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A Value-at-Risk Analysis of Credit Default Swaps and Stocks

Evidence from the European and North American Market

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Abstract

This thesis analyzes credit and equity risk during the period from September 2006 to September 2014. The sample includes pairs of credit default swap (CDS) spreads and stock prices for 113 European and 93 North American companies. A historical simulation is performed to compute Value-at-Risk (VaR) and Expected Tail Loss (ETL) for a CDS short position and a long position in the respective firm's equity. Five different hypotheses are tested and their results are compared across different time horizons, rating classes and industries. Overall findings provide additional insights into the dynamics of the credit and equity market over the last eight years. This paper finds evidence on debt always being less risky than equity as demonstrated by Merton in 1974. However, interesting deviations Merton's predictions with respect to drivers of debt riskiness are found with respect to the European market in the most recent years. Furthermore, a declining trend in both credit and equity risk is observed, with the former decreasing at a higher pace. A finding on pooled market samples proves that the positive correlation between credit and equity market is stronger for low credit quality firms. Lastly, this paper notices that credit and equity market may react differently with respect to time and/or magnitude for a given industry in different geographical markets.

Keywords: Value-at-Risk, credit risk, equity risk, historical simulation, credit default swaps

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1 Introduction

The financial crisis of 2008 has increased interest in credit default swaps (CDS) not only within the financial sector, but also in the general public consciousness. Innovation in the financial derivative market has led to the development of CDSs: a financial instruments introduced with the objective of aiding lenders, especially banks, to manage their credit risk and free up their balance sheets for additional loans. In 2007 complications concerning CDS trades became evident with the bankruptcy of financial institutions and concerns about the misuse of CDSs as speculative tools started to spread among market participants. A series of chain reactions reached its breaking point on September 15th 2008, when the bankruptcy of Lehman Brothers led to a freeze in the credit market (Ciro 2012).

The market for CDSs grew quickly in the pre-crisis years from USD 6.4 trillion in 2004 to USD 58.4 trillion in 2007. In December 2012, however, the total net notional outstanding amounted to USD 25.1 trillion, as a result of compression efforts undertaken by the U.S. Federal Reserve. (ISDA 2013)

Nowadays, the question of whether benefits of CDS trading exceed costs is still being answered (Weistroffer 2009). However, there is a common conception that CDS spreads are better indicators of credit views than bond yields (Stulz 2009).

The main goal of this thesis is to provide additional insights into the credit and the equity market dynamics. Therefore, the trading risk's evolution in the credit and equity European as well as North American markets during the 2006-2014 period is investigated. A Value-at-Risk (VaR) and expected tail loss (ETL) analysis is performed on a short CDS position and a long equity position using historical simulation. A comparative approach with respect to different time periods, rating classes, industries and geographical markets is used to individuate peculiarities. Five hypotheses are the cornerstones of this paper:

1. *CDS VaR is lower than equity VaR*
2. *Credit and equity risk are positively correlated*
3. *Credit and equity risk have decreased in the aftermath of the 2008 financial crisis, with a higher pace of decline of credit risk*
4. *VaR measures are significantly different across ratings*
5. *The risk-return profile of companies vary across industries*

Overall, results are in line with expectations from previous research and the two geographical markets do not show major significant anomalies. The CDS VaR is always exceeded by the equity VaR, albeit the ratio between the two risk measures varies across time periods, rating classes and industries. As such, it is possible to confirm that in all cases debt is less risky than equity as first established by Merton (1974).

Furthermore, this paper finds that the correlation between CDS spreads and stock prices is negative and sheds lights on cross-market differences by observing the lower correlation magnitude (in absolute value) in Europe compared to North America.

Moreover, this thesis proves a reduction in both equity and credit risk measures since Lehman's collapse, with the latter decreasing at a higher rate. However, timing differences are found between the European and North American market.

The analysis on rating subsamples empirically proves that investment grade firms are less risky than high yield ones. Furthermore, the risk of the CDS investment relative to the equity position is higher in Europe than in North America. Additionally, once the two geographical markets are combined the correlation between the credit and equity market is higher for high yield companies.

Lastly, sector subsamples show variations in results for the same industries in different markets, suggesting that financial interconnectedness might be an important driver of debt riskiness.

This thesis begins with a brief introduction to the CDS market and particular features of the indexes, which is presented in Chapter 2. This is followed by a literature review that gives insights into strength and weaknesses of previous research as well as gaps that this paper is filling (Chapter 3) and an overview of the five tested hypotheses (Chapter 4). Chapter 5 describes the sample and methodology adopted for this study, while empirical results are presented and analyzed in Chapter 6. The thesis ends with the outline of limitations as well as suggestions for further research in Chapter 7.

2 The Credit Market

This chapter aims at providing the necessary background to understand the research questions analyzed in this thesis as well as its results. Three key concepts are introduced: CDS, the financial instrument cornerstone of the thesis; the iTraxx and CDX indices, which are crucial for the sampling phase; credit ratings, that are used to test one of the five hypotheses.

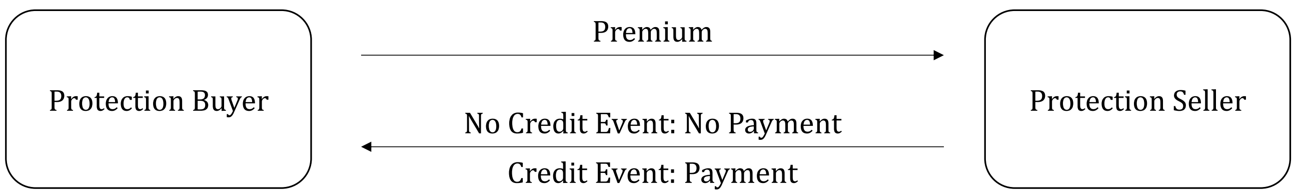
2.1 Credit Default Swaps

The growth in the CDS market has led to their evolution from a niche financial instrument to an important and active credit risk transfer tool. Subsequently, CDSs and their role in the financial markets have been at the core of research concerning credit risk, firm cost of capital and related financing choices (Ashcraft and Santos 2009; Saretto & Tookes 2013; Subrahmanyam et al. 2014), their significance in debtor-creditor relations (Hu & Black 2008; Bolton & Oehmke 2011) and lastly their role during the financial crisis of 2008 (Stulz 2010).

Credit default swaps transfer the risk that an entity (the "reference entity") defaults between two agents, namely the "protection buyer" and the "protection seller". The diagram in Figure 1 shows the cash flows of a CDS contract between the involved counterparties.

Figure 1
Cash flows of a CDS contract

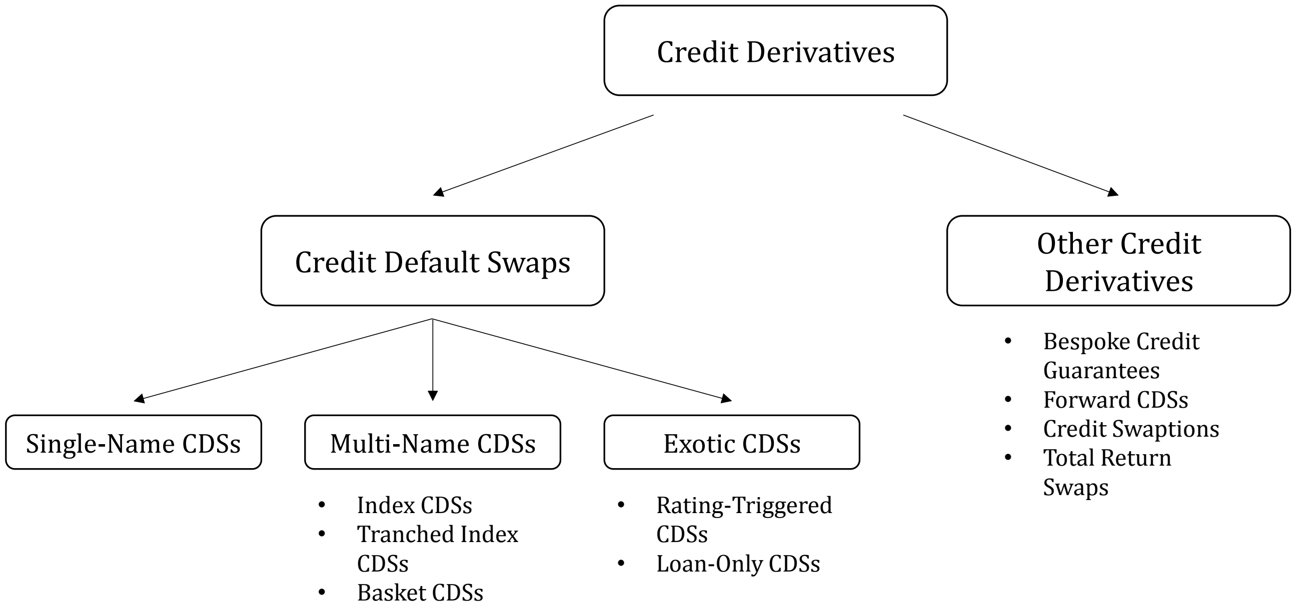
The diagram shows the mutual payment obligations between a seller and a buyer of protection. Source: Weistroffer (2009).



In a CDS transaction, the premium or spread, which the seller of credit risk (i.e. the protection buyer) pays is expressed as an annualized percentage of the notional value of the contract. This value is recorded as the "market price" of the CDS in databases such as Bloomberg. Spreads on a CDS widen when deterioration in credit risk is perceived by the market and tighten in the opposite case. The risk-return structure of a CDS protection seller can be replicated by a trade where the investor buys a corporate bond and hedges the interest rate risk, isolating the credit risk component in the bond (Duffie 1999). Any deviation from this parity creates arbitrage opportunities (Zhu 2006). Thus, CDSs have become the most commonly used credit derivative (Figure 2) because they enable investors to synthetically trade pure credit risk. Furthermore, the unfunded nature of CDS contracts makes them better indicators of credit opinions, since their value is less affected by liquidity issues than the value of bonds (Stulz 2009).

Figure 2
The credit derivatives market

The diagram shows the different derivative contracts available to hedge or trade credit risk. Source: Weistroffer (2009).



A CDS typically has a maturity of one to ten years, with the most liquid tenor being five years. The International Swaps and Derivatives Association (ISDA 2014) provides standardized CDS agreements in which every contract records the transaction details and defines the credit events for which the protection seller needs to compensate the protection buyer. The following five credit events commonly trigger payouts:

- Failure to meet payments when due
- Bankruptcy
- Repudiation
- Material adverse restructuring of debt
- Acceleration or default of obligation

Among the above mentioned contingencies, restructuring is the one creating the most difficulties in being arranged, because the loss suffered by the reference entity is hard to determine and debt of different maturities can remain outstanding with significant differences in value, thus offering arbitrage opportunities to opportunistic protection buyers (Packer and Zhu 2005; Raunig & Scheicher 2009).

A CDS is immediately stopped in the occurrence of any event stipulated in the contract, when the settlement procedure starts. The compensation can either be through cash (i.e. the price difference between the current value and the nominal value of the underlying asset is transferred) or through the delivery of the bond specified in the CDS contract ("physical settlement"). Therefore, any risk measure for a CDS is conditional on the CDS not having defaulted, meaning that the CDS VaR can only be defined in case of no default. (Raunig & Scheicher 2009)

CDSs can be seen as insurance contracts with two relevant differences. First, trading in the CDS market can produce valuable information about a firm's credit risk, while no such information would be produced with trading on somebody's house insurance policy, because not everyone who finds a mispricing in the insurance policy would be able to profit from it. Second, big portfolios of house insurance policies can have very little risk due to diversification, while a large portfolio of CDS contracts is sensitive to macroeconomic factors that are not diversifiable since firms are more likely to default in recessions. (Stulz 2009)

The market for CDSs has grown with accelerated speed in the pre-crisis years from USD 6.4 trillion (net notional amount[1]) in 2004 to USD 58.4 trillion in 2007. Due to the compression requirements aimed at minimizing CDS exposures the market has shrunk to USD 25.1 trillion of net notional value in December 2012. (ISDA 2013)

These clearing and compression policies of portfolios are also known as "tear-up" efforts and led to a considerable reduction in outstanding CDS contracts (ISDA 2014). Compression policies were recommended to the SEC by the G14 members in August 2008 with the following five underlying objectives: capital charges cut, easier usage, gross notional reduction, trade recouponing as well as number of trade outstanding reduction (Markit 2013).

Figure 3 and 4 show the evolution of the CDS market as well as compression efforts respectively.

[1] Transactions between reporting dealers are counted only once. Alternatively, notional values can be reported on a gross basis (i.e. as the sum of the net protection bought across all counterparties)

Figure 3
Annual CDS notional outstanding

The graph displays the annual net notional amount of CDS contracts from 2004 to 2012. Data is in USD tln. Source: BIS (2013).

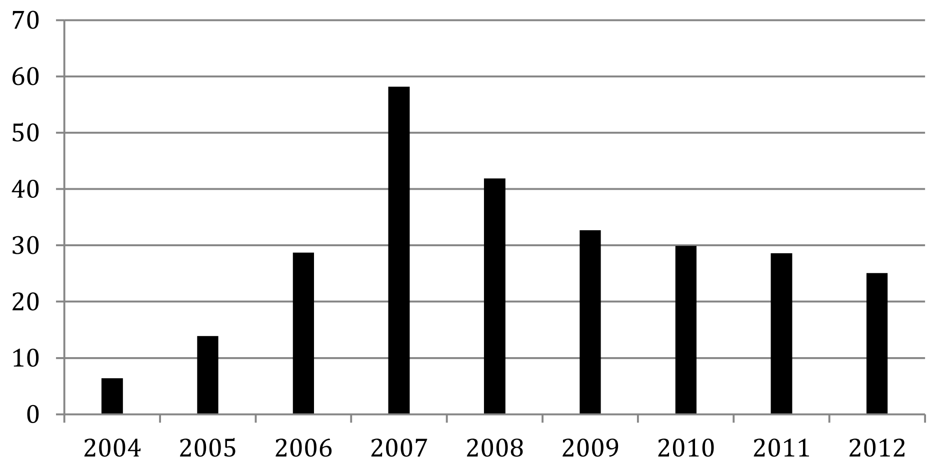
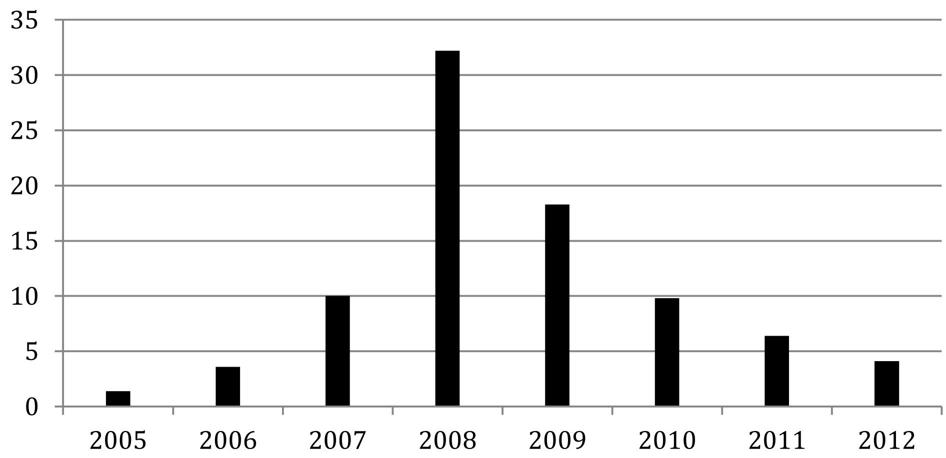


Figure 4
Annual CDS portfolio compression

The graph displays the annual compression efforts on CDS notional outstanding performed from 2005 to 2012. Data is in USD tln. Source: Trioptima and Markit (2013).



