test the robustness of our results we perform additional regressions and discuss the results in section 7. Finally, the paper will be concluded in the last section.

[9] Henceforth CGM.

2 CDS basics

In this section we present a basic explanation of CDS and CDI contracts in order to provide the reader with a better understanding of the topic.

2.1 Credit default swaps (CDS)

A CDS is a contract linked to a specific bond used to protect the buyer (in most cases the bondholder) against the event of a default of the bond issuer.[10] The buyer of a CDS contract commits to make predetermined periodic payments to the seller of the CDS, until the maturity of the CDS contract or earlier in the case of a default. The yearly payment made to the seller of the CDS contract is defined as the *CDS spread*. The size of the spread is dependent on what rating the bond has, i.e. how risky the bond is considered to be. If a default occurs, the CDS seller is committed to buy the defaulted underlying bond from the CDS buyer at a price equal to the par value. Since the par value most likely exceeds the remaining value of the bond after default, the CDS buyer is compensated for some of its losses. The cost incurred by the CDS seller in the event of a default equals the difference between the face value of the bond and the remaining value of the defaulted bond. The CDS contract can hence be seen as an insurance against debt default. Moreover the CDS contracts provide a possibility for investors to separate the credit risk from other risks such as the risks attributed to changes in interest rate or currency values. Although the duration of the CDS contracts can be up to ten years, the predominant time horizon is five years [Longstaff *et al.* , 2004]. The terms and conditions of the CDS contract became standardised in 1999 in order to facilitate the trading and pricing of the contracts. The instruments are traded over the counter (OTC) [Saunders & Allen, 2002].

To make the properties of the CDSs easier to understand, we include a brief numerical example. Consider a situation where you hold a corporate bond with a face value of SEK 1 million, and want to protect yourself against possible losses that would incur if the bond issuing company defaulted. To protect yourself, you buy a five year CDS contract with a notional principal of SEK 1 million (the equivalent amount to the face value of the underlying bond). Assume that the spread of the CDS is determined to 95 bps. This means that you as CDS buyer commit yourself to pay the CDS seller an amount equal to 0,0095 * SEK 1 M = SEK 9500 per year for five years if no default occurs. In the case of a default during the lifetime of the CDS three things will happen. Firstly, you stop paying the yearly fee of SEK 9500. Secondly, you give the defaulted bond

[10] See e.g. Hull and White (2003), Hull, Nelken and White (2004), Hull and White (2005) and Wang, Rachev and Fabozzi (2006) for an introduction to CDSs.

to the CDS seller, or an amount in cash equivalent to the remaining value of the defaulted bond. And thirdly you receive SEK 1 million (the face value of the bond) from the CDS seller.

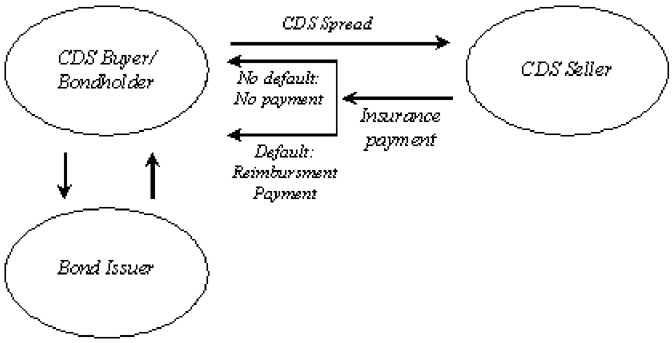

Figure 1: Picture of how a CDS works.

The CDS spread can be seen as a market-based measure of the bond issuer's credit risk. Hence, if assuming that credit risk is priced into the market one can use the market prices to extract the pricing of credit risk [Hull *et al.* , 2004a]. Hull, Predescu and White (2004) showed that the CDS spread, s, is approximately equal to the difference between the par yield on a risky bond, y, and the par yield on a riskless bond, r, 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 on the market could make a risk-free profit by going long in a risk-free bond, shorting a corporate bond and selling the CDS 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 CDS connected with the bond. This relationship shows a strong theoretical link between CDS spreads and corporate bond spreads. The close relationship between CDS spreads and corporate bond spreads has also been confirmed by empirical studies.[11]

[11] See e.g. Blanco, Brennan and Marsh 2003.

2.2 Credit default swap index contracts (CDI)

CDI contracts are slightly different from the ordinary CDS contracts. A CDI contract insures the buyer against defaults of a standardized equally weighted basket of bonds.[12] In the event of a default of one of the bond issuers, the following things occur. Firstly, the underlying basket is reduced by the notional amount of the defaulted bond. The CDI buyer continues to pay a periodic fee, based on the new lower notional amount of the underlying basket. Secondly, the CDI seller reimburses the CDI buyer with an amount equivalent to the face value of the defaulted bond. Thirdly, the CDI buyer transfers the remaining value of the defaulted bond to the CDI seller [Wang *et al.* , 2006]. Because of the similarities between the CDS and the CDI contracts, the spreads of both instruments should be influenced by roughly the same factors.

Two main advantages of CDI compared to CDS contracts are mentioned in literature; the CDIs provide an opportunity for investors to hedge against credit risk on a sector level, and hence facilitate diversification. Also, CDI contracts increase efficiency and liquidity on the market because of the improved transparency of the contracts [Wang *et al.* , 2006]. An additional benefit of the CDI is that the underlying basket of the CDIs have been used as a basis to construct standardized CDOs[13] [Hull & White, 2005].

[12] Another difference to the CDS contracts is that CDIs are divided into groups covering different degrees of risk, so called tranches. We will not explain this further since it is not important to our study. For further explanation see Wang, Rachev and Fabozzi (2006).

[13] A Collateralized Debt Obligation (CDO) is an instrument providing investors with an opportunity to buy a share of a whole portfolio of bonds. See Fabozzi (2004).

3 The analytical framework

In this section we motivate our use of the structural framework and introduce the Merton model. Subsequently, we describe the connection between the Merton model and option pricing theory. Moreover, we present and discuss the variables that affect credit spreads suggested by the model. Finally, we present empirical findings supporting the theoretical relationship between credit spreads and the variables, and include a short discussion suggesting suitable proxies for the variables mentioned in the model.

3.1 Introduction to the Merton model

The most common models used to examine credit risk can be divided into two categories; the reduced form models and the structural models. The reduced form models have been proven to be quite useful in practical applications, but are less commonly used to establish the theoretical determinants of credit risk [Ericsson *et al.* , 2005]. The structural models are more frequently used in literature. This because the structural models have the advantage of providing a clear economic rationale compared to the reduced form models [Wang *et al.* , 2006] and also have a stronger theoretical foundation. Because of the reasons mentioned we choose to use a structural approach.[14]

The structural models are based on Merton's approach to the pricing of bonds, where the loan is seen as an option on the firm value. As mentioned above the structural models have a very intuitive way of explaining the relationship between economic fundamentals and are commonly used in the pricing of various kinds of credit instruments. The Merton model has through the years been extended by different authors, that have been trying to find different improvements of the model by focusing on additional theoretical variables.[15] However we will limit our study to focus on the original Merton model which predicts the theoretical determinants of the credit spreads to be the firm's leverage, the volatility of the stock price and the risk-free spot rate.

[14]This approach was also used by Byström, EJO and CGM.

[15]See e.g. Black and Cox (1976), Longstaff and Schwartz (1995), Anderson and Sundaresan (1996), Leland and Toft (1996) and CGM.

3.2 The Merton model and the link to option theory

The basic idea underlying the Merton model is to look at the equity and the debt as options on the company's assets.[16] Formally the asset value, V, can be seen as the sum of the debt, D, and the equity, S;

$$V_t = S_t + D_t.$$

Figure 2 illustrates two possible realizations of the asset value process. When the firm's asset value falls below a certain threshold, in this case the nominal value of the debt, F, the firm is assumed to no longer be able o pay its obligations and hence default. On the contrary, when the asset value is higher than F the firm will not default according to the model.

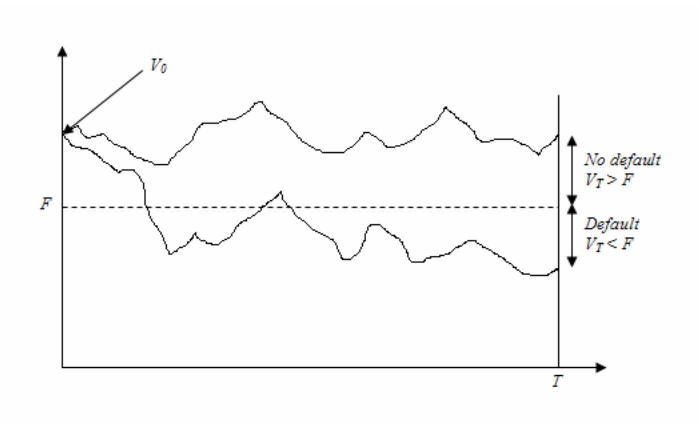

Figure 2: Picture of two realizations of the asset value process. When V falls below the nominal value of the debt, F, the firm is assumed to default. On the other hand, when V is above F there is no default.

If a firm is levered, the equity holders can be said to hold a put option on the company's debt with a strike price equal to the nominal value of the debt, F. This gives the following payoff at the maturity of the loan to the debt holders;

$$\min[F, V_T] = F - \max[0, F - V_T].$$

The payoff function is readily illustrated in figure 3 below. If the company's assets are higher than F, then the equity holders will repay the whole debt to the debt holders. On the other hand, when the company's assets fall under F,

[16] See Black and Scholes (1973) for an explanation on option theory.

the equity holders have the option to give the assets to the debt holders and walk away from their obligations. Hence in such a situation the debt holders will not be fully repaid.