CDS transactions are made over-the-counter and, in contrast to publicly traded securities, are mostly traded bilaterally among private dealers. Banks do not only act as dealers, but also use CDSs to manage their own loan portfolios. Banks, securities firms, hedge funds and other institutional traders use CDSs for proprietary trading purposes as well. Furthermore, as opposed to banks and hedge funds, which can act as both buyers and sellers of CDS contracts, insurers such as AIG, Ambac or MBIA mostly act on the sell side of the market, holding portfolios of credit risks where premiums and losses of contracts offset each other. Such a business model, which proved itself to be quite viable during stable financial markets, became particularly vulnerable during the financial crisis. In the course of the crisis, the simultaneous increase in default risk for a large number of entities left protection sellers with highly correlated exposures. Therefore, agents operating mostly on the sell side of the market accumulated relatively large amounts of net exposures. By the end of 2007, AIG, MBIA and Ambac, which are among the largest players in this field, accounted for roughly USD 1.1 billion of credit protection sold through either CDSs, collateralized debt obligations (CDOs), collateralized loan obligations (CLOs) or other asset-backed securities (ABSs). (Weistroffer 2009)

During the crisis of 2007-2009 it became clear that risk transfer instruments do not necessarily guarantee that financial markets work in an efficient and smooth manner. One of the reasons is that CDSs might have increased financial institutions' vulnerability to systemic shocks by aligning their risk profiles. Second, credit risks may have concentrated in certain parts of the financial system, thus becoming harder to deal with. Third and last, by increasing counterparty risk (i.e. the risk that a counterparty will fail to honor its obligations) CDSs may have constituted a further channel for additional spillover effects, which threatened the markets' stability. (Weistroffer 2009)

There is an active debate on how to establish the means necessary to minimize potential negative externalities of the CDS market. Some criticize the use of CDSs for trading purposes as opposed to hedging. Those against the use of "naked CDSs" (contracts owned by someone who is not exposed in any way to the credit risk of the reference entity) claim that while hedging serves a useful economic purpose by sheltering the lender from potential losses, trading potentially distorts markets and raises systemic risk. In fact, usually the buyer of naked CDS protection tries either to exploit arbitrage opportunities arising from differences in pricing between the bond and the CDS market or to take a position which can benefit from an increase in credit risk. However, trading brings additional liquidity to the market and helps to ensure the efficient processing of information; hence, the presence of traders makes hedging cheaper and easier in terms of potential counterparties availability. From an analytical point of view, it is not yet clear whether selling protection without owning the underlying reference entity does more harm than good. In the context of CDSs, the priority of regulation authorities is to set the right incentives, establish a sound market infrastructure and enhance market transparency. (Weistroffer 2009)

2.2 CDX and iTraxx Indices

In June 2004 the introduction of a new family of indices, namely iTraxx in Europe and Asia and CDX in North America, represented a major event in the credit market development, which led to higher market transparency and liquidity (Raunig & Scheicher 2009). The composition of the iTraxx Europe and CDX North America is the basis for this paper's sample construction, as these indices list the most liquid names with a five-year maturity in the respective markets.

Tradable CDS indexes have been created to give investors a platform to trade quickly market-wide as well as sectorial credit risk. The iTraxx index was created on June 21st, 2004 by merging the two major European CDS indexes at the time, iBoxx and Trac-X. This creation led to more efficiency and positive increases in terms of diversification, liquidity as well as transparency. Moreover, market participants were able to achieve high positive or negative exposures in a diversified risk pool. Furthermore, there are a variety of the iTraxx indexes such as the iTraxx Crossover that lists the 100 most liquid sub-investment grade CDSs. (Byström 2003)

The prevailing index in North America is the CDX index and, as the iTraxx, different versions allow trading in investment grade, high yield as well as high beta or high volatility markets. Their main advantages are the trading efficiency, transparency, liquidity and data integrity, which is obtained by collecting CDS prices from different leading banks and further enhanced by a quality control process performed by Markit Financial Information Services. (Markit 2014)

2.3 Credit Ratings

Credit ratings denote the ability of a firm, municipality or state, to fully meet its debt obligations on time. They measure only the creditworthiness and should not be interpreted as investment recommendations such as "buy", "hold" or "sell" (Standard & Poor's 2014). Ratings can also be assigned to a specific debt issue such as a corporate bond or a mortgage-backed security to express views about its likelihood of default. The three leading credit rating agencies are Standard & Poor's, Moody's Investor Services and Fitch Ratings, all of them headquartered in New York. Each rating agency uses its own models, consisting of specific criteria – which are usually industry-specific – and a scale (Table 1). There are five different categories to which credit ratings are applied: financial institutions, insurance companies, corporate issuers, asset-backed securities and government securities (U.S. SEC 2012). Credit ratings are updated on a constant basis: upgrades and downgrades decisions are led by changes in macroeconomic conditions, business climate, firm and/or debt issue attributes. (Standard & Poor's 2014)

Table 1
S&P's credit rating scale

The table shows the rating scale adopted by Standard & Poor's and gives a short description of the individual characteristics of each rating score. Ratings from 'AA' to 'CCC' may be modified by the addition of a plus (+) or minus (-) sign to show relative standing within the major rating categories. Source: Standard & Poor's (2014).

Rating	Meaning
AAA	Highest Rating: extremely strong capacity to meet financial commitments.
AA	Very strong capacity to meet financial commitments.
A	Strong capacity to meet financial commitments, but somewhat susceptible to adverse economic conditions and changes in circumstances.
BBB	Adequate capacity to meet financial commitments, but more subject to adverse economic conditions.
BBB-	Considered lowest investment grade by market participants.
BB+	Considered highest speculative grade by market participants.
BB	Less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions.
B	More vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments.
CCC	Currently vulnerable and dependent on favorable business, financial and economic conditions to meet financial commitments.
CC	Currently highly vulnerable.
C	Currently highly vulnerable obligations and other defined circumstances.
D	Payment default on financial commitments.

Entities or securities with a fairly high risk of default are defined "high yield", "sub-investment grade" or "speculative". The main underlying reasons of a high yield status are not only financial distress and high leverage, but also small size and early age due to the short track-record of operating results or risky financial plans. High yield debt typically pays a higher interest rate than investment grade debt to compensate investor for higher credit, interest rate, economic and liquidity risk. (U.S. Securities and Exchange Commission 2013)

However there are some weaknesses in the current credit rating system. In 2012 the U.S. SEC calculated that the combined market share of the "Big Three" rating agencies (Standard & Poor's, Moody's Investor Services and Fitch Ratings) was 96%. As such, the extremely high market concentration can put competitive market dynamics into question. It has even been shown that bonds and CDSs, with the latter acting at a faster speed, can determine credit worthiness with higher accuracy, especially when it comes to predictions regarding downgrades (Daniels & Jensen 2005). Norden and Weber (2004) found similar results and stated that both the stock and the CDS market have the ability to foreshadow rating changes.

3 Literature Review

In 1974 Merton published a paper regarding the "Theory of the risk structure of interest rates", where he demonstrated what the drivers of equity and debt value are. Up to Merton's study there was no concrete theory concerning neither high default risk valuation nor interest rate risk composition. Merton's theory is considered one of the milestones in risky debt pricing. He established that corporate debt valuation is contingent on three main elements:

1. Required rate of return of riskless (i.e. default-free) debt;
2. Contract's indentures (i.e. maturity, coupon rate, seniority, callable provisions);
3. Firm's default probability (i.e. inability to satisfy any of the indentures).

Merton's theory was based upon the Black-Scholes Model and the Modigliani-Miller theorem, with a special focus on developing a pricing formula whose empirical inputs can be easily observed, thus being both simplistic and effective. One major objective was to provide the first pricing model for callable coupon bonds. Merton's main finding was that debt can never be riskier than equity. This can be shown by referring to the capital structure's subordination: in case of bankruptcy or default, bond owners would receive their money before equity holders, making the latter position riskier. The strength of Merton's valuation model lies in its transferability to other financial instruments, and subsequent studies have benefited from this possibility.

Raunig and Scheicher (2008) performed a VaR analysis on 86 European firms over the 2003-2006 period and found that equity VaR exceeded CDS VaR by a significant margin; therefore, they proved the validity of Merton's assertions by using CDS values as a proxy for debt values. Furthermore, they found that the co-movement of VaR measures was linear and that both risk measures displayed a downward trend between 2003 and 2006. Moreover, the rate of decline was found to be fairly similar in the two markets. Hence, they concluded that the relative order of magnitude of trading credit risk versus equity risk remained rather stable during the analyzed period. However, there are two major shortcomings in the analysis performed by Raunig and Scheicher (2008). Firstly, as they focused only on the European market, geographically specific events could have not been noted. Secondly, the data consistency is not optimal, as the iTraxx indices did not exist for their entire sampling period.

A subsequent study by Scheicher (2009) analyzed correlations between stock returns and CDS premia changes from a 2003 to 2005 sample, finding an overall negative relationship without significant differences between U.S. and European samples. Moreover, the author concluded that correlation (in absolute value) rises during unstable crisis times. This phenomenon could be linked to a higher correlation in fundamental values (Belke & Gokus 2011) or contagion (Anderson 2010; Fung et al 2008), which typically leads to positive default correlations (Jorion & Zhang 2007). These findings followed a logical pattern: the absolute value of correlation coefficients increases directly after a crisis as a widening of CDS spreads begins after stock returns start to shrink (Belke & Gokus 2011). Kwan (1996), who used bond data to account for risky debt values, proved significant negative and contemporaneous correlation between stock returns and bond yield changes.

Previous studies reached conclusions that were not homogeneous in describing the relationship between stock prices and CDS spreads (Longstaff et al. 2004; Norden & Weber 2004; Pena & Forte 2006). These authors, however, did not distinguish between high and low rated firms. Market participants have demonstrated to rely heavily on credit ratings. Hence, securities behaviors should differ depending on the firm's credit quality. Significant characteristics, which depend on credit ratings, have been individuated in other studies (Kwan 1996; Fung et al. 2008). Kwan (1996) found that while bond yields of highly rated firms were sensitive to changes in risky free rates, but not in stock prices, the opposite happened in the case of low rated bonds; hence, only debt values of low credit quality firms seemed to react to firm-specific information. Fung et al. (2008) found that CDS spreads led stock prices for high yield firms, but the relationship was reverted for investment grade companies.

Few studies have focused on whether industry-related differences influence the relationship between credit and equity risk. Firstly, the industry has been found to be one driver of default correlation, with the coefficient's magnitude being sector-specific (Amato & Remolona 2003). Secondly, the highest perceived credit risk is embedded in the consumer discretionary sector according to a sample of European firms between 2004 and 2005 (Byström 2005). Thirdly, Pereira de Silva et al. (2014) as well as Demirgüç-Kunt and Huizinga (2010) studied stock price and CDS spread dynamics in the banking sector: Pereira de Silva et al. (2014) concluded that the "too-big-to-fail" theory is responsible for deviations from Merton (1974), because credit risk of systemically important banks might not rise as much as expected in the event of financial distress due to government subsidies being granted to bondholders. The "too-big-to-fail" argument is not valid if the country runs large fiscal deficits, as in this case a troubled systemically important bank would experience negative impacts on both stock price and CDS spreads (Demirgüç-Kunt & Huizinga 2010). Lastly, financial interconnectedness may lead in some sectors to a quicker news transmission between the European and North American market (Moghadam & Viñals 2010).

4 Hypotheses

This chapter outlines the five tested hypothesis around which this thesis is structured.

Hypothesis 1: CDS VaR is lower than equity VaR

Results are expected to be consistent with the Merton model, which is commonly used for pricing claims with a payoff determined by default risk. In this model the capital structure of the firm consists of a zero coupon bond and a non-dividend-paying common stock. The model specifies a continuous stochastic process for the company's asset value, where default occurs when the firm's log-normally distributed value falls below the face value of its outstanding debt. The payoff of a risky zero coupon bond maturing at time T will be equal to that of a portfolio which is long in a risk-free bond and short in a put option on the firm's value, if the absence of market frictions, bankruptcy costs and taxes is assumed. Equity represents a long position in a call option on the value of the firm's assets. The strike price of both options equals the face value of debt. Thus, the main prediction of this model is that debt can never be more risky than equity. (Merton 1974)

Hypothesis 2: Credit and equity risk are positively correlated

The correlation between credit and equity markets is expected to be positive, since movements in VaR estimates essentially reflect movements in CDS spreads and stock prices (Raunig & Scheicher 2008; Belke & Gokus 2011). This also holds true when corporate bond spreads are used as a proxy for credit risk (Kwan 1996). Furthermore, this paper finds evidence in support of a second prediction of Merton (1974), which states that the risk of debt increases with the firm's asset volatility and its debt-to-equity ratio.

Hypothesis 3: Credit and equity risk have decreased in the aftermath of the 2008 financial crisis, with a higher pace of decline of credit risk

Raunig and Scheicher (2008) documented a downward trend in CDS and equity VaR and fairly constant equity-to-CDS ratio over the 2003 to 2006 period. The results of this study are expected to display a similar trend for the two risk measures in the years after Lehman Brothers' collapse, as a result of the general recovery from the financial crisis. Furthermore, the equity-to-CDS VaR ratio is presumed to increase, suggesting a reduction in credit risk relative to equity risk.

Hypothesis 4: VaR measures are significantly different across ratings

Firstly, as low credit quality firms are the most vulnerable to credit events and rumors (Standard & Poor's 2014), CDS and equity VaR measures for high yield firms should be significantly higher than those of investment grade firms. Secondly, the two VaR measures for high yield firms should display a stronger positive correlation than those of investment grade firms. Previous studies have reached mixed conclusions on the lead-lag relationship between stock returns, bond spreads and CDS spreads (Longstaff et al. 2004; Norden & Weber 2004; Pena & Forte 2006), however the authors did not disentangle rating differences. Fung et al. (2008), however, found that although stock prices lead CDS spreads for investment grade firms, the opposite holds true for high yield firms. Kwan (1996) asserted that high rated bond prices react to changes in the risk free rate, but are not dependent on stock price returns, while the opposite is true for sub-investment grade bonds. Hence, the results of this paper are expected to be consistent with Kwan (1996) in displaying that firm credit quality affects the strength in correlation between the credit and equity market.

Hypothesis 5: The risk-return profile of companies vary across industries

Amato and Remolona (2003) found that industry is one driver of default correlation, however the magnitude of the coefficient is industry-dependent. Pereira de Silva et al. (2014) demonstrated that the CDS and equity market do not co-move as expected in the banking sector since debt holders are usually protected from bankruptcy costs by governments. Hence, this paper's results should support the evidence about cross-sector differences in the behavior of CDS spreads and stock prices. Last, it is analyzed whether financial interconnectedness influences the timing and strength of spillover effects between geographical markets (Moghadam & Viñals 2010).

5 Sample and Methodology

This section describes in detail the data as well as the procedure followed for the sample selection for the purposes of this study. The second part of the chapter illustrates the methodology adopted to test the hypotheses and the reasoning behind its use.

5.1 Sample

The starting point for the Europe sample is the composition of the iTraxx Europe (125 firms) and the iTraxx Europe Crossover (60 firms) indices, while for the North America sample the reference indices are the CDX North American Investment Grade (125 firms) and the CDX North American High Yield (100 firms).

For the purposes of this study, CDS spreads and stock prices need to match, meaning that all firms whose equity and CDS ticker is not exactly the same have to be removed. This filter allows avoidance of any result distortion related to companies, which have been acquired by other companies since after a deal debt is usually taken over by the acquirer (Raunig & Scheicher 2008). Furthermore, few (high yield) firms for which the CDS underlying debt is not senior unsecured, but subordinated, are removed to make the samples homogeneous with respect to debt seniority.

This study is divided into two parts. Firstly, the evolution of CDS and equity Value-at-Risk is analyzed over eight years centered on the day of Lehman Brothers' collapse, from September 15th, 2006 to September 14th, 2014. Secondly, differences in Value-at-Risk between investment grade and high yield firms as well as ten industry classes are evaluated with an extended sample, using only data post September 15th, 2010. The reason behind this choice is that fewer firms have available data up to 2006, implying that the first sample is smaller and less representative across ratings and industries. The two samples allow to better study time, rating and industry differences.

The industry subsamples are created according to Bloomberg's classification, while the reference for the rating subsamples is Markit, which updates its index annexes twice a year (March and September). Each subsample includes only firms which have been in either the investment grade or the high yield index for the entire two years. The rationale of this choice is to make sure that CDS contracts are comparable in terms of liquidity.

The 2006-2014 samples comprise of 111 firms for Europe and 85 firms for North America, while the 2010-2014 samples include 113 firms and 93 firms respectively (Appendix 1 reports the complete list of firms). All daily data in both geographical markets exactly match by date; when a given day is a bank holiday in one of the markets, but not in the other, i.e. there are available observations for only one of the two markets, then the missing CDS spreads and stock are the previous trading day's closing values. The interest rates used to value CDSs are the five-year[2] EUR Libor for European firms and the five-year USD Libor for North American Firms.

5.2 Methodology

This paper analyzes the credit risk of a firm borne by taking a short position in a CDS and the market risk borne by taking a long position in stocks. VaR and ETL are the chosen measures of risk in this study. VaR is the loss level that will not be exceeded in a fixed time horizon h with x% confidence:

$$VaR_h = F^{-1}(p) \tag{1}$$

where F^{-1} is the inverse of the cumulative probability distribution $F(\Delta V_h)$ of a given portfolio and $p = 1 - x$ is the predefined probability. In this study, the VaR for a position in the CDS is compared with the VaR for a position in shares. The main advantage of VaR as a risk measure is its relative simplicity as it can be used to summarize the risk of positions held by large multinational financial institutions. In fact, this reason has made VaR the adopted risk metric for regulatory purposes (Pritsker 2001). Despite being widely adopted, VaR has the shortcoming of not being a coherent risk measure (Artzener et al. 1999), as it satisfies only the first three of the following conditions:

1. Monotonicity: if one portfolio always produces a worse outcome than another, its risk measure will be greater.
2. Translational invariance: adding an amount of cash K to a portfolio will decrease its risk measure by K.
3. Homogeneity: changing the size of a portfolio by S will increase the risk measure by S.
4. Sub-additivity: a given portfolio will risk an amount, which is at most the sum of the separate amounts risked by its sub-portfolios.

In contrast, ETL not only satisfies all conditions, but also provides information on the magnitude of the loss in the tail. In fact, VaR provides no handle on the extent of the losses that might be suffered beyond a certain threshold confidence level and it is therefore incapable of

[2] The tenor of the Libor curve is equal to the tenor of the CDS contracts.

distinguishing between situations where losses in the tail are only a bit worse and those where they are overwhelming (Cvitanić & Zapatero 2004). ETL is defined as the expected loss conditional on the loss L being greater than the VaR:

$$ETL = E(L|L > VaR) \tag{2}$$

This study measures both VaR and ETL, as the former is still the most widely used risk measure and the latter provides additional information on losses occurring beyond the chosen confidence level.

First, value changes in the CDS and equity positions are computed in order to implement (1) and (2). The chosen confidence levels are 99%, 95% and 90% and the time horizon h is equal to one day. While the change in value of equity positions is simply equal to the change in stock price, the change in value of CDS positions needs to be calculated. Market quotes (the CDS spreads) available in Bloomberg do not represent the value of the positions; instead, each position has to be marked-to-market with a valuation model. The version proposed by Phillips (2006) demonstrated to be fairly accurate in approximating CDS values, despite its simplified underlying assumptions. The model (derived in Appendix 2) assumes a constant interest rate r over the remaining life of the swap, a constant hazard rate λ (i.e. the rate of default at a future time given that the firm has not defaulted up to now) following a Poisson process, the same recovery rate RR (i.e. the percentage of the claim amount of debt which becomes payable on default) for all firms, no counterparty default risk and continuous payments of the spread s_0/annum until either the CDS matures or the underlying bond defaults. Under these assumptions, the value of a long position in a CDS with unitary notional is:

$$V_{CDS} = \left(1 - e^{-(r+s/L)T}\right) \times \left(\frac{s-s_0}{r+s/L}\right) \tag{3}$$

where s_0 is the CDS premium at inception[3], s is the quoted spread at any time, T is the remaining life of the swap and L = 1 – RR is the Loss Given Default (Appendix 3). All these inputs can be found in Bloomberg: s_0 and s are firm-specific, RR is equal to 0.4[4] and T goes from 5.25 to 5 years. Every CDS quote is "rolled" every three months, on International Monetary Market (IMM) dates; more specifically, for every five-year CDS T is equal to 5.25 on an IMM date (five-year tenor of the swap plus time until the next IMM date) and equal to 5 on the day before the following IMM date. Hence, the value of T is interpolated between IMM dates over the time

[3] For the CDS being fairly priced at issuance, s_0 must be such that $V(0)$ = 0.
[4] As estimated by Altman and Kishore (1996) and widely used in academia.

horizon of the samples. Furthermore, the assumption of a constant interest rate is released and daily Libor rates are used, in order to improve the accuracy of CDS values. Since the value of a CDS for a protection seller will increase if $s < s_0$ and it will decrease if $s > s_0$, the value of a short position in the CDS is $-V_{CDS}$.

The second step is to perform a "historical simulation" to obtain the risk metrics for the two investments. The method consists in computing the probability distribution of ΔV for both positions. This is done by computing the empirical distribution of ΔV_h over the chosen time horizons (eight and four years for the 2006-2014 and 2010-2014 sample respectively as well as two years for the subsamples).

The preference for historical simulation over other alternatives resides in its simplicity and popularity among both academics and practitioners. Historical simulation is the most used method for VaR calculation in the banking industry, since it does not make any parametric assumption about the distribution of risk factors. Instead, it only assumes that the distribution of changes in value of today's portfolio can be estimated from the historical time series of past changes in the risk factors. This distinguishing feature might make historical simulation a better method of computing VaR than those assuming a normal distribution of risk factors as the distribution of risk factors, such as asset returns, is often fat-tailed. The main disadvantage of historical simulation is that each day's return is assigned an equal probability weight; this is equivalent to assuming that the risk factors, and hence the historically simulated returns, are independently and identically distributed over time. There are variants of historical simulation, which remove the i.i.d. assumption, such as the model introduced by Boudoukh et al. (1998) which assigns greater weights to most recent observations or the "filtered historical simulation" proposed by Barone-Adesi et al. (1999), which captures both the conditional heteroskedasticity and non-normality of the risk factors by combining historical simulation with conditional volatility models. However, there are still some areas in which both methodologies need to be improved. (Pritsker 2001)

The investor is assumed to enter positions in the credit and equity market for the same magnitude by expressing the VaR as a percentage of the notional N in order to make the CDS and equity VaR comparable. Exchange rate effects between the European and North American market are disregarded, and hence N is set equal to EUR 10 million and USD 10 million for iTraxx and CDX firms respectively. However, all iTraxx positions are converted in Euro by using daily spot rates.[5]

[5] From British Pound (GBP), Norwegian Krone (NOK), Swedish Krone (SEK) and Swiss Franc (CHF).

6 Empirical Results

Figure 5 and 6 show median CDS spreads for the European and North American market between 2006 and 2014. Overall, the median spread follows a similar trend in the two markets. However, there are significant differences in magnitude and smaller disparities in timing. Especially two spikes in the CDS spreads are to be noted: the first one occurred on December, 5th in the North American market and a week later (December, 12th) in the European market; the second occurred on October 4th, 2011 in both markets.

Figure 5
Median CDS spread of iTraxx firms (2006-2014)

The graph shows the median spread in bps of European companies over the last eight years.

Figure 6
Median CDS spread of CDX firms (2006-2014)

The graph shows the median spread in bps of North American companies over last eight years.

In 2008 the U.S. government implemented the Troubled Asset Relief Program (TARP), with three main objectives: to decrease systematic risk through market stabilization, to sustain the housing market through mortgage support and to safeguard taxpayers. No impact of any single undertaken action can be isolated due to interconnectivity between events and markets, the high number of rescue attempts by governments worldwide and the generalized market turmoil. However, the day of the Capital Purchase Program (CPP) on December 5th, 2008, the U.S. Treasury Department acquired preferred stocks from a total of 35 U.S. banks for a total value of USD 4 billion, with the aim of enhancing the institutions' capitalization. The increase in capital levels of banks led to improved confidence of market participants and an inversion of the rising trend in CDS spreads. (U.S. Department of the Treasury 2009)

The second peak in spreads can be attributed to the European sovereign debt crisis. On October 4th the Eurozone finance ministers hesitated with their decision regarding bail-out funds for Greece. The interdependency between financial markets resulting from globalization led to a significant impact on North America, even if with a lower magnitude (Schneider & Kapoor 2011). On October 10th the Franco-Belgian bank Dexia announced a need to be bailed-out and to be eventually nationalized. Furthermore, during this period Fitch downgraded Italy's and Spain's sovereign debts. Hence, the sequence of announcements led to an increase in uncertainty about the political and financial European landscape, reflected by high volatility in the markets. However, the multitude and quick timing of these subsequent events do not allow to pinpoint which events were already incorporated into market prices by participants.

The median spread of iTraxx firms peaked again on November 28th, 2011, due to substantial fears of recession in the global economic outlook. This sentiment was caused by fragile economic data and announcements of various large-scale losses suffered by the financial sector. Although the European governments formed specific policies aimed at stabilizing the banking sector, the trend of decreasing CDS spreads reverted again in the spring of 2012. At the end of May, Spain bailed-out its third largest bank Bankia, going against the European Central Bank's recommendations. On June 1st, Eurostat data announced that eight Eurozone countries (Belgium, Greece, Ireland, Italy, the Netherlands, Portugal, Slovenia and Spain) were in recession, and spread levels rose again. (Eurostat 2012)

This section continues with the analysis of the five hypotheses outlined in Chapter 4. Results are first analyzed separately for Europe and North America and then compared between the two geographical markets. Furthermore, robustness tests are performed to analyze how a change in assumptions regarding the recovery rate and time horizon impacts the results. The end of the chapter summarizes the main findings and puts them into context, by looking at events occurred during the period.

6.1 Hypothesis 1

Risk measures for the two positions are compared over the 2006-2014 period to provide evidence for the first hypothesis, which states that CDS VaR is expected to be lower than equity. The European and North American markets are first analyzed individually and then compared to find relevant differences. Results for the full period as well as for four biannual subsamples are provided. Appendix 4 contains additional VaR measures that take different confidence levels into account, i.e. 95% and 90%.

Europe

The European 2006-2014 sample consists of 231,324 daily observations across 111 firms. Over the whole period, the equity VaR exceeds the CDS VaR by a factor of seven (Table 2). The difference between equity and CDS VaR is positive across all two-year subsamples, ranging from 3.6% to 5.4%. Moreover, equity VaR is characterized by a higher standard deviation than CDS VaR. The expected tail loss is about 1.5 times the VaR for both positions and hence no differences are found between the CDS and equity investments.

Table 2
Descriptive statistics and risk metrics for iTraxx firms (2006-2014)

The table shows the main descriptive statistics for stock and CDS spread returns as well as VaR and ETL measures for the European sample. The first column reports results for the eight-year full sample, while column 2 to 5 report results for biannual subsamples.

	2006-2014		2006-2008		2008-2010		2010-2012		2012-2014	
	CDS	Equity	CDS	Equity	CDS	Equity	CDS	Equity	CDS	Equity
Mdn. Return	-0.07%	0.00%	-0.05%	0.00%	-0.07%	0.00%	-0.06%	0.00%	-0.18%	0.01%
Std. Dev. Return	31.23%	2.17%	32.28%	1.79%	27.78%	2.63%	8.66%	1.90%	16.29%	1.40%
99% VaR	0.61%	4.20%	0.40%	4.62%	0.70%	6.06%	0.51%	4.43%	0.36%	3.96%
Std. Dev. 99% VaR	0.38%	2.63%	0.17%	1.73%	0.57%	1.90%	0.50%	1.32%	0.29%	3.30%
ETL 99% VaR	0.86%	6.11%	0.51%	6.12%	0.94%	7.66%	0.65%	5.37%	0.49%	5.21%
# Obs. in the 1% tail	21	21	6	6	6	6	6	6	6	6
# Total obs.	231324	231324	57720	57720	57720	57720	57942	57942	57609	57609

North America

The North American 2006-2014 sample includes 85 companies and a total of 177,140 daily observations. For North American companies there is a sizeable difference between equity and CDS VaR (Table 3). The equity VaR is about eleven times the CDS VaR during the whole period. The CDS risk measure is consistently lower also in each biannual subsample, as the ratio between equity and CDS VaR ranges between 9 and 19. Furthermore, results document a higher volatility of the equity position as opposed to the CDS one. The ETL order of magnitude relative to the VaR measure is about the same for both the CDS and equity positions.

Table 3
Descriptive statistics and risk metrics for CDX firms (2006-2014)

The table shows the main descriptive statistics for stock and CDS spread returns as well as VaR and ETL measures for the North American sample. The first column reports results for the eight-year full sample, while column 2 to 5 report results for biannual subsamples.

	2006-2014		2006-2008		2008-2010		2010-2012		2012-2014	
	CDS	Equity	CDS	Equity	CDS	Equity	CDS	Equity	CDS	Equity
Mdn. Return	-0.06%	0.00%	-0.06%	0.00%	-0.05%	0.00%	-0.06%	0.00%	-0.07%	0.02%
Std. Dev. Return	23.68%	2.22%	18.01%	1.86%	23.76%	2.87%	6.61%	1.73%	6.45%	1.28%
99% VaR	0.47%	5.10%	0.39%	4.63%	0.63%	5.83%	0.33%	4.65%	0.21%	3.97%
Std, Dev. 99% VaR	0.37%	1.77%	0.29%	1.73%	0.62%	1.58%	0.33%	1.74%	0.33%	1.47%
ETL 99% VaR	0.77%	7.14%	0.56%	5.99%	0.96%	7.44%	0.45%	6.66%	0.34%	5.47%
# Obs. in the 1% tail	21	21	6	6	6	6	6	6	6	6
# Total obs.	177140	177140	44200	44200	44200	44200	44370	44370	44115	44115

Comparison

Over the analyzed eight years Europe has a consistently higher CDS VaR as well as a minimally lower equity VaR than North America, with the exception being the 2008-2010 period. For both markets and across all periods the equity VaR is consistently higher than the CDS VaR. Moreover, the null hypothesis that the difference between the two risk measures is equal or lower than 3% can be rejected (Appendix 4). No specific difference is found in the magnitude of the expected tail loss for the two investments. Moreover, the risk embedded in the equity position is characterized by a higher standard deviation than the risk of the CDS position across all periods. Overall, results for both markets provide empirical evidence in support of one of Merton's predictions, namely that debt can never be more risky than equity (Merton 1974).

6.2 Hypothesis 2

The test of the second hypothesis explores whether credit and equity risk, expressed in VaR terms, are positively correlated. Furthermore, a two-way (firm and time) fixed effects panel regression is performed to prove that the riskiness of debt is a function of the firm's leverage and the volatility of its assets (Merton 1974). The regression performed in this paper uses the daily change on the short CDS position as proxy for the dependent variable, the risk of debt. The explanatory variables are the quoted spread and stock price controlling for the market value of debt and equity respectively, and the equity volatility as a substitute for the (unobservable) asset volatility. The third independent variable is estimated using an exponentially weighted moving average model with λ = 0.94 as proposed by RiskMetrics (Howard 1996).

Europe

Table 4 shows a weak but significant positive correlation between the two risk measures in the European market. Furthermore, a greater tail coverage (90% confidence) in the value changes distribution corresponds to a higher correlation coefficient for the equity position.

Table 4
VaR correlation in Europe

The table shows correlations between CDS and equity VaR for the three confidence levels during the 2010-2014 period. Statistical significance is specified for a 1% (***), 5% (**) and 10% (*) confidence level.

	99% CDS	95% CDS	90% CDS	99% Equity	95% Equity	90% Equity
99% CDS	1					
95% CDS	0.9779***	1				
90% CDS	0.9688***	0.9943***	1			
99% Equity	0.2568***	0.2546**	0.2542**	1		
95% Equity	0.2590***	0.2586***	0.2611***	0.9589***	1	
90% Equity	0.2645***	0.2622***	0.2616***	0.9407***	0.9883***	1

Regression outputs for the European 2010-2014 period are displayed in Table 5, while biannual results are reported in Appendix 5. Over the four-year period only coefficients on spread and price are significant. The spread coefficient is negative as expected, while the price coefficient is surprisingly negative as well. The coefficient of determination is quite high, however it signals that about one third of the change in the CDS position value is not explained by the independent variables.

Table 5
Two-way fixed effects regression output for iTraxx firms (2010-2014)

The dependent variable is the change of the short CDS position, while the independent variables are CDS spread, stock price and estimated equity volatility. Given the use of time fixed effects intercepts are day-specific and therefore have been omitted.

	Coefficient	Robust Std. Err.	t	P>|t|	95% Confidence Interval	
Spread	-0.000349	0.0000	-245.46	0.0000	-0.000352	-0.000346
Price	-0.000003	0.0000	-2.80	0.0050	-0.000005	-0.000001
Volatility	0.001948	0.0030	0.65	0.5190	-0.003971	0.007867
	Nr of obs:	117733	R-squared:	0.6584	Adj R-squared:	0.655

North America

Correlation between CDS and equity VaR in the North American market is moderate (Table 6). Higher coefficients can be seen with lower confidence intervals for CDS position, while no pattern can be individuated with respect to the equity investment.

Table 6
VaR correlation in North America

The table shows correlations between CDS and equity VaR for the three confidence levels during the 2010-2014 period. Statistical significance is specified for a 1% (***), 5% (**) and 10% (*) confidence level.

	99% CDS	95% CDS	90% CDS	99% Equity	95% Equity	90% Equity
99% CDS	1					
95% CDS	0.9757***	1				
90% CDS	0.9737***	0.9933***	1			
99% Equity	0.4187***	0.4525***	0.4735***	1		
95% Equity	0.3628***	0.4005***	0.4204***	0.9814***	1	
90% Equity	0.3830***	0.4182***	0.4395***	0.9785***	0.9942***	1

Table 7 reports regression results for the four-year horizon, while outputs on biannual subsamples are shown in Appendix 5. All three coefficients are statistically significant at 99% and in line with expectations with respect to their sign. Moreover, the change in the dependent variable is fully explained by the three regressors, since the R-squared is close to 1.