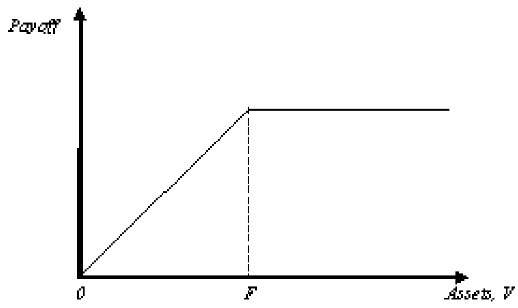

Figure 3: Payoff function of a put option on a company's debt.

Merton (1974) noted that this payoff function is equivalent to the payoff from a sold put option on an underlying security. In this case the underlying security is the assets and the strike is the nominal value of the debt. The option value on risky debt, D, will hence depend on five input variables; the risk-free interest rate, r, the time to maturity, $(T-t)$, the nominal value of debt, F, the market value of the firm's assets, V, and the volatility of the same assets, σ_V;[17]

$$D = p_{BS}(V, F, r, \sigma_V, (T-t)),$$

where p_{BS} is the Black and Scholes price of a put option. Since we consider CDIs which are rebalanced every six months, the time to maturity will be more or less constant and hence this will not affect the variation in the debt by much. Moreover, the value of the debt, D, does not depend on the nominal value of the debt, F, per se but only through its impact on leverage, L;

$$L = \frac{Fe^{-r(T-t)}}{V}.$$

Therefore it is sufficient to consider variations in the leverage ratio instead of variations in the nominal value of debt. Hence from these relationships the variables suggested by the Merton model are the leverage, the volatility and the

[17]For whole formulas see Appendix about the Merton model.

risk-free rate.

Further D is equal to the value of the nominal debt discounted with the risky yield, y;

$$D = Fe^{-y(T-t)}.$$

Solving for y we get;

$$y = -\frac{1}{T-t}\ln(\frac{D}{F}).$$

Merton further defines the credit spread, s, as the difference between the risky yield, y, and the risk-free rate, r;

$$s = y - r.$$

Below we will discuss the effect of leverage, volatility and the risk-free rate on credit spreads.

3.3 Discussion of variables suggested by the Merton model

3.3.1 Leverage

One natural effect when a firm obtains a new loan is that the total interest rate payments on the new higher debt will increase. Thus when the leverage increases the company's profits will be more volatile due to their higher sensitivity towards interest rate changes. The increase in the volatility of the profits will lead to a situation where the future of the company as a whole will become more risky. The riskier a company is the higher interest rate it has to pay for its loans which implies a higher credit spread on its bonds. Hence, the credit spreads are positively related to leverage in the structural Merton model. Empirical research confirms the relationship predicted by the Merton model. EJO's findings concerning leverage are consistent with theory, i.e. they found a positive relationship between the CDS spreads and leverage. CGM also confirms the theoretical relationship between leverage and corporate bond spreads. EJO and CGM calculated the leverage for each firm in their respective studies.[18] Since a CDI is based on a basket of bonds, approximating a combined leverage ratio of the companies within the basket is connected with some difficulties.

[18]For further explanation see EJO and CGM.

An approach commonly used in studies of corporate bond spreads is estimating leverage through stock returns. The idea behind using equity returns as an indicator of leverage is; given that the amount of debt is constant, a drop in stock prices leads to a lower market value of equity and in turn a higher leverage ratio. The credit spread should therefore be a decreasing function of the return on the firm's equity holding everything else constant. Among others, CGM included the stock returns as a proxy for the firm's health when testing for robustness. They found that corporate bond spreads decrease with the equity returns, implying that equity returns should be related to the firm's leverage.[19] Therefore we decide to use the equity returns as an indicator for the leverage, as this is more manageable than calculating the combined leverage.

3.3.2 Volatility

As explained above a debt claim on a firm can be said to have similar characteristics to a short put option where the strike price equals the face value of the debt. From option theory we know that the value of an option increases with volatility. Consequently the Merton model expects that the credit spread is an increasing function of volatility. In this context, a higher volatility means that the probability of default of a particular company increases. The rise in the probability of default implies higher risks connected to any bond issued by the company, leading to a higher credit spread. The volatility used in the Merton model should reflect the risks faced by the whole company; hence the volatility that is most suitable to use in the model is the forward-looking volatility of the total enterprise value (i.e. the volatility of the $debt + equity$).

The theoretical relationship between volatility and credit spreads is supported by previous empirical findings. EJO found a positive relationship between CDS spreads and volatility as predicted by the model. Byström investigated the correlation between equity price volatility and the iTraxx spreads. Byström's results confirm the theoretical relationship by showing that the iTraxx spreads tend to decrease (increase) with decreasing (increasing) volatilities. Moreover several authors have investigated the relationship between corporate bond spreads and volatility. For example Campbell and Taksler (2003) showed that the volatility in equity prices of a firm is important to explain the movements of corporate bond spreads. CGM investigated the impact of theoretical determinants on corporate bond spreads. Although the explanatory power of their model is rather limited, their results corroborate the theoretical relationship between volatility and corporate bond spreads. Furthermore, they found that the changes in the corporate bond spreads are asymmetric to changes in

[19] Interestingly Blanco, Brennan and Marsh (2003) show that CDS spreads are significantly more sensitive to changes in stock returns than corporate bond spreads.

the implied volatility; the impact on the spreads is higher when the volatility increases as opposed to the other way around. Notably, Blanco, Brennan and Marsh (2003) showed a significant relationship between CDS spreads and implied volatility, however they did not find the same relationship between implied volatility and corporate bond spreads.

CGM and EJO have different approaches to what they used as a proxy for the firms' volatilities. EJO used a historical volatility measure by applying an exponentially weighted moving average (EWMA) model on daily stock returns. Using the historical volatility measure of the stock returns has the advantage of being firm specific. The usage of historical volatilities is also supported by the findings of Campbell and Taksler (2003), who found a strong relationship between historical volatility and corporate bond spreads. However, CGM proposed that using implied volatilities extracted from firm specific options, would be the best proxy for the volatility used in the Merton model. Since firm specific options were not available, they used data from the volatility index VIX as a proxy for volatility. Volatility indices are constructed by using implied volatilities from options and are seen as a key measure of the expected short-term volatility reflected by the market. Cremers, Driessen, Maenhout and Weinbaum (2004) also supported the use of implied volatilities; they argued that implied volatilities are superior to historical volatilities since they are forward-looking. If the expected volatility is priced into credit spreads, the pricing of the volatility could only be captured by forward-looking measures. As there are good arguments in favour of using both historical and forward-looking volatility, we decide to consider both in our analysis.

3.3.3 Risk-free rate

In the original Merton model the interest rate is assumed to be constant. However, the framework predicts the credit spreads to be negatively related to the risk-free rate. One explanation is that a higher interest rate decreases the present value of the leverage ratio[20] which in turn decreases the probability of default. The decreased default probability leads to a lower credit spread. Another way to look at this is from the viewpoint of option pricing theory. Arbitrage pricing suggests that there is a risk-adjusted probability measure under which the expected value of the company's assets grows with the risk-free interest rate. Thus, as the risk-free interest rate increases so does the expected value of the assets. A greater expected value of the assets decreases the probability of default which in turn leads to a lower credit spread. As a consequence the firm becomes more sensitive to changes in the risk-free rate the nearer the firm's asset value

[20]See formula for the leverage in section 3.2.

is to the default threshold.

The majority of empirical findings are consistent with the Merton model's predictions of a negative relationship between credit spreads and the risk-free rate. EJO's findings confirm the prediction of the framework since they obtained statistically significant results for the negative relation between the risk-free interest rate and the CDS spreads in their study. As a proxy for the risk-free rate they used the 10-year Treasury bond yield. CGM's results on corporate bond spreads are also consistent with theory; the risk-free rate is estimated with a significant negative sign. We decide to follow EJO's and CGM's practices and use a government 10-year yield.

3.4 Summary of the analytical framework

Table 1 below summarizes the predicted signs of the theoretical determinants of credit spreads suggested by the Merton model.

Variable	Predicted sign
Equity index return	-
Historical volatility	+
Implied volatility	+
Risk-free rate	-

Table 1: Variables and their predicted signs according to the Merton model.

4 Data

In this section we first present descriptive statistics of all the iTraxx data. Further we present the proxies we use for the different factors included in the Merton model and shortly describe our data. Our data consist of daily observations for approximately 27 months giving us 590 observations for each of the variables.

4.1 Descriptive statistics for the iTraxx data

Table 2 summarizes descriptive statistics for the iTraxx spreads.

Variable	Obs	Mean	Std Dev	Min	Max
bauto5y	590	44,496	8,191	31,200	85,893
aauto5y	590	46,630	8,380	33,200	88,464
bcon5y	590	45,471	8,637	28,892	73,857
acon5y	590	47,668	8,768	31,021	76,500
bind5y	590	41,699	6,322	26,417	67,214
aind5y	590	43,713	6,436	28,250	69,250
ben5y	590	23,684	3,342	16,600	33,406
aen5y	590	25,569	3,443	18,500	35,179
bsenfin5y	590	15,908	3,700	8,125	28,469
asenfin5y	590	17,647	3,798	9,937	30,594
bsubfin5y	590	28,033	6,021	15,310	49,143
asubfin5y	590	29,853	6,119	17,110	51,286
btmt5y	590	44,828	8,230	26,500	65,571
atmt5y	590	46,815	8,318	28,300	67,786
bauto10y	590	67,834	8,694	55,333	110,214
aauto10y	590	70,218	8,938	57,850	113,143
bcon10y	590	68,704	8,631	51,588	102,321
acon10y	590	71,440	8,715	54,338	105,036
bind10y	590	64,307	9,523	42,700	93,929
aind10y	590	66,844	9,700	44,800	96,714
ben10y	590	40,357	4,450	31,111	54,893
aen10y	590	42,835	4,506	33,556	57,679
bsenfin10y	590	25,157	4,203	16,854	39,688
asenfin10y	590	27,446	4,270	19,211	42,375
bsubfin10y	590	45,763	6,806	30,386	71,000
asubfin10y	590	48,021	6,905	32,786	73,667
btmt10y	590	71,350	11,049	47,300	94,188
atmt10y	590	74,198	11,404	49,600	96,938

Table 2: Descriptive statistics for iTraxx bid and ask spreads in basis points including all sectors and both 5- and 10-year maturities.

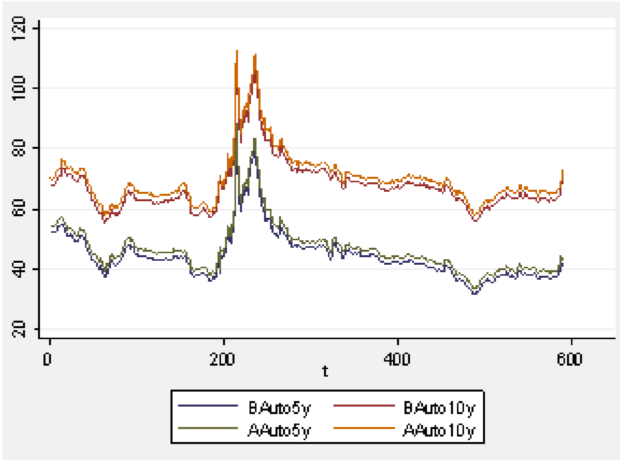

Figure 4: Graph of the 5- and 10-year iTraxx spreads for the Auto sector during the sample period.

Figure 4 shows the iTraxx spreads for the Auto sector during the studied period. It can readily be seen that the 10-year spreads are higher than the 5-year spreads.[21] The same pattern occurs for the other sectors which can be seen in tables 5-10 in Appendix.

4.2 European iTraxx index

The European iTraxx data is downloaded from the International Index Company's (IIC) website.[22] Both bid and ask spreads are available from the 21st of June 2004 when the index was created. The European iTraxx index basket consists of the 125 bonds underlying the most traded CDSs in terms of volume during the previous six months. The European iTraxx index is divided into 8 sector indices; Consumers, Energy, Autos, Industrial, Technology Media Telecom (TMT), Non Financials, Senior Financials and Sub Financials. Each of the indices covers 10-30 entities attributed equal weights. The indices are rebalanced every six months at so called roll dates.[23] If one of the underlying bond issuers defaults between balancing dates, the underlying basket gets reduced by the defaulted bond issuer.

Our dataset consists of end-of-day bid and ask quotes and reaches over the period between the 21st of June 2004 and the 25th of September 2006. We

[21]The ask spreads are of course slightly higher than the bid spreads which also can be seen in the figure.
[22]www.itraxx.com.
[23]The roll date is March 20 and September 20 of a calendar year or the following business days if these days are not business dates.

examine all sector indices except the Non Financials for both 5- and 10-year maturities since these are the only maturities available in the iTraxx. The Non Financials is excluded since it is a combination index including; Consumers, Energy, Autos, Industrial and Technology Media Telecom (TMT).

4.3 European stock indices

As mentioned above we choose to use equity returns as a proxy for leverage. To estimate the influence of stock returns on the iTraxx, Byström creates his own stock indices by combining the stock prices of all the companies included in the underlying basket. As the iTraxx is rebalanced every six months this is quite a time consuming operation. Due to time limitations we choose to use data from existing indices. We are however aware that Byström's method could be a more appropriate proxy for the leverage component of the Merton model.

We use European equity indices that are as closely related to the different sectors of the iTraxx index as possible. Daily values for the equity indices are collected from DataStream for the period 21st of June 2004 until the 25th of September 2006. The indices that we use are FTSE Euromid Auto & Parts Europe, FTSE European Consumer Cyclical, S&P Europe 350 Industrials, S&P Europe 350 Energy, S&P Europe 350 Financials, and S&P Europe 350 Telecom sys. The S&P Europe 350 Financials is used for both the Senior Financials and the Subordinated Financials sectors in the iTraxx index.

4.4 Volatility proxies

As stated above there is no consensus in the previous empirical research about what measure of volatility should be used in the Merton model. Since there are theoretical arguments in favour of both volatility measures and the correlation between EWMA volatility and VSTOXX proved to be weak[24] we decided to test both volatilities by including them in the model both separately and simultaneously.[25] Both volatility measures show high significance in all the regressions. This implies that they could be proxies for different things. Therefore we decide that it could be interesting to include both volatilities in the final model.

4.4.1 Historical volatility - EWMA

In order to capture the sector specific stock volatility, we calculate historical time series volatilities using the daily returns of the stock indices of each sector. Similar to EJO, we use an exponentially weighted moving average (EWMA) model

[24]See table 7 in Appendix.
[25]See table 8 in Appendix for results.

when estimating the volatilities. The EWMA model captures the dynamic characteristics of volatility by giving the latest observation a higher weight in the estimation. The benefit of using this model is that the estimated volatility reacts faster to the impact of e.g. economic shocks. The estimator is calculated as follows;[26]

$$\sigma_t^2 = r_{t-1}^2(1-\lambda) + \sigma_{t-1}^2\lambda$$

where σ_t is the volatility at time t, σ_{t-1} is the volatility at $t-1$ and r_{t-1} is the stock return at time $t-1$. As the weight λ we choose 0,94, a weight used by RiskMetrics (formerly a part of JP Morgan) when estimating volatility for daily observations [Longerstaey & Spencer, 1996].

4.4.2 Implied volatility - VSTOXX

As a proxy for the forward-looking volatility we use Dow Jones EURO STOXX 50 Volatility (VSTOXX), a volatility index covering the Eurozone region. VSTOXX is constructed to measure the near-term market expectations of volatility using the DJ EURO STOXX 50 option prices as a base. The index covers most of the Eurozone including Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. The data consist of daily quotes that were kindly presented to us by Dow Jones Customer Service.[27]

4.5 Germany government 10-year rate

The instantaneous risk-free rate used in most theoretical frameworks is unobservable. Hence finding a good proxy for the risk-free rate has been a topic of debate in literature. We choose to follow EJO and CGM and use a local 10-year benchmark government rate. Moreover the 10-year yield should match the maturity of the CDS spreads reasonably well. The 10-year rate should maturity-wise be a good match primarily for the 10-year iTraxx spreads. Trying to determine which country's interest rate that we should use as a proxy for the Eurozone risk-free rate, we examined the correlation between the interest rates of some of the strongest economies in Europe. We found the interest rates of Germany, UK and France to be strongly correlated[28] Previous research has also found the differences between the interest rates of the European countries

[26] See e.g. Alexander (2001) for more on the EWMA model.
[27] www.dowjones.com.
[28] See table 6 in Appendix.

to be insignificant in most cases. However, the German bonds have been pointed out as having a somewhat higher liquidity and lower credit risk than the bonds of other countries [Koller *et al.* , 2005]. Further we believe the German yield to be a good proxy for the Eurozone interest rate level because of the country's importance in the European economy. Hence we choose to use the Germany government benchmark 10-year yield which is downloaded from DataStream.

5 Methodology

In this section we present our model and discuss the method by which the model is estimated. As mentioned above our method is closely related to the one used by EJO and the one used by CGM. We integrate the methods and modify the approaches slightly to suit our data. The robustness test will be discussed in a later section.

5.1 Method and model

In contrast to the data examined by EJO, our data consist of time series that are sufficiently long to test for stationarity. We therefore test the stationarity of all the variables through performing a Dickey-Fuller test on the levels. The majority of the variables, with few exceptions, were found to be non-stationary.[29] In order to make our time series stationary, we take the logarithm of every variable. To capture the percentage changes in the variables we thereafter take the first differences of the logged variables. One advantage of taking the first differences of the logged variables is that it will be easier to interpret our results (holding all else equal, a one percent change in one of the explanatory variables will lead to a "beta" percentage change in the dependent variable). Performing the regression on the first differences of the variables also concurs with the method of CGM. We only use first differences of the logarithm of the variables in our further analysis.

The second step of our analysis is very similar to the one of EJO. As EJO, we perform both panel and time series regressions testing the influence of the explanatory variables leverage, equity volatility and the risk-free rate. We will first include all three variables suggested by the structural Merton model in the regression, and then examine each variable separately. We perform panel regressions on both the bid and the ask quotes for the 5- and 10-years CDI maturities respectively. As discussed above we do not perform our regressions on levels as the time series have been found to be non-stationary. Hence, our model is specified as follows:

$$\Delta \ln CDI_t^i = \alpha + \beta_1^i \Delta \ln ret_t^i + \beta_2^i \Delta \ln vol_t^i + \beta_3^i \Delta \ln VOX_t + \beta_4^i \Delta \ln r_t^{10} + \nu_i + \epsilon_t^i \quad (1)$$

where the iTraxx spreads in sector i at time t is denoted by CDI_t^i, the return on the equity index of sector i at time t is denoted by ret_t^i and vol_t^i denotes the historical volatility of sector i at time t. VOX_t denotes the forward-looking

[29] See tables 9-10 in Appendix for the results.

volatility VSTOXX at time t and finally, the risk-free spot rate is defined as the 10-year German government yield at time t and is denoted by r_t^{10}.

Following the method of EJO we also extend our analysis to investigate each of the independent variables separately. Hence in addition, the following models are estimated:

$$\Delta \ln CDI_t^i = \alpha + \beta_1^i \Delta \ln ret_t^i + \nu_i + \epsilon_t^i \tag{2}$$

$$\Delta \ln CDI_t^i = \alpha + \beta_1^i \Delta \ln vol_t^i + \nu_i + \epsilon_t^i \tag{3}$$

$$\Delta \ln CDI_t^i = \alpha + \beta_1^i \Delta \ln VOX_t + \nu_i + \epsilon_t^i \tag{4}$$

$$\Delta \ln CDI_t^i = \alpha + \beta_1^i \Delta \ln r_t^{10} + \nu_i + \epsilon_t^i \tag{5}$$

In order determine if we should control for fixed or random effects when running the panel data regressions we perform Hausmann tests on all panel regressions.[30] The Hausmann test shows that the GLS estimators are consistent for all of our regressions. Hence we find it safe to use the random effects estimator in all our regressions.