Table 7
Two-way fixed effects regression output for CDX firms (2010-2014)

The dependent variable is the change of the short CDS position, while the independent variables are CDS spread, stock price and estimated equity volatility. Given the use of time fixed effects intercepts are day-specific and therefore have been omitted.

	Coefficient	**Robust Std. Err.**	**T**	**P>|t|**	**95% Confidence Interval**	
Spread	-0.000402	0.0000	-451.55	0.0000	-0.000404	-0.000401
Price	0.000025	0.0000	31.67	0.0000	0.000024	0.000027
Volatility	-0.016914	0.0018	-9.52	0.0000	-0.020396	-0.013433
	Nr of obs:	94409	R-squared:	0.9963	Adj R-squared:	0.9963

Comparison

Overall results on correlation coefficients align with previous findings, however the strength is lower than the one reported in past studies (Raunig & Scheicher 2008). Furthermore, correlation between the two risk measures in the European market is about half the one observed in the North American market.

On the other hand, regression outcomes support predictions of Merton (1974) to a limited extent. More specifically, coefficients relative to the North American sample allow to conclude that the risk borne by a seller of credit protection is positively related to CDS spreads and equity volatility and negatively related to stock prices. Thus, the value change of the short CDS position is negatively related to CDS spreads and equity volatility and positively related to stock prices. This does not appear to hold for the European market, where the stock price coefficient is inconsistently negative. Results on the two-year samples show that this unexpected relationship occurred in the 2012-2014 period. A second aspect is related to the change in coefficient signs observed in the biannual subsamples. More specifically, it is found that equity volatility in the North American case changes from positive to negative, but this does not seem to impact the R-squared. The variance inflation factor (VIF) is computed to understand whether multicollinearity across explanatory variables may be an issue for each of them. The VIF informs about how much the variance of an estimated coefficient increases because of multicollinearity:

$$VIF = \frac{1}{1-R^2} \tag{4}$$

Hence, the VIF can range between one and infinity; the closer it is to 1, the lower the magnitude of collinearity. Spread, price and equity volatility are regressed on the other two explanatory variables and the three coefficients of determination are used to compute the VIF. Results reported in Appendix 5 show that the VIF is between 1 and 1.05 for the European sample and between 1 and 1.03 for the North American sample, which implies that multicollinearity can be excluded.

6.3 Hypothesis 3

Empirical evidence on the reduction of credit and equity risk in the post-Lehman bankruptcy period is needed to support the third hypothesis. Moreover, it is tested whether the magnitude of trading credit risk relative to equity risk has decreased from 2010 onwards.

Europe

The null hypothesis that CDS and equity VaR are the same across subsamples can be rejected for the European sample as results of two ANOVA tests (reported in Appendix 6) confirm. Moreover, two-year subsample values displayed in Table 8 document that both CDS and equity VaR decreased in the two most recent biannual periods. The ETL for each period remains quite stable over time relatively to the VaR measure and does not show significant differences in magnitude between the CDS and the equity case.

A third ANOVA test compares the ratio between equity and CDS VaR across two-year subsamples (Table 9). Overall, results suggest that the risk of the CDS short position relative to the equity position in the European market has peaked in the 2010-2012 period, while a rise in the median equity-to-CDS VaR ratio can be observed in the last two years.

Table 8
Descriptive statistics and risk metrics for iTraxx firms (2010-2014)

The table shows the main descriptive statistics for stock and CDS spread returns as well as VaR and ETL measures for the European sample. The first column reports results for the four-year full sample, while column 2 and 3 report results for biannual subsamples.

	2010-2014		**2010-2012**		**2012-2014**	
	CDS	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**
Mdn. Return	-0.10%	0.00%	-0.06%	0.00%	-0.18%	0.01%
Std. Dev. Return	23.62%	1.69%	8.66%	1.90%	16.29%	1.39%
99% VaR	0.48%	4.31%	0.51%	4.43%	0.36%	3.96%
Std. Dev. 99% VaR	0.41%	1.16%	0.50%	1.08%	0.29%	3.77%
ETL 99% VaR	0.63%	5.73%	0.65%	5.37%	0.49%	5.17%
# Obs. in the 1% tail	11	11	6	6	6	6
# Total obs.	117746	117746	58986	58986	58647	58647

Table 9
ANOVA test results on Equity-to-CDS VaR ratio for iTraxx firms (2006-2014)

The table shows results of the ANOVA test performed on the ratios between 99% equity and CDS VaR for the four biannual subsamples. The low p-value allows to reject the null hypothesis that the difference between each pair of ratios is equal to zero.

Groups	Count	Sum	Average	Median	Variance
2006-2008	111	1471.0950	13.2531	11.5504	42.2031
2008-2010	111	1087.6574	9.7987	9.1321	53.3662
2010-2012	111	1106.3697	9.9673	8.4408	67.3355
2012-2014	111	1628.1752	14.6682	11.4559	133.6145

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1958.3641	3	652.7880	8.8060	0.0000	3.8264
Within Groups	32617.1200	440	74.1298			
Total	34575.4841	443				

North America

VaR measures of North American companies for both positions are statistically different across biannual subsamples (Appendix 6) and display a decreasing trend from 2010 onwards (Table 10). More specifically, the highest VaR estimates are found in the aftermath of Lehman's collapse (2008–2010), while the lowest occur in the most recent period. In addition, average losses in the tail of both CDS and equity value change distributions represent a similar proportion of the VaR measure over time.

The ANOVA test on equity-to-CDS ratios (Table 11) proves that there is a significant difference between each subsample. Furthermore, the trend observed for the ratio signals that the median CDS VaR relative to equity VaR in North America started to decrease in the third quarter of 2010.

Table 10
Descriptive statistics and risk metrics for CDX firms (2010-2014)

The table shows the main descriptive statistics for stock and CDS spread returns as well as VaR and ETL measures for the North American sample. The first column reports results for the four-year full sample, while column 2 and 3 report results for biannual subsamples.

	2010-2014		**2010-2012**		**2012-2014**	
	CDS	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**
Mdn. Return	-0.07%	0.01%	-0.06%	0.00%	-0.07%	0.02%
Std. Dev. Return	16.36%	1.60%	6.61%	1.80%	6.30%	1.29%
99% VaR	0.31%	4.99%	0.35%	4.68%	0.21%	3.98%
Std. Dev. 99% VaR	0.28%	2.29%	0.34%	1.91%	0.34%	1.51%
ETL 99% VaR	0.49%	7.04%	0.46%	6.76%	0.35%	5.54%
# Obs. in the 1% tail	11	11	6	6	6	6
# Total obs.	96906	96906	48546	48546	48267	48267

Table 11
ANOVA test results on Equity-to-CDS VaR ratio for CDX firms (2006-2014)

The table shows results of the ANOVA test performed on the ratios between 99% equity and CDS VaR for the four biannual subsamples. The low p-value allows to reject the null hypothesis that the difference between each pair of ratios is equal to zero.

Groups		**Count**	**Sum**	**Average**	**Median**	**Variance**
2006-2008		85	1097.6411	12.9134	10.1047	63.2731
2008-2010		85	868.8646	10.2219	8.8563	28.0610
2010-2012		85	1482.2728	17.4385	15.6259	116.2478
2012-2014		85	1532.1588	18.0254	17.1647	81.2570
Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Between Groups	3552.36	3	1184.1209	16.3984	0.0000	3.8404
Within Groups	24262.46	336	72.2097			
Total	27814.82	339				

Comparison

The reduction of VaR measured in absolute terms is consistent with findings of Raunig and Scheicher (2008) relative to the 2003-2006 period. This paper, however, finds evidence of a reduction of CDS VaR relative to equity VaR that occurred over the most recent years. Additionally, timing differences between the European and North American market are observed. With this respect, results provide additional insights on dynamics involving credit and equity risk, since the established literature (Raunig & Scheicher 2008) did not find evidence of changes in the ratio between the two risk measures, but instead found it to be fairly stable.

6.4 Hypothesis 4

An analysis of high yield and investment grade firms is performed to test the fourth hypothesis to observe relationships between changes in VaR based on credit ratings. Moreover, CDS and equity VaR are tested for their correlation to understand any existing links and differences.

Each subsample includes only investment grade and high yield companies whose CDS is included in the corresponding index for the entire reference period (i.e. four index annexes) as reported by Markit. Thus, the number of firms in each biannual subsample varies.

Europe

In the European market the proportion of investment grade to high yield firms is approximately eight to one in both two-year periods. Although the high yield sample size is small, results allow to single out relevant differences. Table 12 lists VaR results for the two rating classes and time periods, while Appendix 7 reports outputs for additional confidence intervals. The equity VaR for investment grade companies is about nine times the CDS VaR in 2010-12 and thirteen in 2012-2014. On the contrary, ratios for high yield companies are four and six respectively. No clear rating-specific pattern is found with respect to the magnitude of ETL relative to VaR.

Table 12
Descriptive statistics and risk metrics for iTraxx firms by rating class (2010-2014)

The table shows the main descriptive statistics for stock and CDS spread returns as well as VaR and ETL measures for the European sample. Column 1 and 3 report results for investment grade firms, while column 2 and 4 report results for high yield firms.

	2010-2012 IG		**2010-2012 HY**		**2012-2014 IG**		**2012-2014 HY**	
	CDS	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**
Mdn. Return	-0.07%	0.00%	-0.04%	0.00%	-0.18%	0.01%	-0.12%	0.01%
Std. Dev. Return	10.62%	1.85%	4.34%	2.64%	26.35%	1.34%	3.86%	1.79%
99% VaR	0.48%	4.15%	1.45%	5.26%	0.29%	3.81%	1.01%	5.86%
Std. Dev. 99% VaR	0.38%	1.37%	0.49%	0.87%	0.24%	3.45%	0.13%	2.22%
ETL 99% VaR	0.60%	5.29%	1.77%	7.22%	0.43%	4.99%	1.25%	8.08%
# Obs. in the 1% tail	6	6	6	6	6	6	6	6
# Total obs.	45414	45414	5742	5742	48267	48267	6228	6228

North America

The number of North American high yield firms is about 10% of the total in each subsample. Table 13 displays VaR results by rating class and time horizon, while Appendix 7 provides further details for lower confidence levels (95% and 90%). The equity-to-CDS VaR ratio for investment grade companies is between 16 (2010-2012) and 20 (2012-2014). Ratios for high yield firms are fairly lower, amounting to seven and nine in the two periods. No relevant differences between the two rating groups are found with respect to the ETL-to-VaR ratio.

Table 13
Descriptive statistics and risk metrics for CDX firms by rating class (2010-2014)

The table shows the main descriptive statistics for stock and CDS spread returns as well as VaR and ETL measures for the North American sample. Column 1 and 3 report results for investment grade firms, while column 2 and 4 report results for high yield firms.

	2010-2012 IG		**2010-2012 HY**		**2012-2014 IG**		**2012-2014 HY**	
	CDS	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**
Mdn. Return	-0.06%	0.00%	-0.14%	0.00%	-0.07%	0.02%	-0.07%	0.01%
Std. Dev. Return	7.82%	1.64%	2.75%	2.65%	7.82%	1.25%	4.22%	2.00%
99% VaR	0.29%	4.58%	1.06%	6.94%	0.20%	3.94%	0.66%	6.03%
Std. Dev. 99% VaR	0.29%	1.64%	0.34%	2.11%	0.33%	1.40%	0.20%	1.34%
ETL 99% VaR	0.43%	6.25%	1.35%	9.09%	0.31%	5.23%	1.03%	8.74%
# Obs. n the 1% tail	6	6	6	6	6	6	6	6
# Total obs.	40716	40716	4698	4698	42558	42558	4152	4152

Comparison

The higher VaR for high yield companies clearly reflects the fact that low credit quality firms are riskier than investment grade companies (Standard & Poor's 2014). Interestingly, the equity VaR in the North American market is higher than in the European market, while the opposite holds true for the CDS risk measure. This is also reflected by the higher equity-to-CDS ratio observed in all North American subsamples. Hence, the riskiness of the CDS position relative to the equity investment is higher in the European market.

The second part of the rating-based analysis focuses on the correlation between CDS and equity VaR. Table 14 and 15 display results for the combined European and North American rating samples. The choice of pooling the two geographical markets is motivated by the relatively low size of the two high yield samples and hence the low significance of the individual markets' coefficients. Results reported in Appendix 7 show that the correlation coefficient for high yield European firms is surprisingly negative; it is, however, not significant even at the least conservative confidence level (10%).

Table 14
VaR correlation for European and North American investment grade firms (2010-2014)

The table shows correlations between 99% CDS and equity VaR. Statistical significance is specified for a 1% (***), 5% (**) and 10% (*) confidence level.

	CDS IG	Equity IG
CDS IG	1.0000	
Equity IG	0.2208***	1.0000

Table 15
VaR correlation for European and North American investment grade firms (2010-2014)

The table shows correlations between 99% CDS and equity VaR. Statistical significance is specified for a 1% (***), 5% (**) and 10% (*) confidence level.

	CDS HY	Equity HY
CDS HY	1.0000	
Equity HY	0.4851***	1.0000

The correlation between CDS and equity VaR for high yield firms is twice as high as for investment grade companies. Kwan (1996) found that AAA-rated bond prices are sensitive to changes in the risk free rate, but do not seem to react to movements in stock prices; on the contrary, sub-investment grade bonds are highly responsive to firm-specific information (i.e. stock price returns), but not to changes in the risk-free rate. Therefore, results of this paper are found to be consistent with both expectations and previous research.

Appendix 7 reports time series of median spreads and prices for investment grade and high yield firms in the two markets, which illustrate differences related to credit quality. The rating groups include five firms which have been in the same rating class over the eight-year period. The investment grade group comprises of firms with the lowest median spread, while high yield firms are chosen for their highest median spread between 2006 and 2014. Axes are in the same scale in order to facilitate the comparison. It can be seen that in both markets movements of spread and price tend to be fairly specular. Furthermore, changes for high yield firms are far more extreme: the median spread among both markets ranges between 78 bps (observed in North America) and 1583 bps (Europe); conversely, the median spread of investment grade firms falls in the 10-83 bps range (North America). Last, graphs allow to see that while the price of investment grade firms at the end of the period is higher than in 2006, the opposite is true for high yield firms.

6.5 Hypothesis 5

The last hypothesis involves an analysis of VaR measures and trends across sectors in order to individuate peculiarities.

The ANOVA tests reported in Appendix 8 provide statistical significance on the existence of differences in CDS as well as equity VaR crosswise sectors. Results for the two geographical markets over the 2010-2014 period follow.

Europe

From results on the European sample (Table 16), it can be seen that financials and technology are the two industries with the lowest equity-to-CDS VaR ratio. Hence, in these cases the CDS position has a higher relative risk than other industries. Furthermore, the financial sector is characterized by the highest CDS VaR and the second highest equity VaR across all industries. On the other hand, the lowest CDS risk in both absolute and relative terms is observed for health care firms. Last, consumer staples is found to be the sector with the lowest equity VaR.

Table 16
Descriptive statistics and risk metrics for iTraxx firms by industry class (2010-2014)
The table shows the main descriptive statistics for stock and CDS spread returns as well as VaR and ETL measures for the European sample. Each column reports results for the four year period.

	Communications		**Consumer Discretionary**		**Consumer Staples**		**Energy**		**Financials**	
	CDS	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**
Mdn. Return	-0.08%	0.02%	-0.10%	0.02%	-0.14%	0.00%	-0.11%	0.01%	-0.14%	0.00%
Std. Dev. Return	24.45%	1.43%	5.90%	1.90%	34.63%	1.28%	28.64%	1.43%	19.21%	2.10%
99% VaR	0.30%	3.86%	0.54%	5.21%	0.32%	3.59%	0.38%	3.81%	0.83%	4.46%
Std. Dev. 99% VaR	0.31%	0.79%	0.53%	1.45%	0.19%	0.76%	0.24%	0.75%	0.34%	1.90%
ETL 99% VaR	0.42%	5.32%	0.72%	7.17%	0.46%	4.63%	0.56%	5.05%	0.97%	5.72%
# Obs. in the 1% tail	11	11	11	11	11	11	11	11	11	11
# Total obs.	16672	16672	17714	17714	15630	15630	5210	5210	20840	20840
	Health		**Industrials**		**Materials**		**Technology**		**Utilities**	
	CDS	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**
Mdn. Return	-0.11%	0.04%	-0.16%	0.00%	-0.09%	0.00%	0.04%	0.02%	0.00%	0.00%
Std. Dev. Return	4.59%	1.48%	23.89%	1.89%	23.94%	1.96%	27.92%	1.72%	37.11%	1.72%
99% VaR	0.24%	4.30%	0.48%	4.04%	0.69%	4.93%	0.62%	4.15%	0.47%	3.77%
Std. Dev. 99% VaR	0.07%	0.83%	0.31%	1.53%	0.41%	0.71%	0.52%	0.60%	0.34%	0.72%
ETL 99% VaR	0.35%	5.60%	0.75%	5.43%	1.00%	6.43%	0.69%	7.01%	0.67%	5.16%
# Obs. in the 1% tail	11	11	11	11	11	11	11	11	11	11
# Total obs.	4168	4168	9378	9378	12504	12504	4168	4168	11462	11462

North America

In North America (Table 17) the lowest ratio between equity and CDS VaR as well as the highest spread volatility is found for technology and financial firms. Health care and industrials are the two sectors with the least risky CDS positions, as it appears from the lowest CDS VaR as well as the highest equity-to-CDS VaR. The energy industry has the highest equity VaR, followed by technology.