[30]See Appendix for more detailed explanation of the test and table 11 for results.

6 Results and discussion

In this section we present and discuss the results of our regressions. The results are then compared with the findings of EJO, CGM and Byström.

6.1 Panel data regressions

	Ask 5	Bid 5	Ask 10	Bid 10
α	-0,0008**	-0,0008**	-0,0003	-0,0003
$\Delta \ln ret_t^i$	-0,1478***	-0,1501***	-0,0824**	-0,1040***
$\Delta \ln vol_t^i$	0,0304***	0,0289***	0,0185***	0,0213***
$\Delta \ln VOX_t$	0,0490***	0,0517***	0,0416***	0,0404***
$\Delta \ln r_t^{10}$	-0,0882***	-0,0852***	-0,0708***	-0,0624***
R^2	0,3003	0,3058	0,3266	0,3328

Table 3: Panel data regressions using all explanatory variables. *** indicates that the variable is significant at the 1% level, ** at the 5% level and * at the 10% level.

Table 3 presents the panel data regression results of model (1). As can be seen in the table, all the explanatory variables are estimated with the sign predicted by the model and are highly significant. Furthermore, the results are confirmed by our one-by-one regressions (2)-(5), where all explanatory variables show the correct signs and are significant at the 5% level.[31] Our results are not only consistent with theory, but also concur in terms of signs and significance with previous empirical studies on credit spreads.[32] Hence, the variables suggested by the Merton model seem to have a statistically significant effect on the iTraxx spreads.

Notably, the high significance and the predicted signs of both the historical volatility and the VSTOXX imply that the iTraxx spreads are affected by both volatility measures. As mentioned above, the volatility variable suggested by the Merton model is meant to be forward-looking and firm specific. Assuming that the VSTOXX is a correct proxy of the implied volatility, the VSTOXX is a forward-looking measure. However as stated above, the VSTOXX is not a measure of sector specific volatility but rather a measure of the European market-wide volatility. Hence using only the VSTOXX measure would leave sector specific events without consideration. On the other hand using only the historical volatility would instead provide a good proxy for sector specific volatility during the time period, but not take the investors expectations of future volatility into account. In order to see if both variables can be included we also

[31]See table 13 in Appendix for estimated models.
[32]See findings of EJO, CGM and Byström.

examine the regression for multicollinearity. We find no signs of multicollinearity[33] and hence we believe that including both of the variables in the regression might better reflect the volatility included in the Merton model than using just one of the measures. The regression results might however be improved if we could have used a sector specific volatility index or combined implied volatilities calculated from options on the companies included in the iTraxx index.

Using the regression results for economic interpretation we find that on average a 1% increase in the equity returns, all else equal, decreases the iTraxx spreads by approximately 0,08-0,15%. A 1% increase in the historical volatility leads to approximately a 0,02-0,03% increase in the iTraxx spreads. Further, an increase of 1% in the VSTOXX volatility gives on average an increase of 0,04-0,05% in the spreads. Finally, the results for the risk-free yield suggest approximately a 0,06-0,09% decrease in the spreads as the yield increases by 1%. Hence, changes in the equity index and the risk-free rate have considerably higher impact on changes in the iTraxx spreads than the two volatility measures. The relatively higher importance of the risk-free rate and the leverage variables are also confirmed by the one-by-one regressions. From the results we also see that the 5-year spreads are more sensitive to changes in the explanatory variables than the 10-year spreads. This is intuitive since contracts with shorter maturity should be more sensitive to changes in short-term variables.

Assuming that the stock index returns are a good proxy for the sector levels of leverage we can conclude from the regression results that leverage seem to have a strong influence on the iTraxx spreads. Stock index returns could however also be viewed as a proxy for the overall state of the different sectors. It is intuitive that if the sector is performing well, the probability of default of companies within the sector will decrease which in turn lead to lower credit spreads. However stock returns and leverage have been proven to be highly correlated and are, as stated above, commonly used as a proxy for a company's health instead of leverage.

Further in table 3 it can be seen that the impact of a change in the volatility coefficient on the spreads is higher for the VSTOXX volatility than for the historical volatility. This might suggest that the changes in the iTraxx spreads are slightly more dependent on the volatility expectations of the market, than on the historical volatility. However since the difference is very small it is difficult to draw any conclusions.

As we can see the R-squares of the original model are quite low lying around 30-33%. This might suggest that the variables suggested by the Merton model are not sufficient to explain all of the variation in the iTraxx spreads. However it is normal to obtain lower R-squares when using first differences than when

[33]See Appendix for a more detailed explanation of the test and table 12 for results.

using levels.

6.2 Time series regressions

Following the method used by EJO we also performed time series regressions, hoping to detect variations across sectors. However no clear patterns can be detected when examining the coefficients. Due to the limited data sample the regressions yield several insignificant coefficients, some coefficients estimated with the wrong sign and overall extremely low R-squares. Therefore we do not discuss our results further and refer to tables 14-15 in the Appendix.

6.3 Comparison with EJO, CGM and Byström

As stated above we obtain significant coefficients with the signs predicted by theory. The results also concur with EJO's and CGM's results concerning credit spreads. Byström's results regarding the strong relationship between stock returns and the iTraxx spreads are also confirmed by our study. As stated above Byström also found the iTraxx spreads and historical volatility to be positively correlated. We are able to verify his findings by including the two different measures of volatility in our model and finding them to have significant influence on the iTraxx spreads. Importantly, Byström also found the iTraxx spreads to be autocorrelated. This might suggest that there is information priced in the market that can not be captured by the Merton model.

One can only directly compare R-squares across different models if the number of observations included in the sample and the dependent variable are the same.[34] It could however be useful to highlight the R-squares of the models most closely related to our. EJO obtained R-squares of approximately 70% when running fixed effect panel regressions on the levels of CDS spreads, leverage, volatility and interest rate. This is a considerably higher explanatory power than the 30% we obtain from our regressions. Similarly to our results, CGM also obtained rather limited R-squares ranging from 20% to 30%. The higher R-squares in the study by EJO could be due to trending behaviour of the regressors. In general, a model regressed on non-stationary data might yield spurious results and the estimated coefficients would in this case not represent any causal relationships. Therefore, we argue that our model, constructed on first differences, should be preferred to a model made on levels. Byström's R-squares are even lower, with the highest explanatory power of 25%. The reason behind this could possibly be that he only uses the first 10 months of the iTraxx index in his study which is a very short time period.

[34] See Gujarati (2003).

7 Robustness test

In this section we test the robustness of our findings by including additional explanatory variables in the original regression. We also shortly discuss the added variables. The results of the robustness regression are then discussed.

7.1 Robustness method and model

Similarly to EJO we test our results for robustness by including additional variables suggested by CGM in a panel data regression. CGM investigated the determinants of changes in corporate bond spreads. They based their method in a structural approach and regressed the changes in corporate bond spreads on proxies for changes in the spot rate, changes in the slope of the yield curve, changes in leverage, changes in volatility, changes in the magnitude and probability of a downward jump in firm value and changes in the business climate as explanatory variables. We use all variables included by EJO except the proxy for jumps in firm value approximated by "the slope of the smirk". Since it was hard to obtain the correct data, this variable was excluded due to limitation of time. Finally we add a measure of liquidity and the lag of the iTraxx spreads.[35] In order to ensure the stationarity we first take the logarithm and then take the first differences of the variables as done in our first model. This also helps us to capture the percentage changes for an easy interpretation.

We specify our robustness regressions by extending our model with the slope of the yield curve, the square of the risk-free rate, the FTSE 350, the lag of the spreads and the difference between the ask and bid price, giving us the following model:

$$\begin{aligned}\Delta \ln CDI_t^i = {} & \alpha + \beta_1^i \Delta \ln ret_t^i + \beta_2^i \Delta \ln vol_t^i + \beta_3^i \Delta \ln VOX_t + \beta_4^i \Delta \ln r_t^2 \\ & + \beta_5^i \Delta \ln (r_t^2)^2 + \beta_6^i \Delta \ln FTS_t^i + \beta_7^i \Delta \ln slope_t^i \\ & + \beta_8^i \Delta \ln CDI_{t-1}^i + \beta_9^i \Delta \ln diff_t^i + \nu_i + \epsilon_t^i \qquad (6)\end{aligned}$$

As for our previous panel data regressions, the Hausmann test indicated that we should use random effects in the robustness panel regression as well.

[35] For the relationship between liquidity and credit spreads see Tang and Yan (2006) and for autocorrelation in the iTraxx spreads see Byström.

7.2 Additional variables

7.2.1 Interest rate variables

In order to test the effect of other maturities of the term structure variables than the risk-free rate used in regression (1) we include a shorter maturity yield and the slope of the yield curve. As the short-term interest rate we use the 2-year German government benchmark rate. The 10-year maturity rate is then excluded from the regression in order to avoid multicollinearity. The coefficient of the 2-year interest rate should have the same negative sign as the 10-year interest rate. Similarly to EJO, we calculate the slope of the yield curve as the difference between the 10-year yield and the 2-year yield. According to the expectation hypothesis, the slope of the yield curve reflects the market's expectations of the future interest rate level. Hence an increase in the slope of the yield curve would mean that the market expects a rise in the short-term interest rate.[36] The expectations of a higher interest rate should therefore in turn lead to a decrease in the credit spreads, implying a negative relationship between the slope of the yield curve and the iTraxx spreads. Finally the square of the 2-year yield is included in order test for possible non-linearities in the relationship between the iTraxx spreads and the interest rate variables.

7.2.2 FTSE 350

EJO add the returns of the S&P 500 to their regression in order to test for the effects of the overall state of the American economy. As a proxy of the overall state of the European market, we instead include the returns of the FTSE 350. The FTSE 350 is a European equity index that includes the 350 largest companies fully listed on the London Stock Exchange.[37] The FTSE 350 is expected, as the other equity indices, to have a negative impact on the iTraxx spreads.

7.2.3 The difference between the ask and the bid iTraxx spreads

Tang and Yan (2006) found that CDS spreads are significantly affected both by the liquidity in the CDS market as well as by so called liquidity spillover effects from the option, bond and stock markets.[38] We therefore find it interesting to include a liquidity measure in the robustness regression. One commonly used proxy for liquidity is the difference between the ask and the bid price [Tang & Yan, 2006]. The closer the difference is to zero, the closer demand

[36]See Fabozzi (2004).
[37]www.ftse.com.
[38]Liquidity has also been found to influence corporate bond spreads, see Longstaff, Mithal and Neis (2004).

matches the supply in the market, implying a more liquid market. Hence if the difference between the ask and the bid spreads decreases, the liquidity in the market increases. The higher liquidity should in turn be reflected in a lower ask price (at which a CDS can be bought) and a higher bid price (at which a CDS can be sold). Therefore the difference between the spreads should be positively correlated with the ask price and negatively correlated with the bid price.

7.2.4 The lag of the iTraxx spreads

Finally we investigate if there is information about the future movements of the iTraxx index integrated in the spreads. This because Byström found strong autocorrelation in the iTraxx spreads and hence found the lagged spreads to have significant positive influence on the spreads in his regressions. He argued that this autocorrelation reflected inefficiencies in the iTraxx market. We therefore include the lag of the iTraxx spreads in order to examine if this variable will improve our original regression (1).

7.3 Robustness results

	Ask 5	Bid 5	Ask 10	Bid 10
α	-0,0005	-0,0005	-0,0003	-0,0003
$\Delta \ln ret_t^i$	-0,1788***	-0,1978***	-0,1204***	-0,1379***
$\Delta \ln vol_t^i$	0,0236***	0,0235***	0,0155***	0,0165***
$\Delta \ln VOX_t$	0,0547***	0,0582***	0,0462***	0,0479***
$\Delta \ln r_t^2$	-0,1215***	-0,1267***	-0,0848***	-0,0777***
$\Delta \ln(r_t^2)^2$	-1,6576	-2,1496	0,1021	0,0117
$\Delta \ln FTS_t^i$	0,1209	0,1402*	0,1034	0,1103*
$\Delta \ln slope_t^i$	0,0030	0,0057	0,0060	0,0077
$\Delta \ln CDI_{t-1}^i$	0,1958***	0,2011***	0,1533***	0,1571***
$\Delta \ln diff_t^i$	0,0373***	-0,0168***	0,0225***	-0,0099***
R^2	0,8885	0,8664	0,9346	0,8965

Table 4: Robust panel data regression. *** indicates that the variable is significant at the 1% level, ** at the 5% level and * at the 10% level.

The results from the robustness panel regression (6) are displayed in table 4. We obtain similar results for the proxies of the leverage, the volatilities and the risk-free spot rate in this regression as in the original panel data regression. All the variables of the original model are highly significant, even at the 1% level, and the estimates show the signs predicted by the Merton model. This is also true for the 2-year rate, which in this regression is used as an alternative proxy for the risk-free rate. The result is interesting because the 10- and the 2-year

German government rates are only moderately correlated.[39] Hence it raises the question whether the 10-year yield is the best proxy for the risk-free rate when applying the Merton model to the iTraxx spreads. We used the 10-year yield in the original regression since it is commonly used as a proxy for the risk-free rate in empirical studies. However it could be important to find a proxy that reflects the maturity of the iTraxx spreads better. The 10-year rate should be the best match for the 10-year spreads, however the 5-year spreads might be better matched by a yield with shorter maturity.

The slope of the yield curve and the square of the 2-year yield are insignificant implying that the variables have no impact on the iTraxx spreads. The FTSE 350 variable is found to have very low significance for the bid spreads and no significance for the ask spreads. This indicates that the state of the European economy does only have a very limited effect on the spreads. That the FTSE 350 is insignificant while the sector equity indices are highly significant can be interpreted as only the leverage affect the iTraxx spreads and not the overall state of the European economy. We do however note that it is possible that there exists some multicollinearity between the FTSE 350 and the sector equity indices, which could cause insignificant variables.

More importantly, both the lagged changes in the iTraxx spreads and the liquidity proxy are found to be highly significant and estimated with the predicted signs. Furthermore the robustness regression renders substantially higher R-squares than the original model. Hence the results of the robustness regression imply that even though the Merton model does have some explanatory power of the iTraxx spreads, adding new explanatory variables might radically improve the performance of the model. Next we therefore run regressions adding the liquidity and the lag to the original model. The model is specified as follows:

$$\begin{aligned}\Delta \ln CDI_t^i = \alpha + \beta_1^i \Delta \ln ret_t^i + \beta_2^i \Delta \ln vol_t^i + \beta_3^i \Delta \ln VOX_t + \beta_4^i \Delta \ln r_t^{10} \\ + \beta_5^i \Delta \ln CDI_{t-1}^i + \beta_6^i \Delta \ln diff_t^i + \nu_i + \epsilon_t^i \qquad (7)\end{aligned}$$

The results from model (7) can be found in table 5. All variables in the final regression are found to be highly significant rendering an R-square of more than 90%. The high significance of the lagged changes in the spreads confirms the finding of Byström, implying that the iTraxx spreads do incorporate information about future spreads. The results further show that the influence of the lagged variable seems to be relatively large. The positive relationship might suggest that the spreads exhibit some trending behaviour which means that a positive

[39]See table 6 in Appendix.

	Ask 5	Bid 5	Ask 10	Bid 10
α	-0,0006*	-0,0006**	-0,0002	-0,0006
$\Delta \ln ret_t^i$	-0,1326***	-0,1443***	-0,0810**	-0,1443***
$\Delta \ln vol_t^i$	0,0241***	0,0240***	0,0159***	0,0240***
$\Delta \ln VOX_t$	0,0471***	0,0496***	0,0400***	0,0496***
$\Delta \ln r_t^{10}$	-0,0824***	-0,0839***	-0,0651***	-0,0839***
$\Delta \ln CDI_{t-1}^i$	0,1973***	0,2026***	0,1538***	0,2026***
$\Delta \ln diff_t^i$	0,0375***	-0,0165***	0,0224***	-0,0165***
R^2	0,9343	0,9226	0,9731	0,9502

Table 5: Panel data regression using significant coefficients from the robust regression. *** indicates that the variable is significant at the 1% level, ** at the 5% level and * at the 10% level.

change yesterday leads to a positive change today holding all else constant. The significance of the liquidity measure implies that the iTraxx do incorporate some liquidity in their spreads.

Importantly the variables of the original model remain significant and estimated with correct signs. Even though the explanatory power increases substantially when adding the lag and the difference of the spreads, the original variables suggested by the Merton model do have some significant effect on the iTraxx spreads. This confirms the importance of using the variables suggested by the Merton model, but does however also suggest that the original model might be misspecified omitting important explanatory variables.

8 Conclusion

The variables suggested by the Merton model (leverage, volatility and the risk-free rate) have a strong theoretical relationship with the iTraxx spreads. Moreover, the theoretical relationship can be confirmed by our empirical study. We find the proxies for leverage, volatility and the risk-free rate to significantly influence the iTraxx spreads. These results concur with previous studies. The model is however found to have quite limited explanatory power, explaining only approximately 30% of the variations in the iTraxx spreads, implying that important variables might be omitted.

Importantly, our choices of proxies of the variables included in the model could be discussed. As mentioned above using the equity index returns as a proxy for leverage is somewhat problematic. The equity indices might influence the iTraxx index because they reflect the economic performance of the sector rather than the leverage level of the sector. Hence using the equity index returns as a proxy for leverage could be improved by either creating indices that perfectly reflect the iTraxx basket as done by Byström, or by calculating a combined leverage ratio of the companies included in the basket. Furthermore, finding an appropriate proxy for the volatility is also somewhat challenging. We do believe that using both the VSTOXX and the historical volatility is a better option rather than using one of them separately. By using both we manage to combine both the forward-looking and the sector specific properties of the volatility in the Merton model. The best alternative for our study would however be if there existed a sector specific volatility index, or if one could calculate a combined implied volatility from options on the companies included in the iTraxx basket. As for the proxy for the risk-free rate, finding an interest rate with a suitable maturity is important. Our findings suggest that both the 2-year yield and the 10-year yield have significant effects on the iTraxx spreads. Also the results might change slightly if replacing the German government rate by another European interest rate. However, even if the suitable proxies in our study could be improved we still believe that our model have tested if the theoretical determinants of the Merton model affect the iTraxx spreads.

The significance of the variables of the Merton model also holds for our robustness test. However the results of the robustness regression also indicate that liquidity and the changes in the lagged iTraxx spreads significantly influence the variations of the iTraxx spreads. Including these variables in the original model renders an R-square of approximately 90%. This suggests that our original model omits important variables. Hence, in conclusion we find that even though the variables suggested by the Merton model do have a significant impact on the iTraxx spreads, using only leverage, volatility and the risk-free rate to explain these spreads might leave us with a misspecified model.

As only limited amounts of research have been performed on the iTraxx spreads there are several areas that could be interesting for further research. Firstly, the effects of liquidity and liquidity spillover on the iTraxx spreads should be investigated more thoroughly. Secondly, it could be interesting to examine the predictive ability of our final model, testing it out of sample. Finally, as our data sample was too limited we did not find and sector specific variations. When longer time series becomes available, iTraxx spreads should be investigated more thoroughly for sector specific variations.