Table 17
Descriptive statistics and risk metrics for CDX firms by industry class (2010-2014)

The table shows the main descriptive statistics for stock and CDS spread returns as well as VaR and ETL measures for the North American sample. Each column reports results for the four year period.

	Communications		Consumer Discretionary		Consumer Staples		Energy		Financials	
	CDS	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**
Mdn. Return	-0.07%	0.03%	-0.07%	0.00%	-0.06%	0.00%	-0.07%	0.03%	-0.07%	0.00%
Std. Dev. Return	7.97%	1.48%	15.99%	1.72%	18.61%	1.16%	25.24%	2.10%	28.49%	1.35%
99% VaR	0.23%	4.85%	0.36%	6.04%	0.27%	3.95%	0.43%	7.19%	0.35%	4.83%
Std. Dev. 99% VaR	0.31%	2.34%	0.35%	2.13%	0.28%	1.14%	0.18%	4.70%	0.24%	0.82%
ETL 99% VaR	0.33%	7.10%	0.63%	8.06%	0.45%	6.11%	0.64%	10.21%	0.47%	5.84%
# Obs. in the 1% tail	11	11	11	11	11	11	11	11	11	11
# Total obs.	7294	7294	19798	19798	12504	12504	7294	7294	10420	10420

	Health		Industrials		Materials		Technology		Utilities	
	CDS	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**
Mdn. Return	-0.04%	0.00%	-0.04%	0.04%	-0.12%	0.04%	-0.08%	0.00%	-0.07%	0.00%
Std. Dev. Return	3.94%	1.28%	2.91%	1.51%	13.87%	1.71%	25.78%	1.91%	14.33%	0.99%
99% VaR	0.17%	5.08%	0.19%	4.67%	0.38%	5.51%	0.64%	4.82%	0.21%	3.05%
Std. Dev. 99% VaR	0.06%	1.14%	0.20%	0.78%	0.24%	1.11%	0.23%	1.21%	0.09%	0.19%
ETL 99% VaR	0.28%	7.38%	0.25%	7.12%	0.59%	7.05%	0.86%	7.22%	0.28%	4.05%
# Obs. the 1% tail	11	11	11	11	11	11	11	11	11	11
# Total obs.	7294	7294	12504	12504	7294	7294	7294	7294	5210	5210

Comparison

A deeper analysis is conducted for five sectors, namely consumer discretionary, consumer staples, financials, industrials and materials. Each group includes the five firms with the lowest median spread between 2006 and 2010. The rationale behind the choice of including firms with the highest credit merit is to remove rating-related effects and isolate industry-specific features. Graphs for all selected sectors in both the European and North American market are reported in Appendix 8.

From the two graphs displaying CDS spreads as well as stock prices for all five industries it can be seen that sectors tend to follow the same trend over time. However, time and magnitude differ across sectors as well as geographical markets.

Firms in the consumer discretionary industry have been more severely hit in North America than in Europe. The spread of North American firms reached the highest level among all sectors in early March 2009, hence reflecting the delayed impact of the financial crisis on private spending. Nonetheless, it can be seen that the impact on European consumption has been notably lower. Furthermore, stock prices of European firms have more than doubled since 2006, as opposed to achieving an 83% growth of North America.

Conversely, movements in median spread and price for the consumer staples sector reflect the non-cyclical nature of products part of this category, even though the stock price of European firms has been more negatively hit.

The median spread of financial firms falls in the middle – suggesting a "too-big-to-fail effect" (Pereira de Silva et al. 2014) – and shows a similar pattern in the two markets. However, stock prices of European firms experience a far stronger negative impact than North American peers.

An interesting geographical difference can be seen in the industrial sector: while the median spread in North America is among the lowest two throughout the eight years, in Europe it is the one reaching the highest peaks. Furthermore, the median price of North American firms is about 26% higher than its 2006 starting level, but 28% lower in the case of European companies.

Strong cross-market similarities are found with respect to the materials industry. The commodities sector is well known for being cyclical as well as positively correlated with financial markets (Lombardi & Ravazzolo 2013), as graphs clearly confirm. Furthermore, there are strong similarities between Europe and North America with respect to time and magnitude of the movements.

6.6 Robustness Tests

Results for the 2010-2014 period are tested for robustness in two instances. The choice of the four-year sample is motivated by the fact that it is more numerous and diverse with respect to credit quality and industry. In the first robustness test the holding period is adjusted from 1 to 20 trading days. The second test changes the recovery rate (*RR*) to 0.6 instead of 0.4. Table 18 and 19 as well as tables in Appendix 9 show VaR measures with the changed holding period and recovery rate respectively.

Overall, empirical findings are robust to changes in assumptions and bring additional information on the relationship between CDS and equity VaR. It can be seen that the ratio between CDS VaR and equity VaR decreases with a longer holding period (*T*). This behavior is consistent with prevailing literature in this field and suggests that CDSs become relatively more risky than equity with an increased time horizon (Raunig & Scheicher 2008). Interestingly, over the four-year period the ratio decrease is stronger in the North American (-27%) than in the European (-13%) market.

When looking at the rating subsamples, a higher decline in the ratio is observed for high yield firms than investment grade ones in North America. However, results for European sub-investment grade firms during the 2012-2014 period are unexpected, as the ratio increases with the holding period.

In both markets the change in loss given default leads to a slight reduction in the CDS VaR for high yield firms, while it does not impact the risk measure of investment grade ones. This is to be expected, since an increase in recoverable portion of debt in the event of default is of greater benefit for firms with a higher likelihood of default.

Table 18
Risk metrics for iTraxx firms with T = 20 (2010-2014)

The table shows the main VaR and ETL measures for the European sample. The first column reports results for the four-year full sample, while column 2 and 3 report results for biannual subsamples.

	2010-2014		**2010-2012**		**2012-2014**	
	CDS	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**
99% VaR	2.18%	17.19%	2.43%	17.57%	1.25%	13.54%
Std. Dev. 99% VaR	2.26%	5.82%	2.75%	6.81%	0.98%	17.82%
ETL 99% VaR	2.42%	19.77%	2.70%	19.51%	1.52%	14.83%
# Obs. in the 1% tail	11	11	6	6	5	5
# Total obs.	115599	115599	56839	56839	56500	56500

Table 19
Risk metrics for CDX firms with T = 20 (2010-2014)

The table shows the main VaR and ETL measures for the North American sample. The first column reports results for the four-year full sample, while column 2 and 3 report results for biannual subsamples.

	2010-2014		**2010-2012**		**2012-2014**	
	CDS	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**
99% VaR	1.67%	19.92%	1.73%	21.53%	1.01%	13.36%
Std. Dev. 99% VaR	1.82%	15.87%	2.10%	12.96%	1.17%	8.60%
ETL 99% VaR	2.01%	23.12%	1.86%	24.07%	1.24%	14.87%
# Obs. in the 1% tail	11	11	6	6	5	5
# Total obs.	95139	95139	46779	46779	46500	46500

6.7 Discussion and Remarks

Overall, results in relation to the five hypotheses outlined in Chapter 4 are in line with expectations. This section summarizes the above described findings as well as suggests plausible interpretations.

With respect to Hypothesis 1, empirical evidence supports the expectation that equity VaR is significantly and consistently higher than CDS VaR. One explanation is that over a short time horizon default risk is very low (Liu et al. 2007). Hence, given that the holding period assumed in this study is one trading day, the main risk of the CDS position may be the one arising from spread volatility. The relative increase in CDS VaR relative to equity VaR in the robustness test signals that default risk is increasing in the holding period (Raunig & Scheicher 2008). As such, the first prediction of Merton (1974), namely that debt is always less risky than equity, is supported by the presented findings.

It is worthwhile mentioning an important difference between credit and equity risk. The risk of default, as opposed to the risk of equity, is typically characterised by a small probability of extreme losses and no comparable gains (Amato & Remolona 2003). As graphs in Appendix 10 show, the CDS VaR distribution is indeed highly negatively skewed, while the shape of the equity VaR distribution is more symmetric. The negative skewness in returns implies that it is more difficult to diversify idiosyncratic risk in the credit market than in the equity one; yet, the portion of diversifiable risk is lower for equities, given that stock returns are far more correlated than default probabilities (Amato & Remolona 2003).

Correlation between VaR for the two positions, short CDS versus long equity, over the 2010-2014 period provides support for Hypothesis 2. Results suggest that CDS spreads and stock prices are negatively correlated (also in Raunig & Scheicher 2008; Belke and Gokus 2011). However, the magnitude of correlation coefficients in the European sample is fairly lower than in the North American sample. Previous studies document an increase in (the absolute value of) correlation coefficients between CDS spreads and stock prices during periods of crises (Belke & Gokus 2011). Hence, results of this paper are surprising because, according to the established literature, one would not expect correlation between the two VaR measures to be lower in Europe, given that both markets have gone through two critical periods such as the 2008 financial crisis and the European sovereign debt crisis.

An additional analysis finds support in favor of a second prediction of Merton (1974), who asserted that the riskiness of debt as measured by its standard deviation increases with the firm's debt-to-equity ratio and the volatility of its assets. Results of the two-way fixed effects panel regression with the CDS position value change as dependent variable and spread, stock price and estimated equity volatility as regressors are consistent with this conclusion to a certain extent. More specifically, while statistical significance is found in all cases but one, there is lack of economic significance in some circumstances: the negative stock price coefficient in the European 2012-2014 sample is the most relevant example, which the established literature finds hard to explain. Moreover, the relevant difference observed in the R-squared for the two markets suggests that there may be some other factor affecting changes in the risk of debt. Hence, trading volume is one potential driver which is worthwhile investigating, since it is strongly agreed that liquidity premium is a relevant component in many markets. In the corporate credit market, it has been proved that liquidity premia increase when market conditions deteriorate (Hibbert et al. 2009). Liquidity premia and transaction costs are responsible for changes in bond spreads that are unexplained by the Merton model (1974). (Hull et al. 2004). The higher activity observed in the investment grade segment of the CDS market as opposed to the high yield one (Hibbert et al. 2009) raises the question about whether liquidity may influence CDS spreads as well. Graphs reported in Appendix 10 show relevant differences in trading volumes between Europe and North America, especially among low credit quality firms (DTCC 2014). These divergences suggest that liquidity deserves further attention when analyzing potential drivers of debt riskiness.

Results in connection to Hypothesis 3 support expectations about a decreasing trend in credit and equity risk since Lehman's collapse. Furthermore, timing differences are found between the two geographical markets: the reduction in VaR measures begins in the 2010-2012 period in North America and one period after in Europe. A possible explanation may be that the North American market started to recover in the outbreaks of the European sovereign debt crisis. In addition, the progressive increase detected in the equity-to-CDS VaR ratio, as opposed to previous findings (Raunig & Scheicher 2008), provides further insights on dynamics between credit and equity risk.

Hypothesis 4 is found to be true, as one would expect from high yield firms being riskier than investment grade ones (Standard & Poor's 2014). Furthermore, the equity VaR in the North American market is higher than in the European market, while the opposite holds for the CDS risk measure. Thus, the riskiness of the CDS position relative to the equity investment is higher in the European market.

On a pooled geographical level, the correlation between CDS and equity VaR for high yield firms is twice as high as that of investment grade companies. Results are in line with Kwan (1996), who found that AAA-rated bond prices react to changes in the risk free rate, but not to movements in stock prices, while the opposite happens in the case of sub-investment grade bonds. Hence, results of this paper are consistent with expectations as well as previous research. It should be noted, however, that the correlation coefficient between CDS and equity VaR for European high yield firms is found to be neither statistically nor economically significant.

With respect to Hypothesis 5, the established literature might be helpful in understanding some of the outlined industry-specific dynamics. The greater relative risk of the CDS position of technology and financial firms may be due to volatility in spreads rather than default risk, since over a one-day horizon the probability of default is very low (Liu et al. 2007). Hence, the relative riskiness of the CDS position might be due to higher spread standard deviation in these two sectors (Raunig & Scheicher 2008). This is confirmed in the North American sample, where the highest spread volatility is found for companies in the financial and technology industry. However, spread volatility for European financial firms is the third lowest among the ten sectors. Two studies focusing on the banking industry may be helpful in understanding the underlying reasons of these results. Pereira de Silva et al. (2014) found that the "too-big-to-fail" theory leads to deviation from what asserted by Merton (1974): poor financial conditions of a systemically important bank do not negatively affect creditors as much as one would expect, since they are typically protected by government subsidies; hence, while stockholders' wealth is severely hit, bondholders are bailed-out. In addition, the Demirgüç-Kunt and Huizinga (2010) found that the "too-big-to-fail" argument is valid only in countries with "healthy" fiscal budgets; on the contrary, in countries running large fiscal deficits a troubled systemically important bank experiences negative impacts on both stock price and CDS spread. Hence, the high risk of the CDS position relative to the equity position for financial firms might have different explanations: in the North American case the high spread volatility could reasonably be the main driver; on the other hand, the debt sovereign crisis may, despite the short holding period, introduce the default risk component for European firms.

A possible explanation to the geographical differences noticed in the industrials industry might be the halt in corporate lending occurred in the Eurozone, due to the financial crisis and the subsequent tightening of regulatory capital requirements (Kaya & Meyer 2014). Results suggest that during the analyzed period the industrial sector was considered riskier by the market than other industries; this contrasts with results relative to North America as well as previous findings on the European market between 2004 and 2005, where firms in the consumer discretionary industry are found to incorporate the highest perceived credit risk (Byström 2005).

A further reflection concerns a third difference, observed between two very cyclical sectors, namely materials and consumer discretionary. In the former case, the impact of financial interconnectedness (Moghadam & Viñals 2010) is reflected by the time and magnitude analogies between Europe and North America. On the other hand, these analogies are not found between spreads and prices of firms in the consumer discretionary industry, as externalities between economies are more related to international trade than financial markets.

An additional remark can be made by having a closer look at American International Group (AIG:NYSE), as it provides a very good illustration of interactions between credit and counterparty risk. Until the third quarter of 2008, AIG's collateral requirements as established by ISDA standards were low due to its high credit rating (AA-). At that time, the insurance company was highly exposed to short positions in CDSs, many of them referenced to CDOs on US (prime and subprime) mortgages. Hence, AIG experienced high decreases in asset values as well as increases in liability values as a result of the US subprime crisis. In September the company was downgraded by credit rating agencies, and its counterparties started to ask for more collateral on derivative exposures. Eventually, AIG had to ask the U.S. Fed for assistance, as it found itself unable to honor its contractual obligations. One week after Lehman Brother's bankruptcy, the Fed decided to bail-out AIG, mostly to not leave other financial institutions with an uncovered exposure (bought from AIG) on Lehman. Time series for CDS spread and stock price (Appendix 10) allow to graphically follow how credit risk negatively affecting counterparty risk further worsened AIG's troubled financial conditions. (Weistroffer 2009)

7 Limitations and Suggestions for Further Research

The main shortcoming of this thesis is the limited number of companies not only in the main 2006 to 2014 period, but also more importantly in the subsamples. A trade-off between quality and quantity of data has emerged due to the fairly long time period chosen for the purposes of this study. Four filters have been applied to remove companies and thus improve the data quality:

- Ticker consistency: no change in ticker must have occurred during the analyzed period;
- Data availability: the whole time series of daily market quotes must have been obtainable from either 2006 or 2010 until 2014;
- Trading liquidity: each company must have been part of one of the four Markit indices.
- Seniority correspondence: all CDS market quotes must refer to senior unsecured debt.

Consequently, the number of high yield companies declined the most, primarily because these firms are more likely to change status either through improving their creditworthiness or by defaulting. The use of an additional sample from 2010 to 2014 to perform the rating analysis is aimed at (partly) overcoming this limitation. Each rating subsample took into account only companies that were listed on the investment grade or high yield index for the entire two biannual periods. Hence, companies that were not included in all of the four annexes published during each specific time period are not part of the rating subsamples.