References

[dow, Accessed 25th November 2006] Accessed 25th November 2006. *www.dowjones.com.*

[fts, Accessed 5th January 2007] Accessed 5th January 2007. *www.ftse.com.*

[itr, Accessed 5th October 2006] Accessed 5th October 2006. *www.itraxx.com.*

[Alexander, 2001] Alexander, C. 2001. *Market Models - a Guide to Financial Data Analysis.* Wiley & Sons.

[Anderson & Sundaresan, 1996] Anderson, R., & Sundaresan, S. 1996. Design and Valuation of Debt Contracts. *Review of Financial Studies*, **9**, 37–68.

[Black & Cox, 1976] Black, F., & Cox, J. 1976. Valuing Corporate Securities: Some Effects of Bond Indenture Provisions. *Journal of Finance*, **31**, 351–367.

[Black & Scholes, 1973] Black, F., & Scholes, M. 1973. The Pricing of Options and Corporate Liabilities. *The Journal of Political Economy*, **81, No. 3**, 637–654.

[Blanco *et al.* , 2003] Blanco, R., Brennan, S., & Marsh, I. 2003. An Empirical Analysis of the Dynamic Relationship Between Investment Grade Bonds and Credit Default Swaps. *Bank of England Working paper no. 211.*

[Byström, 2005] Byström, H. 2005. Credit Default Swaps and Equity Prices: the iTraxx CDS Index Market. *Working paper, Lund University.*

[Campbell & Taksler, 2003] Campbell, J., & Taksler, G. 2003. Equity Volatility and Corporate Bond Yields. *Journal of Finance*, **58**, 2321–2349.

[Collin-Dufresne *et al.* , 2001] Collin-Dufresne, P., Goldstein, R., & Martin, S. 2001. The Determinants of Credit Spread Changes. *Journal of Finance*, **56**, 2177–2207.

[Cremers *et al.* , 2004] Cremers, M., Driessen, J., Maenhout, P., & Weinbaum, D. 2004. Individual Stock-Option Prices and Credit Spreads. *Yale ICF Working paper no. 0414.*

[Ericsson *et al.* , 2005] Ericsson, J., Jacobs, K., & Oviedo, R. 2005. The Determinants of Credit Default Swap Premia. *Working paper, McGill University.*

[Fabozzi, 2004] Fabozzi, F. 2004. *Bond Markets, Analysis, and Strategies 5th Edition.* Pearson Prentice Hall.

[Fornari, 2005] Fornari, F. 2005. *Quarterly Review June 2005*. Tech. rept. Bank of International Settlement.

[Gujarati, 2003] Gujarati, D. 2003. *Basic Econometrics, Fourth Edition*. McGraw-Hill.

[Houweling & Vorst, 2005] Houweling, P., & Vorst, T. 2005. Pricing default swaps: Empirical evidence. *Journal of International Money and Finance*, **24**, 1200–1225.

[Hull & White, 2003] Hull, J., & White, A. 2003. The Valuation of CDS Options. *Working paper, University of Toronto*.

[Hull & White, 2005] Hull, J., & White, A. 2005. New layers of protection. *Financial Times*, via www.ft.com, accessed 25th January.

[Hull *et al.* , 2004a] Hull, J., Nelken, I., & White, A. 2004a. Merton's Model, Credit Risk, and Volatility Skews. *Working paper, University of Toronto*.

[Hull *et al.* , 2004b] Hull, J., Predescu, M., & White, A. 2004b. The Relationship Between Credit Default Swap Spreads, bond Yields, and Credit Rating Announcements. *Working paper, University of Toronto*.

[Koller *et al.* , 2005] Koller, T., Goedhart, M., & Wessels, D. 2005. *Valuation. Measuring and managing the value of companies, 4th Edition*. John Wiley & Sons.

[Leland & Toft, 1996] Leland, H. E., & Toft, K. B. 1996. Optimal Capital Structure, Endogeneous Bankruptcy and the Term Structure of Credit Spreads. *Journal of Finance*, **51**, 987–1019.

[Longerstaey & Spencer, 1996] Longerstaey, J., & Spencer, M. 1996. *RiskMetrics - Technical Document 4th Edition*. Tech. rept. J.P. Morgan/Reuters.

[Longstaff & Schwartz, 1995] Longstaff, F., & Schwartz, E. 1995. A Simple Approach to Valuing Risky Fixed and Floating Rate Debt. *Journal of Finance*, **50**, 789–819.

[Longstaff *et al.* , 2004] Longstaff, F., Mithal, S., & Neis, E. 2004. Corporate Yield Spreads: Default Risk or Liquidity? - New Evidence from the Credit Default Swap Market. *Journal of Finance*, **LX, No 5**, 2213–2253.

[Merton, 1974] Merton, R. 1974. On the pricing of Corporate Debt: The Risk Structure of Interest Rates. *Journal of Finance*, **29, No. 2**, 449–470.

[Micu & Upper, 2006] Micu, M., & Upper, C. 2006. *Quarterly Review June 2006*. Tech. rept. Bank of International Settlement.

[Saunders & Allen, 2002] Saunders, A., & Allen, L. 2002. *Credit Risk Measurement - New Approaches to Value at Risk and Other Paradigms, Second Edition.* John Wiley & Sons, Inc.

[StataCorp., 2003] StataCorp. 2003. *STATA Cross-Sectional Time-Series Reference Manual Release 8.* Stata Press.

[Sundaresan, 2002] Sundaresan, S. 2002. *Fixed Income Markets and Their Derivatives, Second Edition.* South-Western Thompson Learning.

[Tang & Yan, 2006] Tang, D. Y., & Yan, H. 2006. Liquidity, Liquidity Spillover and Credit Default Swap Spreads. *Working paper, Kennesaw State University and University of South Carolina.*

[Wang *et al.* , 2006] Wang, D., S.Rachev, & Fabozzi, F. 2006. Pricing Tranches of a CDO and a CDS Index: Recent Advances in Future Research. *Working papaer, University of California and Yale School of Management.*

[Wooldridge, 2002] Wooldridge, J. 2002. *Econometric Analysis of Cross Section and Panel Data.* The MIT Press.

Appendix

Merton's model

Merton's model values loans as options.[40] In the case of default, the equity holders have an option to walk away from their obligations by giving the assets to the debt holders. Hence, the equity holders of a leveraged company can be said to hold a put option. The strike price is set to be the nominal value of the debt and the spread corresponds to the put option value. In the pricing of loans as options Black and Scholes option pricing model can be used in a slightly modified version. The model assumes frictionless markets, no taxes and no bankruptcy costs. We have that the value of a firm, V, is:

$$V_t = S_t + D_t, \tag{8}$$

where the equity value is denoted by S and the market value of debt is denoted by D. The debt holder's payoff at maturity, T, is:

$$\min[F, V_T] = F - \max[0, F - V_T],$$

where V_T denotes the asset value at maturity and F denotes the face value of debt. Thus the equity payoff can be seen as a call on the firm's assets:

$$\max[0, V_T - F].$$

By using Black and Scholes option pricing model in this context, the equity value can be written as:

$$S = V_t N(d_1) - F e^{-r(T-t)} N(d_2), \tag{9}$$

where

$$d_1 = \frac{\ln(\frac{V}{F}) + (r + \frac{\sigma_V^2}{2})(T-t)}{\sigma_V \sqrt{T-t}},$$

[40] See Sundaresan (2002) for an explanation of the Merton model.

and

$$d_2 = d_1 - \sigma_V \sqrt{T-t},$$

where t is the current date, r is the risk-free rate and σ_V is the asset volatility. $N(d_1)$ and $N(d_2)$ is a value from the statistical tables on the standard normal distribution. The bond holders face the following payoff at maturity:

$$\min[F, V_T] = F - \max[0, F - V_T].$$

Combining equation (8) and (9) we obtain the debt value at t as:

$$D = Fe^{-r(T-t)}N(-d_2) - V_t N(-d_1).$$

If y is the yield to maturity on a corporate bond, the following equation must be satisfied:

$$D = Fe^{-y(T-t)}.$$

Solving for the risky yield, y, we get:

$$y = -\frac{1}{T-t}\ln(\frac{D}{F}).$$

Merton further defines the default spread, s, as the difference between y and r where r is a risk-free interest rate:

$$s = y - r.$$

Finally, the leverage, L, is defined as:

$$L = \frac{Fe^{-r(T-t)}}{V}.$$

Correlation between European interest rates

	Ger 10y	Ger 2y	UK 10y	French 10y
Ger 10y	1,000			
Ger 2y	0,521	1,000		
UK 10y	0,861	0,116	1,000	
French 10y	0,995	0,497	0,864	1,000

Table 6: Correlations between European interest rates.

Correlation between volatility measures

	vstoxx	autovol	convol	indvol
vstoxx	1			
autovol	-0,013	1		
convol	-0,012	0,398	1	
indvol	0,035	0,451	0,757	1
envol	0,033	0,176	0,301	0,374
senfinvol	0	0,431	0,731	0,789
subfinvol	0	0,431	0,731	0,789
tmtvol	0,034	0,249	0,418	0,509
	envol	senfinvol	subfinvol	tmtvol
vstoxx				
autovol				
convol				
indvol				
envol	1			
senfinvol	0,297	1		
subfinvol	0,297	1	1	
tmtvol	0,193	0,487	0,487	1

Table 7: Correlation matrix for volatilities.