The same issue extends to the industry analysis, which does not contain a sufficient number of companies in the following three sectors: technology, health care and energy. The graphical analysis in Chapter 6.5 has been performed to better understand sectors for which VaR and ETL measures are considered to be not exhaustive.

Therefore, the primary suggestion for further research is to work with a greater number of companies, especially for the credit rating and industry analyses. The significant improvement in the data availability since 2010, a trend which is expected to continue in the upcoming years, should allow for more representative samples.

Moreover, further research should investigate the reasons behind this paper's findings, which deviate from the theory. As of 2014, established studies are not able to explain the impact of the most recent financial crises on the relationship between the behavior of CDS spreads and stock prices. The majority of studies has either focused on the years leading up to the financial crisis of 2008, or analyzed events occurred during precedent market turmoil periods. Therefore, it is advised to investigate the underlying motivations behind the following three findings:

1. Correlation between the credit and equity VaR in the European market. In general, one would expect a stronger negative correlation between CDS spreads and stock prices (i.e. a stronger positive correlation between CDS and equity VaR) during crisis times (Belke & Gokus 2011) and for low credit quality firms (Kwan 1996). However, correlation in Europe has been found to be about half that of North America. Keeping in mind the events in the European market surrounding the sovereign debt crisis, these findings were hard to explain (Chapter 6.2). Furthermore, correlation coefficients of VaR measures for high yield European firms were found to be negative, implying a positive relationship between CDS spreads and stock prices, in contrast with Kwan (1996). As such, it would be interesting to gain a better understanding of how the most recent financial crises and subsequently different regulations affect the correlation between the credit and equity markets.

2. Panel regression results for the European market. The panel regression for the European market over the 2010-2014 period produced unexpected results concerning lack of economic significance (Chapter 6.2). While looking at biannual outputs, it has been found that these discrepancies were referring to the 2012-2014 period. Moreover, the R-squared was fairly lower for the European sample than for the North American one. Future studies could focus on the European market to investigate if a firm's debt-to-equity ratio and asset volatility are the only drivers of debt riskiness during crises and to which extent they affect it. For example, a suggestion is to analyze whether liquidity is a relevant factor by controlling for trading volumes.

3. Robustness tests for European high yield firms during the 2012-2014 period. The robustness tests revealed that the equity-to-CDS VaR ratio for European sub-investment grade firms between 2012 and 2014 increases when the holding period is extended to 20 trading days (Chapter 6.6). This goes against predictions, as a longer holding period suggests that the default probability will increase and hence CDS VaR should approach equity VaR (Raunig & Scheicher 2008). Hence, further research may be able to explain

why the CDS VaR has decreased with a longer holding period, instead of having increased more than the equity VaR as one would expect.

A last suggestion concerns an aspect which has not been touched in this paper, as it was beyond its scope. The lead-lag relationship between CDS spreads and stock prices has not been fully explained so far, since it has not been investigated during the most recent years. The first researches into lead-lag relationships between the bond, stock and CDS markets reached mixed conclusions about existing linkages (Longstaff et al. 2003; Norden & Weber 2004; Pena & Forte 2006). The greatest degree of evidence was individuated by Pena and Forte (2006), who found that stock returns led CDS spreads for 67% of the analyzed companies. Fung et al. (2008) were able to show relevant differences in the lead-lag relationship between the equity and credit market during the 2001-2007 period. More specifically, the authors found that while stock returns led CDS spreads for investment grade firms, the opposite relation held for high yield firms. It was also established that the CDS market played a more important role in volatility spillovers, while the stock market was found to be more efficient in transmitting information to prices. (Fung et al. 2008)

As these aspects were out of the scope of this paper, the lead-lag relationship between the markets has not been further investigated. However, an analysis based on the financial crisis years and their aftermath will bring more insights and guidance to investors and researchers alike.

8 Conclusion

In this thesis the credit and equity risk of a maximum 113 European and 93 North American companies have been compared. Two risk measures, namely Value-at-Risk and expected tail loss, have been computed for a short CDS position and a long equity position in the same entity using the historical simulation method. The analyzed time period goes from September 2006 to September 2014, with 231,324 and 177,140 daily observations for the European and North American market respectively. Overall, findings have mirrored previous studies in credit VaR always being substantially lower than equity VaR (Raunig & Scheicher 2008). As such, it has been confirmed again that equity is always riskier than debt (Merton 1974), although differences in magnitude have been observed for different time periods, credit ratings and industries.

One key assumption was the use of daily trading data to calculate VaR, whose main implication is a very small default probability (Liu et al. 2007). Robustness tests, however, confirmed the findings: even after an increase due to a longer holding period – and hence, higher default probabilities – credit risk has been found to be lower than equity risk.

The correlation analysis confirmed that credit and equity risk are positively correlated. Moreover, panel regression results partly validated Merton (1974), who asserted that debt riskiness rises with a company's debt-to-equity ratio as well as its asset volatility. However, it has been found that this relationship does not hold in all cases. More specifically, results for the European sample were missing of economic significance in the aftermath of the European sovereign debt crisis. The unexpected correlation behavior raises the need for a deeper study on the impact of financial crises on securities returns.

It has been proved that both credit and equity risk have decreased from 2010 onwards, with the former declining at a higher pace than the latter. In addition, the trend has been found to start later in Europe, reflecting the delayed recovery connected to the European sovereign debt crisis.

The credit quality analysis has proved that high yield firms are riskier than investment grade ones. Furthermore, the riskiness of the CDS investment relative to the equity position has been found to be higher in the European market. Pooled results on rating subsamples document a higher correlation between the credit and equity market for high yield companies. The evidence on the European market alone, however, provided neither statistical nor economic significance, hence being in contrast with expectations as well as previous research (Kwan 1996).

The analysis of industry-specific dynamics showed that the market behavior is influenced by the political environment, especially with respect to the "too-big-to-fail" phenomenon and holding requirements. Furthermore, the observed variations in results for the same industries in different markets suggest that financial interconnectedness is an important driver of debt riskiness.

This thesis has contributed to showcase that equity risk exceeds credit risk across time periods, industries and credit ratings even during market turmoil periods. However, it has further proved that the correlations and industry-specific dynamics do not necessarily follow a similar pattern in different geographical markets due to variations in the underlying market conditions. Panel regression results are a suggested starting point for further research concerning underlying drivers of debt riskiness, as leverage and asset volatility seem not to be the only explanatory variables in a crisis scenario.

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Appendix 1: List of Companies

Table 20 and 21 provide an overview of the companies included in this thesis as well as their market, credit risk class (investment grade or high yield) for the two-year periods of 2010-2012 and 2012-2014. Lastly, the company's sector is listed according to Bloomberg's industry classifications. The national markets for the European countries are listed to show necessary currency conversions into EUR and give necessary information about trading markets.

Table 20
iTraxx Europe companies

The table shows the list of companies for the European sample. Companies are listed on the stock exchange markets of one of the following countries: Belgium (BB), Finland (FH), France (FP), Germany (GR), Italy (IM), United Kingdom (LN), the Netherlands (NA), Norway (NO), Portugal (PL), Spain (SM), Sweden (SS) and Switzerland (VX). Companies with an asterisk (*) are not included in the full time sample (2006 to 2014) but instead only in the post 2010 sample.

Company	Market	2010-2012	2012-2014	Sector
Accor SA	FP		IG	Consumer Discretionary
Aegon NV	NA	IG	IG	Financials
Airbus Group NV	FP	IG	IG	Industrials
Akzo Nobel NV	NA	IG	IG	Materials
Allianz SE	GR	IG	IG	Financials
Anglo American PLC	LN	IG	IG	Materials
Assicurazioni Generali SpA	IM	IG	IG	Financials
AstraZeneca PLC	LN		IG	Health Care
Atlantia SpA	IM		IG	Industrials
Aviva PLC	LN	IG	IG	Financials
AXA SA	FP	IG	IG	Financials
BAE Systems PLC	LN	IG	IG	Industrials
Banco Bilbao Vizcaya Argentaria SA	SM	IG		Financials
Banco Santander SA	SM	IG	IG	Financials
BASF SE	GR	IG	IG	Materials
Bayer AG	GR	IG	IG	Health Care
Bayerische Motoren Werke AG	GR	IG	IG	Consumer Discretionary
BNP Paribas SA	FP	IG	IG	Financials
Bouygues SA	FP	IG	IG	Industrials
BP PLC	LN	IG	IG	Energy
British American Tobacco PLC	LN	IG	IG	Consumer Staples
British Sky Broadcasting Group PLC	LN		IG	Communications
British Telecommunications PLC	LN	IG	IG	Communications
Carrefour SA	FP	IG	IG	Consumer Staples

Casino Guichard Perrachon SA	FP	IG	IG	Consumer Staples
Centrica PLC	LN	IG	IG	Utilities
Cie de St-Gobain	FP	IG	IG	Materials
Cie Financiere du Groupe Michelin Senard	FP	IG	IG	Consumer Discretionary
Commerzbank AG	GR	IG	IG	Financials
Compass Group PLC	LN	IG	IG	Consumer Discretionary
Continental AG	GR	HY		Consumer Discretionary
Credit Agricole SA	FP	IG	IG	Financials
Daimler AG	GR	IG	IG	Consumer Discretionary
Danone SA	FP	IG	IG	Consumer Staples
Deutsche Bank AG	GR	IG	IG	Financials
Deutsche Telekom AG	GR	IG	IG	Communications
Diageo PLC	LN	IG	IG	Consumer Staples
E.ON SE	GR	IG	IG	Utilities
Electricite de France SA	FP	IG	IG	Utilities
Electrolux AB	SS		IG	Consumer Discretionary
Enel SpA	IM	IG	IG	Utilities
Eni SpA	IM		IG	Energy
Experian Finance PLC	LN	IG	IG	Technology
Fortum OYJ	FH	IG	IG	Utilities
Gas Natural SDG SA	SM	IG	IG	Utilities
GDF Suez	FP	IG	IG	Utilities
Gecina SA*	FP			Financials
Hannover Rueck SE	GR	IG	IG	Financials
Henkel AG & Co KGaA	GR	IG	IG	Consumer Staples
Holcim Ltd	VX	IG	IG	Materials
Iberdrola SA	SM	IG	IG	Utilities
Imperial Tobacco Group PLC	LN	IG	IG	Consumer Staples
Intesa Sanpaolo SpA	IM	IG	IG	Financials
Kingfisher PLC	LN	IG	IG	Consumer Discretionary
Koninklijke Ahold NV	NA	IG	IG	Consumer Staples
Koninklijke DSM NV	NA	IG	IG	Materials
Koninklijke KPN NV	NA	IG	IG	Communications
Koninklijke Philips NV	NA	IG	IG	Health Care
Linde AG	GR	IG	IG	Materials
LVMH Moet Hennessy Louis Vuitton SA	FP	IG	IG	Consumer Discretionary
Marks & Spencer PLC	LN	IG	IG	Consumer Discretionary
Metro AG	GR	IG	IG	Consumer Staples

Muenchener Rueckversicherungs AG	GR	IG	IG	Financials
Nestle SA	VX	IG	IG	Consumer Staples
Orange SA	FP			Communications
Pearson PLC	LN	IG	IG	Communications
Pernod Ricard SA	FP			Consumer Staples
Publicis Groupe SA	FP	IG	IG	Communications
Reed Elsevier PLC	LN	IG	IG	Communications
Repsol SA	SM	IG		Energy
RWE AG	GR	IG	IG	Utilities
Safeway Ltd	LN	IG	IG	Consumer Staples
Sanofi	FP	IG	IG	Health Care
SES SA*	FP			Communications
Siemens AG	GR	IG	IG	Industrials
Societe Generale SA	FP	IG	IG	Financials
Sodexo	FP	IG	IG	Consumer Discretionary
Solvay SA	BB	IG	IG	Materials
Statoil ASA	NO		IG	Energy
Swiss Reinsurance Co Ltd	VX	IG	IG	Financials
Tate & Lyle PLC	LN		IG	Consumer Staples
Telefonaktiebolaget LM Ericsson	SS		IG	Technology
Telefonica SA	SM	IG	IG	Communications
Telenor ASA	LN	IG	IG	Communications
TeliaSonera AB	SS	IG	IG	Communications
Tesco PLC	LN	IG	IG	Consumer Staples
Total SA	FP	IG	IG	Energy
UBS AG	VX	IG	IG	Financials
UniCredit SpA	IM	IG	IG	Financials
Unilever NV	NA	IG	IG	Consumer Staples
Veolia Environnement SA	FP	IG	IG	Utilities
Vinci SA	FP	IG	IG	Industrials
Vivendi SA	FP	IG	IG	Communications
Vodafone Group PLC	LN	IG	IG	Communications
Volkswagen AG	GR	IG	IG	Consumer Discretionary
Wolters Kluwer NV	NA	IG	IG	Technology
Volvo AB	SS		IG	Industrials
WPP 2005 Ltd	LN	IG	IG	Communications
Zurich Insurance Co Ltd	VX	IG	IG	Financials
Alstom SA	FP	IG		Industrials

Dixons Retail PLC	LN	HY	HY	Consumer Discretionary
EDP - Energias de Portugal SA	PL		HY	Utilities
Fiat SpA	IM	HY	HY	Consumer Discretionary
Finmeccanica SpA	IM		HY	Industrials
HeidelbergCement AG	GR	HY	HY	Materials
Ladbrokes PLC	LN	HY	HY	Consumer Discretionary
Lafarge SA	FP	HY	HY	Materials
Nokia OYJ	FH		HY	Technology
Peugeot SA	FP	HY	HY	Consumer Discretionary
Telecom Italia SpA	IM	IG		Communications
ThyssenKrupp AG	GR	HY	HY	Materials
TUI	GR	HY	HY	Consumer Discretionary
UPM-Kymmene OYJ	FH	HY	HY	Materials
2006 – 2014 sample	111			
Post 2010 sample	113			
Investment Grade (IG)		86	92	
High Yield (HY)		10	12	
None		17	9	
Communications				16
Consumer Discretionary				17
Consumer Staples				15
Energy				5
Financials				20
Health Care				4
Industrials				9
Materials				12
Technology				4
Utilities				11

Table 21
CDX North American companies

The table shows the list of companies for the North American sample. Companies with an asterisk (*) are not included in the full time sample (2006 to 2014) but instead only in the post 2010 sample.