Regressions using the volatility measures separately

	Ask 5	Bid 5	Ask 10	Bid 10
α	-0,0007**	-0,0007**	-0,0002	-0,0002
$\Delta \ln ret_t^i$	-0,3058***	-0,3169***	-0,2166***	-0,2342***
$\Delta \ln vol_t^i$	0,0307***	0,0292***	0,0188***	0,0215***
$\Delta \ln r_t^{10}$	-0,0933***	-0,0906***	-0,0752***	-0,0667***
R^2	0,3041	0,3094	0,3281	0,3336
α	-0,0007**	-0,0008**	-0,0003	-0,0003
$\Delta \ln ret_t^i$	-0,1480***	-0,1503***	-0,0825**	-0,1042***
$\Delta \ln VOX_t$	0,0493***	0,0520***	0,0418***	0,0406***
$\Delta \ln r_t^{10}$	-0,0891***	-0,0860***	-0,0713***	-0,0630***
R^2	0,3029	0,3083	0,3227	0,3296

Table 8: Panel data regressions using the volatility and the VSTOXX separately. *** indicates that the variable is significant at the 1% level, ** at the 5% level and * at the 10% level.

Dickey-Fuller test for stationarity

We use a Dickey-Fuller test to test the variables for stationarity. The test is implemented as follows, we first estimate the following regression:

$$\Delta \ln Y_t = \alpha + \beta_1 T + \beta_2 \ln Y_{t-1} + \epsilon_t$$

Where $\Delta \ln Y_t$ denotes the first-difference of the logged variable and Y_{t-1} denotes the log of the variable lagged one period. The variable is then tested for a unit root, i.e. if the series is non stationary by testing the following hypotheses;

$$H_0 : \beta_2 = 0$$
$$H_1 : \beta_2 < 0.$$

If H_0 can be rejected the series is found to be stationary. The null hypothesis can be rejected at a 5% significance level if the t-value (following a τ - distribution) of the estimated coefficient, is smaller than $\tau = -3,567$. Tables 9-10 below shows in what cases the hypothesis can be rejected.

Variable	Test stat.	Variable	Test stat.	Variable	Test stat.
bauto5y	-2,186	aauto10y	-1,878	spfin	-2,561
aauto5y	-2,190	bcon10y	-1,255	spen	-1,345
bcon5y	-1,764	acon10y	-1,250	ftseconsc	-2,864
acon5y	-1,760	bind10y	-1,529	ftseeuromi	-1,720
bind5y	-1,835	aind10y	-1,527	vrspind	-2,199
aind5y	-1,816	ben10y	-1,467	vrsptelec	-3,645**
ben5y	-2,607	aen10y	-1,483	vretspfin	-2,430
aen5y	-2,536	bsenfin10y	-1,624	vrspen	-2,520
bsenfin5y	-1,520	asenfin10y	-1,688	vrftseeuro	-3,381*
asenfin5y	-1,531	bsubfin10y	-1,420	gergov10y	-1,839
bsubfin5y	-1,668	asubfin10y	-1,386	gergov2y	-2,055
asubfin5y	-1,695	btmt10y	-1,771	ftse350	-2,764
btmt5y	-1,835	atmt10y	-1,812	vstoxx	-3,709**
atmt5y	-1,872	spind	-2,168	vrftsecsc	-2,060
bauto10y	-1,921	sptelec	-2,365	sauto5y	-9.342***

Table 9: Dickey-Fuller test for stationarity on all variables.*** indicates that the variable is significant at the 1% level, ** at the 5% level and * at the 10% level.

Variable	Test stat.	Variable	Test stat.	Variable	Test stat.
lbauto5y	-2.062	ssubfin5y	-9.218***	laind10y	-1.312
laauto5y	-2.077	lbsubfin5y	-1.098	sen10y	-6.723***
scon5y	-8.551***	lasubfin5y	-1.156	lben10y	-1.248
lbcon5y	-0.943	stmt5y	-10.697***	laen10y	-1.299
lacon5y	-0.965	lbtmt5y	-1.530	ssenfin10y	-10.911***
sind5y	-11.013***	latmt5y	-1.549	lbsenfin10y	-1.030
lbind5y	-1.791	sauto10y	-6.535***	lasenfin10y	-1.213
laind5y	-1.776	lbauto10y	-1.940	ssubfin10y	-7.338***
sen5y	-7.254***	laauto10y	-1.889	lbsubfin10y	-0.937
lben5y	-2.065	scon10y	-9.512***	lasubfin10y	-0.961
laen5y	-2.069	lbcon10y	-0.758	stmt10y	-5.711***
ssenfin5y	-7.149***	lacon10y	-0.783	lbtmt10y	-1.191
lbsenfin5y	-0.707	sind10y	-7.206***	latmt10y	-1.153
lasenfin5y	-0.844	lbind10y	-1.332		

Table 10: Dickey-Fuller test for stationarity on all variables.*** indicates that the variable is significant at the 1% level, ** at the 5% level and * at the 10% level.

Hausmann test

The Hausmann test is performed in order to determine if the GLS (random effects) or the LSDV (fixed effects) method should be used in estimating the panel regessions.[41] In the Hausmann test the null hypothesis that exogenous random effects are uncorrelated with the explanatory variables are tested. If H_0 can not be rejected, i.e. no correlation with the explanatory variables, the random effects GLS estimators are found to be consistent. The test statistic follows a $\chi^2(k')$ distribution where k is the number of variables. As can be seen from the table 11 below the GLS estimators were found to be consistent for all of our regressions. Hence we used the random effects estimator.

	Ask5	Bid5	Ask10	Bid10
Panel all	0.9886	0.9862	0.9724	0.9734
Index	0.6947	0.6762	0.6082	0.5973
Vol	0.9988	0.9987	0.9904	0.9909
Vstoxx	1.0000	1.0000	1.0000	1.0000
Ggov10	0.9924	0.9922	0.9912	0.9911
Robust	1.0000	0.9999	0.9994	0.9994

Table 11: P-values from the Hausmann test for all panel data regressions. A p-value below $< 0,05$ indicates that H_0 is rejected at the 5% significance level.

[41] See e.g. Wooldridge (2002) and StataCorp (2003).

Multicollinearity

Consistent with Gujarati (2003) we evaluate the model according to several parameters in order to check for presence of multicollinearity in model (1). Gujarati argues that mullticollinearity should be suspected if:

1. Insignificant variables in combination with a high R-square. This parameter clearly implies no existence of mullticollinearity, since we obtain moderate R-squares and high significance of the explanatory variables in all our regression.

2. Strong pair-wise correlation ($> 0,8$) between the explanatory variables. When examining the pair-wise correlations between variables we find that all correlations lie below 0,2. Hence also according to this parameter there is no implication of mullticollinearity.

3. Condition index number greater than 10 suggest moderate multicollinearity and higher than 30 indicate severe multicollinearity. As can be seen from table 12 below the Condition index numbers of our regressions does not exceed 2,1, i.e. there is no reason to suspect multicollinearity.

Based on these three tests we conclude that there is no reason to suspect the presence of multicollinearity in our regressions.

	Ask 5		Bid 5	
	Eigenvalue	CI	Eigenvalue	CI
1	1,711	1,000	1,710	1,000
2	1,051	1,276	1,046	1,279
3	1,010	1,302	1,009	1,302
4	0,955	1,338	0,955	1,338
5	0,882	1,393	0,889	1,387
6	0,391	2,092	0,391	2,091
Condition No		2,092		2,091
	Ask 10		Bid 10	
	Eigenvalue	CI	Eigenvalue	CI
1	1,701	1,000	1,701	1,000
2	1,036	1,281	1,038	1,280
3	1,011	1,297	1,012	1,296
4	0,957	1,333	0,956	1,334
5	0,905	1,371	0,903	1,372
6	0,391	2,087	0,391	2,086
Condition No		2,087		2,091

Table 12: Condition index (CI) and eigenvalues.

One-by-one panel data regressions

	Ask 5	Bid 5	Ask 10	Bid 10
α	-0,0007**	-0,0008**	-0,0002	-0,0003
$\Delta \ln ret_t^i$	-0,3201***	-0,3308***	-0,2279***	-0,2444***
R^2	0,3064	0,3115	0,3275	0,3329
α	-0,0009***	-0,0009***	-0,0003	-0,0004
$\Delta \ln vol_t^i$	0,0313***	0,0299***	0,0192***	0,0220***
R^2	0,0004	0,0004	0,0060	0,0052
α	-0,0008***	-0,0009***	-0,0003	-0,0003
$\Delta \ln VOX_t$	0,0682***	0,0711***	0,0528***	0,0539***
R^2	0,0000	0,0000	0,0000	0,0000
α	-0,0008***	-0,0009***	-0,0003	-0,0003
$\Delta \ln r_t^{10}$	-0,1164***	-0,1145***	-0,0914***	-0,0843***
R^2	0,3008	0,2908	0,2880	0,2763

Table 13: Panel data regressions using the explanatory variables one-by-one. *** indicates that the variable is significant at the 1% level, ** at the 5% level and * at the 10% level.