Company	2010 - 2012	2012 - 2014	Sector
ACE Ltd	IG	IG	Financials
Aetna Inc	IG	IG	Health Care
Altria Group Inc	IG	IG	Consumer Staples
American Electric Power Co Inc	IG	IG	Utilities
American Express Co	IG	IG	Financials
American International Group Inc	IG	IG	Financials
Amgen Inc	IG	IG	Health Care
Anadarko Petroleum Corp	IG	IG	Energy
Arrow Electronics Inc	IG	IG	Technology
AT&T Inc	IG	IG	Communications
AutoZone Inc	IG	IG	Consumer Discretionary
Avnet Inc	IG	IG	Technology
Avon Products Inc*			Consumer Staples
Barrick Gold Corp*	IG	IG	Materials
Baxter International Inc	IG	IG	Health Care
Boston Scientific Corp		IG	Health Care
Bristol-Myers Squibb Co	IG	IG	Health Care
Campbell Soup Co	IG	IG	Consumer Staples
Cardinal Healty Inc	IG	IG	Health Care
Carnival Corp	IG	IG	Consumer Discretionary
Caterpillar Inc	IG	IG	Industrials
CBS Corp	IG	IG	Communications
Computer Sciences Corp	IG	IG	Technology
ConAgra Foods Inc	IG	IG	Consumer Staples
ConocoPhillips	IG	IG	Energy
CSX Corp	IG	IG	Industrials
CVS Caremark Corp	IG	IG	Consumer Staples
Deere & Co	IG	IG	Industrials
Devon Energy Corp	IG	IG	Energy
Dominion Resources Inc/VA	IG	IG	Utilities
Eastman Chemical Co	IG	IG	Materials
EI du Pont de Nemours & Co	IG	IG	Materials
Exelon Corp		IG	Utilities
FirstEnergy Corp	IG	IG	Utilities

General Mills Inc	IG	IG	Consumer Staples
Halliburton Co	IG	IG	Energy
Hewlett-Packard Co	IG	IG	Technology
Honeywell International Inc	IG	IG	Industrials
International Business Machines Corp	IG	IG	Technology
International Paper Co	IG	IG	Materials
Johnson Controls Inc*	IG	IG	Consumer Discretionary
Lockheed Martin Corp	IG	IG	Industrials
Loews Corp	IG	IG	Financials
Lowe's Cos Inc	IG	IG	Consumer Discretionary
Macy's Inc		IG	Consumer Discretionary
Marriott International Inc/DE	IG	IG	Consumer Discretionary
Marsh & McLennan Cos Inc*	IG	IG	Financials
McDonald's Corp	IG	IG	Consumer Discretionary
McKesson Corp	IG	IG	Health Care
MeadWestvaco Corp		IG	Industrials
MetLife Inc	IG	IG	Financials
Newell Rubbermaid Inc	IG	IG	Consumer Discretionary
Nordstrom Inc	IG	IG	Consumer Discretionary
Norfolk Southern Corp	IG	IG	Industrials
Northrop Grumman Corp	IG	IG	Industrials
Omnicom Group Inc	IG	IG	Communications
Pitney Bowes Inc		IG	Technology
Raytheon Co	IG	IG	Industrials
Reynolds American Inc	IG	IG	Consumer Staples
Ryder System Inc	IG	IG	Industrials
Safeway Inc	IG	IG	Consumer Staples
Sempra Energy	IG	IG	Utilities
Southwest Airlines Co	IG	IG	Consumer Discretionary
Staples Inc		IG	Consumer Discretionary
Starwood Hotels & Resorts Worldwide Inc		IG	Consumer Discretionary
Target Corp	IG	IG	Consumer Staples
The Allstate Corp	IG	IG	Financials
The Chubb Corp	IG	IG	Financials
The Dow Chemical Co	IG	IG	Materials
The Gap Inc	IG	IG	Consumer Discretionary
The Hartford Financial Services Group Inc	IG	IG	Financials
The Home Depot Inc	IG	IG	Consumer Discretionary

The Kroger Co	IG	IG	Consumer Staples
The Sherwin-Williams Co	IG	IG	Materials
The Walt Disney Co	IG	IG	Communications
Time Warner Inc	IG	IG	Communications
Tyson Foods Inc		IG	Consumer Staples
Union Pacific Corp	IG	IG	Industrials
Valero Energy Corp	IG	IG	Energy
Wal-Mart Stores Inc	IG	IG	Consumer Staples
Weatherford International PLC			Energy
Weyerhaeuser Co	HY		Financials
Whirlpool Corp	IG	IG	Consumer Discretionary
Xerox Corp	IG	IG	Technology
Bombardier Inc	HY	HY	Industrials
CenturyLink Inc	IG		Communications
Gannett Co Inc	HY	HY	Communications
KB Home*	HY	HY	Consumer Discretionary
Lennar Corp*	HY	HY	Consumer Discretionary
Olin Corp*		HY	Materials
Royal Caribbean Cruises Ltd	HY	HY	Consumer Discretionary
Tesoro Corp*	HY	HY	Energy
The Goodyear Tire & Rubber Co	HY	HY	Consumer Discretionary
2006 – 2014 sample	85	85	
Post 2010 sample	93	93	
Investment Grade (IG)	74	81	
High Yield (HY)	8	8	
None	11	4	
Communications			7
Consumer Discretionary			19
Consumer Staples			12
Energy			7
Financials			10
Health Care			7
Industrials			12
Materials			7
Technology			7
Utilities			5

Appendix 2: CDS Valuation Formula

The CDS pricing formula in (3) proposed by Phillips (2006) simplifies the reduced form model of Hull and White (2000) by making the following assumptions:

1. The default process is Poisson with constant intensity λ, i.e. the time to default is exponentially distributed with mean $1/\lambda$.

2. The Libor curve and the CDS spread curve are both assumed to be flat, and the risk free rate r is the value of Libor curve evaluated at the tenor of the CDS.

3. The CDS spread is s_0/annum and payments are made continuously until the swap matures or the underlying bond defaults.

4. In the event of a default, the buyer of protection is immediately paid the product of the recovery rate of the underlying bond RR and the notional amount of the CDS. The loss rate L is defined as $1 - RR$.

If the credit spread is pure compensation for default, a long position in a risky bond is equivalent to a long position in a riskless bond and a short position in a CDS, both with the same maturity and notional value as the risky bond. Assuming constant coupon payments at a rate of $s_0 + r$ per annum terminating at either the maturity of the bond T or its default at t, whichever the earliest, the value of the bond in a risk neutral world is given by:

$$\begin{aligned} V_{Risky\ Bond} = {} & E_t(PV[Coupon\ payments + Recovery\ Value \mid Bond\ defaults\ at\ t < T]) \\ & + PV[Coupon\ payments\ + Principal\ Amount] \times P[No\ default] \end{aligned}$$

$$= \int_0^T \left(\int_0^t (r + s_0)\, e^{-r\tau} d\tau + (1 - L) e^{-rt} \right) \lambda e^{-\lambda t} dt + \left(\int_0^T (r + s_0)\, e^{-r\tau} d\tau + e^{-rT} \right) \int_T^{\infty} \lambda e^{-\lambda t} dt$$

Evaluating the integrals and collecting the terms ultimately yields:

$$V_{Risky\ Bond} = 1 - \left(1 - e^{-(r+\lambda)T}\right) \times \left(\frac{L\lambda - s}{r + \lambda}\right) = V_{Riskless\ Bond} - V_{CDS}$$

The protection must be fairly priced at issuance, implying that $s_0 = L\lambda$. The value of the CDS with a notional value N to a buyer of protection at any quoted spread s can be therefore written as:

$$V_{CDS} = N \times \left(1 - e^{-(r+s/L)T}\right) \times \left(\frac{s - s_0}{r + s/L}\right)$$

Appendix 3: Expected Loss

The expected loss (EL) is the mean value of the probability distribution of future losses. It is estimated ex ante by the lender, which hedges its risk by adding a spread to the interest rate charged on the loan so that if the borrower default occurs as expected, the lender would obtain exactly the net return anticipated at issuance. The expected loss on a credit exposure requires three parameters to be estimated:

1. The exposure at default (EAD), which is the expected value of the exposure in the event of default, represented by the current exposure plus the possible variation in the size of the loan which may occur until the date of possible default.
2. The probability of default (PD) of the borrower.
3. The loss given default (LGD), i.e. the percentage of exposure that the lender forecasts to be unable to recover in the event of default; it is equal to one minus the expected recovery rate (RR) on the exposure.

Hence, the expected loss can be expressed as:

$$EL = \overline{EAD} \times PD \times \overline{LGD}$$

The exposure at default represents a stochastic variable whose volatility depends on the type of facility granted to the borrower. For example, in the case of a credit line, the bank undertakes to lend a certain amount of funds to the customer, which chooses which portion to use and when. Therefore, the actual exposure of the lender may vary over time due to external decisions.

The probability of default can be estimated from a historical database of actual defaults using techniques such as logistic regression (mostly in the case of privately owned counterparties), or also from the observable prices of credit default swaps, bonds, and options on common stock. Many banks use rating agencies' estimates from past default experience.

The loss given default is calculated in different ways. The so-called "gross" LGD, is computed as the ratio between total losses and exposure at default. Gross LGD is the most popular in academia, because researchers only have access to bond market data. Alternatively, losses can be divided by the unsecured portion of a credit line to compute the "Blanco" LGD. Blanco LGD is mostly used by banks, because it allows to decompose total losses losses between those on unsecured portions and those on secured portions due to decrease in collateral quality. (Resti & Sironi 2007)

Appendix 4: Additional Results for Hypothesis 1

Table 22
Additional risk metrics for iTraxx firms (2006-2014)

The table shows VaR and ETL measures with a 95% and 90% confidence interval for the European sample. The first column reports results for the eight-year full sample, while column 2 to 5 report results for biannual subsamples.

	2006-2014		2006-2008		2008-2010		2010-2012		2012-2014	
	CDS	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**	**CDS**	**Equity**
95% VaR	0.27%	2.38%	0.20%	2.68%	0.35%	3.28%	0.30%	2.65%	0.17%	2.33%
90% VaR	0.16%	1.65%	0.13%	1.99%	0.21%	2.30%	0.18%	1.96%	0.10%	1.72%
Std. Dev. 95% VaR	0.19%	1.07%	0.11%	0.94%	0.27%	0.79%	0.27%	0.80%	0.16%	1.96%
Std. Dev. 90% VaR	0.12%	0.73%	0.07%	0.67%	0.18%	0.57%	0.19%	0.56%	0.10%	1.30%
ETL 95% VaR	0.48%	3.62%	0.34%	4.10%	0.62%	5.08%	0.44%	3.86%	0.29%	3.53%
# Obs. in the 5% tail	105	105	26	26	26	26	27	27	26	26
ETL 90% VaR	0.35%	2.80%	0.25%	3.21%	0.42%	3.96%	0.34%	3.12%	0.21%	2.76%
# Obs. in the 10% tail	209	209	52	52	52	52	53	53	52	52
# Total obs.	231324	231324	57720	57720	57720	57720	57942	57942	57609	57609

Table 23
Additional risk metrics for CDX firms (2006-2014)

The table shows VaR and ETL measures with a 95% and 90% confidence interval for the North American sample. The first column reports results for the eight-year full sample, while column 2 to 5 report results for biannual subsamples.

	2006-2014		2006-2008		2008-2010		2010-2012		2012-2014	
	CDS	Equity	CDS	Equity	CDS	Equity	CDS	Equity	CDS	Equity
95% VaR	0.19%	2.80%	0.17%	2.92%	0.25%	3.42%	0.15%	2.64%	0.11%	2.23%
90% VaR	0.11%	1.96%	0.08%	2.12%	0.15%	2.40%	0.09%	1.95%	0.07%	1.58%
Std. Dev. 95% VaR	0.15%	1.05%	0.13%	1.14%	0.28%	0.83%	0.16%	1.01%	0.10%	0.77%
Std. Dev. 90% VaR	0.09%	0.76%	0.07%	0.83%	0.17%	0.66%	0.10%	0.74%	0.06%	0.52%
ETL 95% VaR	0.37%	4.26%	0.33%	4.22%	0.50%	5.03%	0.27%	4.20%	0.20%	3.40%
# Obs. in the 5% tail	105	104	26	26	26	26	27	27	26	26
ETL 90% VaR	0.25%	3.30%	0.22%	3.34%	0.33%	3.96%	0.20%	3.19%	0.14%	2.65%
# Obs. in the 10% tail	209	208	52	52	52	52	53	53	52	52
# Total obs.	177140	177140	44200	44200	44200	44200	44370	44370	44115	44115

Table 24
T-test results on iTraxx firms (2006-2014)

The table shows results of the one-tailed t-test performed on the difference between 99% equity and CDS VaR for the European sample. The low p-value allows to reject the null hypothesis that the difference between the two risk measures is equal or below 3%.

	99% Equity VaR	99% CDS VaR
Mean	0.0462	0.0068
Variance	0.0007	0.0000
Observations	111	111
Hypothesized Mean Difference	0.0300	
Df	115	
t Stat	3.7002	
P(T<=t) one-tail	0.0002	
t Critical one-tail	2.3592	

Table 25
T-test results on CDX firms (2006-2014)

The table shows results of the one-tailed t-test performed on the difference between 99% equity and CDS VaR for the North American sample. The low p-value allows to reject the null hypothesis that the difference between the two risk measures is equal or below 3%.

	99% Equity VaR	99% CDS VaR
Mean	0.0520	0.0058
Variance	0.0003	0.0000
Observations	85	85
Hypothesized Mean Difference	0.0300	
Df	91	
t Stat	7.8941	
P(T<=t) one-tail	0.0000	
t Critical one-tail	2.3680	

Appendix 5: Additional Results for Hypothesis 2

Table 26
Two-way fixed effects regression output for iTraxx firms (2010-2012)

The dependent variable is the change of the short CDS position, while the independent variables are CDS spread, stock price and estimated equity volatility. Given the use of time fixed effects intercepts are day-specific and therefore have been omitted.

	Coefficient	**Robust Std. Err.**	**t**	**P>|t|**	**95% Confidence Interval**	
Spread	-0.000333	0.0000	-197.72	0.0000	-0.000336	-0.000330
Price	0.000018	0.0000	12.82	0.0000	0.000016	0.000021
Volatility	-0.048205	0.0044	-11.02	0.0000	-0.056780	-0.039629
	Nr of obs:	58979	R-squared:	0.8521	Adj R-squared:	0.8505

Table 27
Two-way fixed effects regression output for iTraxx firms (2012-2014)

The dependent variable is the change of the short CDS position, while the independent variables are CDS spread, stock price and estimated equity volatility. Given the use of time fixed effects intercepts are day-specific and therefore have been omitted.

	Coefficient	**Robust Std. Err.**	**t**	**P>|t|**	**95% Confidence Interval**	
Spread	-0.000393	0.0000	-158.17	0.0000	-0.000398	-0.003880
Price	-0.000029	0.0000	-3.14	0.0020	-0.000048	-0.000011
Volatility	0.008694	0.0020	4.27	0.0000	0.004703	0.012686
	Nr of obs:	58754	R-squared:	0.4566	Adj R-squared:	0.4506

Table 28
Two-way fixed effects regression output for CDX firms (2010-2012)

The dependent variable is the change of the short CDS position, while the independent variables are CDS spread, stock price and estimated equity volatility. Given the use of time fixed effects intercepts are day-specific and therefore have been omitted.

	Coefficient	**Robust Std. Err.**	**t**	**P>|t|**	**95% Confidence Interval**	
Spread	-0.000392	0.0000	-325.55	0.0000	-0.000394	-0.000390
Price	0.000032	0.0000	22.50	0.0000	0.000029	0.000035
Volatility	0.105290	0.0164	6.43	0.0000	0.073184	0.137396
	Nr of obs:	48546	R-squared:	0.9971	Adj R-squared:	0.997

Table 29
Two-way fixed effects regression output for CDX firms (2012-2014)

The dependent variable is the change of the short CDS position, while the independent variables are CDS spread, stock price and estimated equity volatility. Given the use of time fixed effects intercepts are day-specific and therefore have been omitted.

	Coefficient	Robust Std. Err.	t	P>|t|	95% Confidence Interval	
Spread	-0.000421	0.0000	-574.32	0.0000	-0.000422	-0.000419
Price	0.000012	0.0000	26.88	0.0000	0.000011	0.000013
Volatility	-0.002002	0.0005	-3.94	0.0000	-0.002998	-0.001007
	Nr of obs:	48360	R-squared:	0.9987	Adj R-squared:	0.9987

Table 30
Variance inflation factor for iTraxx firms (2010-2014)

The table displays coefficients of determination as well as the VIF for the three regressions performed to test for multicollinearity. for the European sample.

Y	X1	X2	R-squared	Tolerance (1 - R-squared)	VIF
Spread	Price	Volatility	0.0453	0.9547	1.0474
Price	Spread	Volatility	0.0427	0.9573	1.0446
Volatility	Spread	Price	0.0033	0.9967	1.0033

Table 31
Variance inflation factor for CDX firms (2010-2014)

The table displays coefficients of determination as well as the VIF for the three regressions performed to test for multicollinearity. for the North American sample.

Y	X1	X2	R-squared	Tolerance (1 – R-squared)	VIF
Spread	Price	Volatility	0.0324	0.9676	1.0334
Price	Spread	Volatility	0.0307	0.9693	1.0316
Volatility	Spread	Price	0.0019	0.9981	1.0019

Appendix 6: Additional Results for Hypothesis 3

Table 32
ANOVA test results on 99% CDS VaR for iTraxx firms (2006-2014)

The table shows results of the ANOVA test performed on CDS risk measures for the four biannual subsamples. The low p-value allows to reject the null hypothesis that the difference between each pair of metrics is equal to zero.

Groups	Count	Sum	Average	Variance
2006-2008	111	0.4668	0.0042	0.0000
2008-2010	111	0.9772	0.0088	0.0000
2010-2012	111	0.7886	0.0071	0.0000
2012-2014	111	0.5258	0.0047	0.0000

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.0015	3	0.0005	25.9748	0.0000	3.8264
Within Groups	0.0086	440	0.0000			
Total	0.0101	443				

Table 33
ANOVA test results on 99% equity VaR for iTraxx firms (2006-2014)

The table shows results of the ANOVA test performed on equity risk measures for the four biannual subsamples. The low p-value allows to reject the null hypothesis that the difference between each pair of metrics is equal to zero.

Groups	Count	Sum	Average	Variance
2006-2008	111	5.4334	0.0489	0.0003
2008-2010	111	7.0036	0.0631	0.0004
2010-2012	111	5.1165	0.0461	0.0002
2012-2014	111	5.0358	0.0454	0.0011

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.0229	3	0.0076	15.6395	0.0000	3.8264
Within Groups	0.2147	440	0.0005			
Total	0.2376	443				

Table 34
ANOVA test results on 99% CDS VaR for CDX firms (2006-2014)

The table shows results of the ANOVA test performed on CDS risk measures for the four biannual subsamples. The low p-value allows to reject the null hypothesis that the difference between each pair of metrics is equal to zero.