Time series regressions

Auto	Ask 5	Bid 5	Ask 10	Bid 10
α	-0,0004	-0,0004	0,0001	0,0001
$\Delta \ln ret_t^i$	-0,2646***	-0,2655***	-0,1922***	-0,2044
$\Delta \ln vol_t^i$	0,0329*	0,0346*	0,0188	0,0158
$\Delta \ln VOX_t$	0,0772***	0,0803***	0,0597***	0,0612***
$\Delta \ln r_t^{10}$	-0,1575**	-0,1408*	-0,1351***	-0,1357***
R^2	0,0755	0,0768	0,0855	0,0848
Consumer	**Ask 5**	**Bid 5**	**Ask 10**	**Bid 10**
α	-0,0011	-0,0010	-0,0004	-0,0005
$\Delta \ln ret_t^i$	-0,1028	-0,1433	-0,0486	-0,0544
$\Delta \ln vol_t^i$	0,0299**	0,0297**	0,0221**	0,0235
$\Delta \ln VOX_t$	0,0502***	0,0403**	0,0152**	0,0337**
$\Delta \ln r_t^{10}$	-0,1548***	0,0548***	-0,1291***	-0,1359***
R^2	0,0546	0,0515	0,045	0,0461
Energy	**Ask 5**	**Bid 5**	**Ask 10**	**Bid 10**
α	-0,0011	-0,0010	-0,0006	-0,0006
$\Delta \ln ret_t^i$	-0,0497	-0,0189	0,0321	0,0156
$\Delta \ln vol_t^i$	-0,0062	-0,0024	-0,0035	0,0000
$\Delta \ln VOX_t$	0,0404*	0,0437**	0,0399***	0,0383**
$\Delta \ln r_t^{10}$	-0,0091	-0,0166	-0,0171	0,0022
R^2	0,0126	0,0144	0,0152	0,0131
Industrial	**Ask 5**	**Bid 5**	**Ask 10**	**Bid 10**
α	-0,0003	-0,0002	0,0000	0,0001
$\Delta \ln ret_t^i$	-0,0794	-0,1191	0,1158	0,0768
$\Delta \ln vol_t^i$	0,0298*	0,0342**	0,0213	0,0240*
$\Delta \ln VOX_t$	0,0551**	0,0490*	0,0607***	0,0566***
$\Delta \ln r_t^{10}$	-0,0852	-0,0757	-0,0595	-0,0619
R^2	0,0299	0,0332	0,0291	0,0281

Table 14: Time series regressions using all explanatory variables in the Auto, Consumer, Energy and Industrial sectors. *** indicates that the variable is significant at the 1% level, ** at the 5% level and * at the 10% level.

Sen Financial	Ask 5	Bid 5	Ask 10	Bid 10
α	-0,0014	-0,0013	-0,0007	-0,0007
$\Delta \ln ret_t^i$	-0,1389	-0,0560	-0,1904	-0,2289
$\Delta \ln vol_t^i$	0,0377*	0,0375**	0,0062	0,0216
$\Delta \ln VOX_t$	0,0501*	0,0539**	0,0313	0,0280
$\Delta \ln r_t^{10}$	-0,0561	-0,0820	-0,0351	0,0302
R^2	0,0287	0,0306	0,0176	0,0192
Sub Financial	**Ask 5**	**Bid 5**	**Ask 10**	**Bid 10**
α	-0,0013	-0,0013	-0,0007	-0,0007
$\Delta \ln ret_t^i$	-0,2205	-0,2382	-0,2687**	-0,3408**
$\Delta \ln vol_t^i$	0,0486**	0,0556***	0,0445***	0,0441***
$\Delta \ln VOX_t$	0,0458*	0,0388	0,0270	0,0214
$\Delta \ln r_t^{10}$	-0,0644	-0,0869	-0,0606	-0,0595
R^2	0,0398	0,0455	0,0512	0,0527
TMT	**Ask 5**	**Bid 5**	**Ask 10**	**Bid 10**
α	-0,0002	-0,0002	0,0003	0,0003
$\Delta \ln ret_t^i$	-0,1122	-0,1205	-0,0118	-0,0174
$\Delta \ln vol_t^i$	0,0261	0,0218	0,0176	0,0188
$\Delta \ln VOX_t$	0,0549**	0,0474**	0,0417***	0,0410**
$\Delta \ln r_t^{10}$	-0,0730	-0,0728	-0,0593	-0,0793
R^2	0,0286	0,0251	0,0271	0,0272

Table 15: Time series regressions using all explanatory variables in the Senior Financial, Subordinated Financial and TMT sector. *** indicates that the variable is significant at the 1% level, ** at the 5% level and * at the 10% level.

Graphs over the iTraxx spreads sector-wise

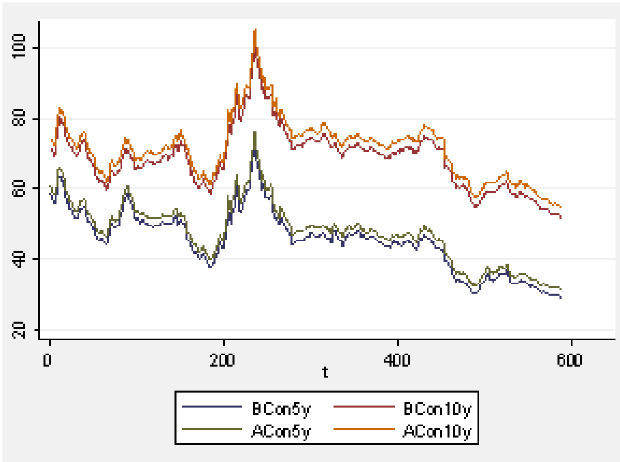

Figure 5: Graph of the 5- and 10-year iTraxx spreads for the Consumer sector during the sample period.

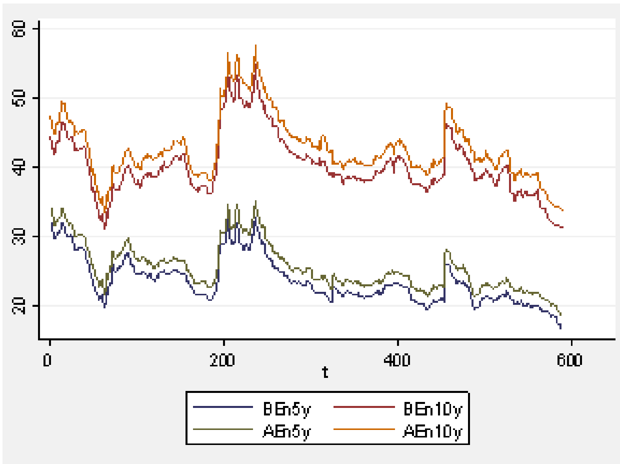

Figure 6: Graph of the 5- and 10-year iTraxx spreads for the Energy sector during the sample period.

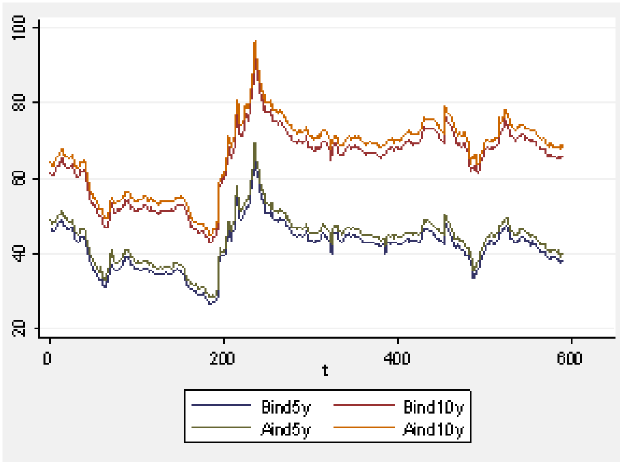

Figure 7: Graph of the 5- and 10-year iTraxx spreads for the Industrial sector during the sample period.

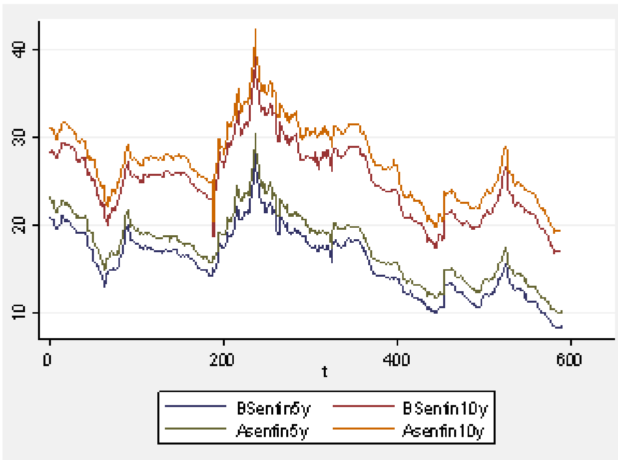

Figure 8: Graph of the 5- and 10-year iTraxx spreads for the Senior Financial sector during the sample period.

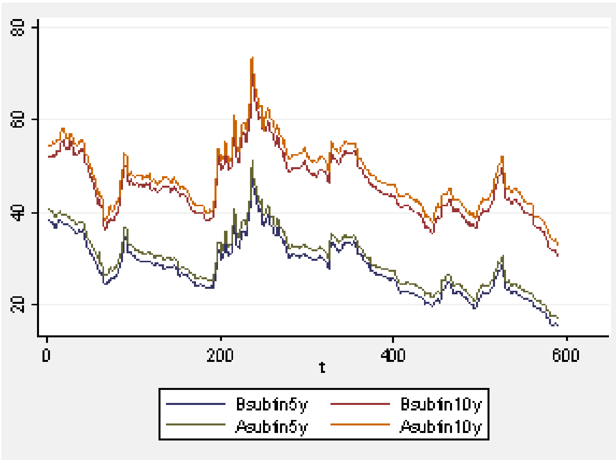

Figure 9: Graph of the 5- and 10-year iTraxx spreads for the Subordinated Financial sector during the sample period.

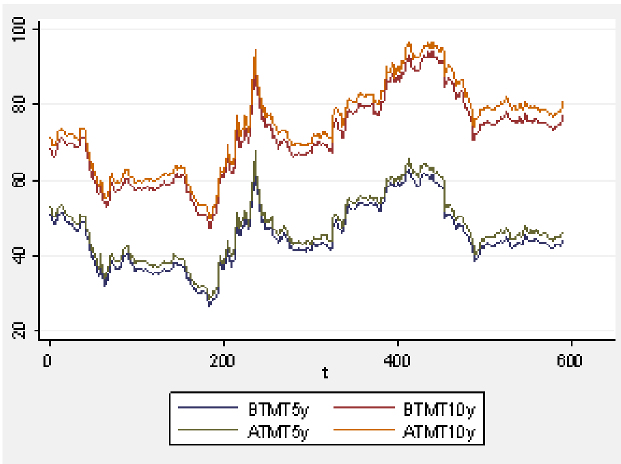

Figure 10: Graph of the 5- and 10-year iTraxx spreads for the TMT sector during the sample period.