Groups	Count	Sum	Average	Variance
2006-2008	85	0.4227	0.0049	0.0000
2008-2010	85	0.6984	0.0082	0.0000
2010-2012	85	0.3588	0.0042	0.0000
2012-2014	85	0.2855	0.0033	0.0000

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.0011	3	0.0003	22.0459	0.0000	3.84
Within Groups	0.0058	336	0.0000			
Total	0.0069	339				

Table 35
ANOVA test results on 99% equity VaR for CDX firms (2006-2014)

The table shows results of the ANOVA test performed on equity risk measures for the four biannual subsamples. The low p-value allows to reject the null hypothesis that the difference between each pair of metrics is equal to zero.

Groups	Count	Sum	Average	Variance
2006-2008	85	4.1714	0.0491	0.0003
2008-2010	85	5.2035	0.0612	0.0003
2010-2012	85	4.2703	0.0502	0.0003
2012-2014	85	3.5728	0.0420	0.0002

Source of Variation	SS	Df	MS	F	P-value	F crit
Between Groups	0.0160	3	0.0053	18.2551	0	3.8404
Within Groups	0.0983	336	0.0003			
Total	0.1144	339				

Appendix 7: Additional Results for Hypothesis 4

Table 36
Additional risk metrics for iTraxx firms by rating class (2010-2014)

The table shows VaR and ETL measures with a 95% and 90% confidence interval for the European sample. Column 1 and 3 report results for investment grade firms, while column 2 and 4 report results for high yield firms.

	2010-2012 IG		2010-2012 HY		2012-2014 IG		2012-2014 HY	
	CDS	Equity	CDS	Equity	CDS	Equity	CDS	Equity
95% VaR	0.27%	2.61%	0.81%	3.27%	0.14%	2.23%	0.48%	3.62%
90% VaR	0.16%	1.92%	0.55%	2.46%	0.09%	1.62%	0.34%	2.56%
Std. Dev. 95% VaR	0.23%	0.81%	0.22%	0.62%	0.12%	2.08%	0.09%	1.10%
Std. Dev. 90% VaR	0.16%	0.56%	0.15%	0.47%	0.07%	1.37%	0.06%	0.82%
ETL 95% VaR	0.41%	3.69%	1.18%	4.82%	0.25%	3.39%	0.79%	5.20%
# Obs. in the 5% tail	27	27	27	27	26	26	26	26
ETL 90% VaR	0.32%	2.93%	0.93%	3.85%	0.18%	2.63%	0.59%	4.10%
# Obs. in the 10% tail	53	53	53	53	52	52	52	52
# Firms	87	87	11	11	93	93	12	12

Table 37
Additional risk metrics for CDX firms by rating class (2010-2014)

The table shows VaR and ETL measures with a 95% and 90% confidence interval for the North American sample. Column 1 and 3 report results for investment grade firms, while column 2 and 4 report results for high yield firms.

	2010-2012 IG		2010-2012 HY		2012-2014 IG		2012-2014 HY	
	CDS	Equity	CDS	Equity	CDS	Equity	CDS	Equity
95% VaR	0.13%	2.59%	0.51%	4.26%	0.11%	2.20%	0.37%	3.64%
90% VaR	0.08%	1.88%	0.32%	3.32%	0.07%	1.55%	0.24%	2.49%
Std. Dev. 95% VaR	0.14%	0.95%	0.17%	1.40%	0.08%	0.73%	0.09%	0.80%
Std. Dev. 90% VaR	0.09%	0.71%	0.11%	1.09%	0.05%	0.49%	0.06%	0.65%
ETL 95% VaR	0.23%	3.96%	0.84%	6.00%	0.19%	3.39%	0.60%	5.37%
# Obs. in the 5% tail	27	27	27	27	26	26	26	26
ETL 90% VaR	0.17%	3.09%	0.63%	4.88%	0.14%	2.63%	0.44%	4.17%
# Obs. in the 10% tail	53	53	53	52	52	52	52	52
# Firms	78	78	9	9	82	82	8	8

Table 38
VaR correlation in Europe for investment grade firms (2010-2014)

The table shows correlations between 99% CDS and equity VaR. Statistical significance is specified for a 1% (***), 5% (**) and 10% (*) confidence level.

	CDS IG	Equity IG
CDS IG	1	
Equity IG	0.1972***	1

Table 39
VaR correlation in Europe for high yield firms (2010-2014)

The table shows correlations between 99% CDS and equity VaR. Statistical significance is specified for a 1% (***), 5% (**) and 10% (*) confidence level.

	CDS HY	Equity HY
CDS HY	1	
Equity HY	-0.2017	1

Table 40
VaR correlation in North America for investment grade firms (2010-2014)

The table shows correlations between 99% CDS and equity VaR. Statistical significance is specified for a 1% (***), 5% (**) and 10% (*) confidence level.

	CDS IG	Equity IG
CDS IG	1	
Equity IG	0.2221**	1

Table 41
VaR correlation in North America for high yield firms (2010-2014)

The table shows correlations between 99% CDS and equity VaR. Statistical significance is specified for a 1% (***), 5% (**) and 10% (*) confidence level.

	CDS HY	Equity HY
CDS HY	1	
Equity HY	0.8884**	1

Figure 7
Median CDS spread and stock price of iTraxx investment grade firms (2006-2014)

The graph shows the median spread and price of five investment grade European companies over the last eight years.

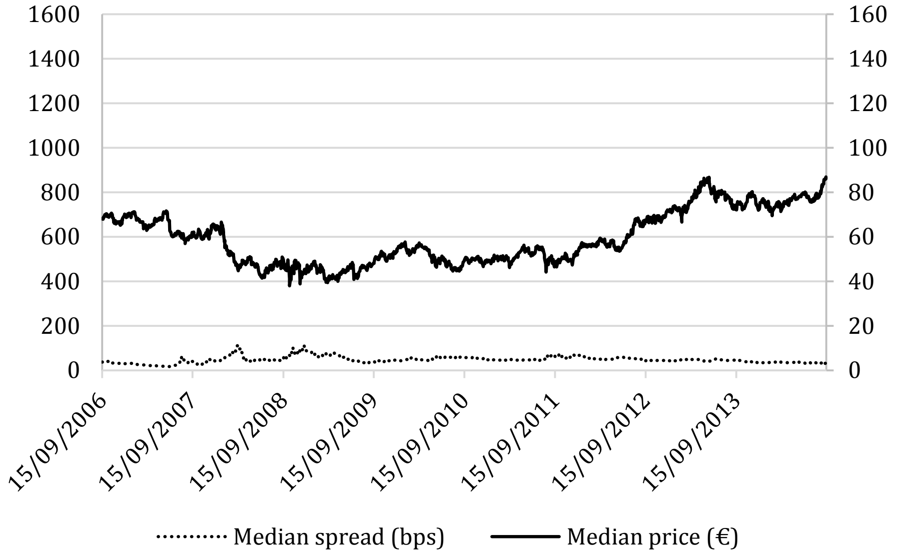


Figure 8
Median CDS spread and stock price of iTraxx high yield firms (2006-2014)

The graph shows the median spread and price of five high yield European companies over the last eight years.

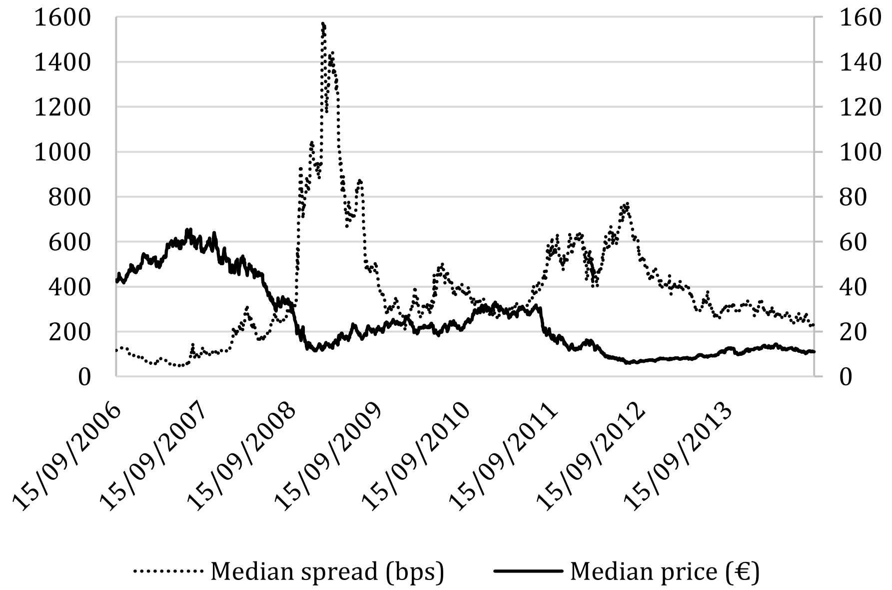


Figure 9

Median CDS spread and stock price of CDX investment grade firms (2006-2014)

The graph shows the median spread and price of five investment grade North American companies over the last eight years.

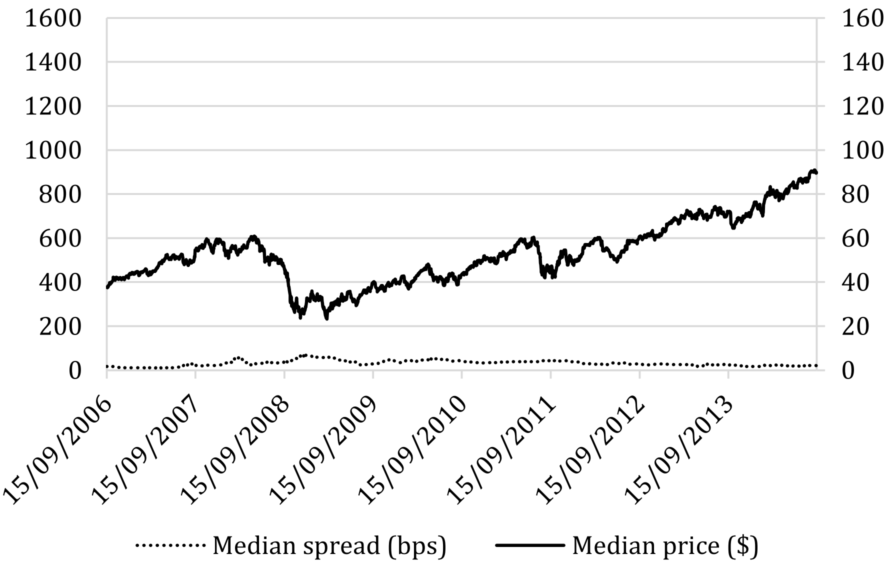
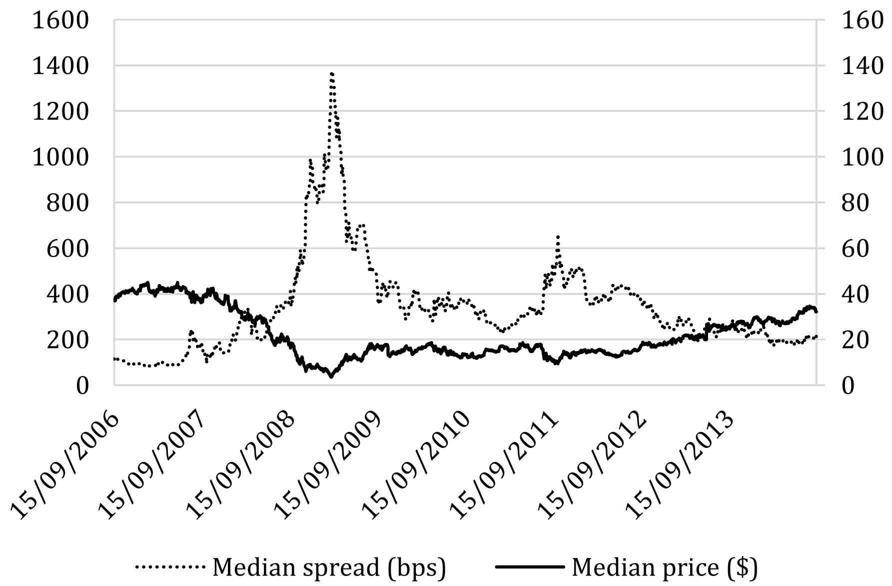


Figure 10

Median CDS spread and stock price of CDX high yield firms (2006-2014)

The graph shows the median spread and price of five high yield North American companies over the last eight years.



Appendix 8: Additional Results for Hypothesis 5

Table 42
ANOVA test results on 99% CDS VaR for iTraxx firms by industry class (2010-2014)

The table shows results of the ANOVA test performed on CDS risk measures for the ten industry subsamples. The low p-value allows to reject the null hypothesis that the difference between each pair of metrics is equal to zero.

Groups	Count	Sum	Average	Variance
Communications	16	0.0618	0.0039	0.0000
Consumer Discretionary	17	0.1329	0.0078	0.0000
Consumer Staples	15	0.0566	0.0038	0.0000
Energy	5	0.0226	0.0045	0.0000
Financials	20	0.1633	0.0082	0.0000
Health	4	0.0095	0.0024	0.0000
Industrials	9	0.0586	0.0065	0.0000
Materials	12	0.0914	0.0076	0.0000
Technology	4	0.0311	0.0078	0.0000
Utilities	11	0.0690	0.0063	0.0000

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.0004	9	0.0000	3.1680	0.0020	2.5844
Within Groups	0.0015	103	0.0000			
Total	0.0019	112				

Table 43
ANOVA test results on 99% equity VaR for iTraxx firms by industry class (2010-2014)

The table shows results of the ANOVA test performed on CDS risk measures for the ten industry subsamples. The low p-value allows to reject the null hypothesis that the difference between each pair of metrics is equal to zero.

Groups	Count	Sum	Average	Variance
Communications	16	0.6305	0.0394	0.0001
Consumer Discretionary	17	0.9146	0.0538	0.0002
Consumer Staples	15	0.5577	0.0372	0.0001
Energy	5	0.2039	0.0408	0.0001
Financials	20	0.9854	0.0493	0.0004
Health	4	0.1684	0.0421	0.0001
Industrials	9	0.4285	0.0476	0.0003
Materials	12	0.6124	0.0510	0.0001
Technology	4	0.1694	0.0424	0.0000
Utilities	11	0.4307	0.0392	0.0001

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.0041	9	0.0005	2.8326	0.0051	2.5844
Within Groups	0.0167	103	0.0002			
Total	0.0208	112				

Table 44
ANOVA test results on 99% CDS VaR for CDX firms by industry class (2010-2014)

The table shows results of the ANOVA test performed on CDS risk measures for the ten industry subsamples. The low p-value allows to reject the null hypothesis that the difference between each pair of metrics is equal to zero.

Groups	Count	Sum	Average	Variance
Communications	11	0.0298	0.0027	0.0000
Consumer Discretionary	19	0.0984	0.0052	0.0000
Consumer Staples	12	0.0430	0.0036	0.0000
Energy	7	0.0306	0.0044	0.0000
Financials	10	0.0433	0.0043	0.0000
Health	7	0.0124	0.0018	0.0000
Industrials	12	0.0326	0.0027	0.0000
Materials	7	0.0301	0.0043	0.0000
Technology	7	0.0439	0.0063	0.0000
Utilities	5	0.0129	0.0026	0.0000

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.0001	9	0.0000	2.1989	0.0295	2.6182
Within Groups	0.0007	87	0.0000			
Total	0.0008	96				

Table 45
ANOVA test results on 99% equity VaR for CDX firms by industry class (2010-2014)

The table shows results of the ANOVA test performed on CDS risk measures for the ten industry subsamples. The low p-value allows to reject the null hypothesis that the difference between each pair of metrics is equal to zero.

Groups	Count	Sum	Average	Variance
Communications	7	0.3940	0.0563	0.0006
Consumer Discretionary	19	1.1898	0.0626	0.0005
Consumer Staples	12	0.4916	0.0410	0.0001
Energy	7	0.6191	0.0884	0.0026
Financials	10	0.4802	0.0480	0.0001
Health	7	0.3785	0.0541	0.0002
Industrials	12	0.5783	0.0482	0.0001
Materials	7	0.3827	0.0547	0.0001
Technology	7	0.3751	0.0536	0.0002
Utilities	5	0.1583	0.0317	0.0000

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.0150	9	0.0017	4.1154	0.0002	2.6287
Within Groups	0.0337	83	0.0004			
Total	0.0488	92				

Figure 11
Median CDS spread of iTraxx companies by industry class (2006-2014)

The graph shows the median spread for five European industries over the last eight years.

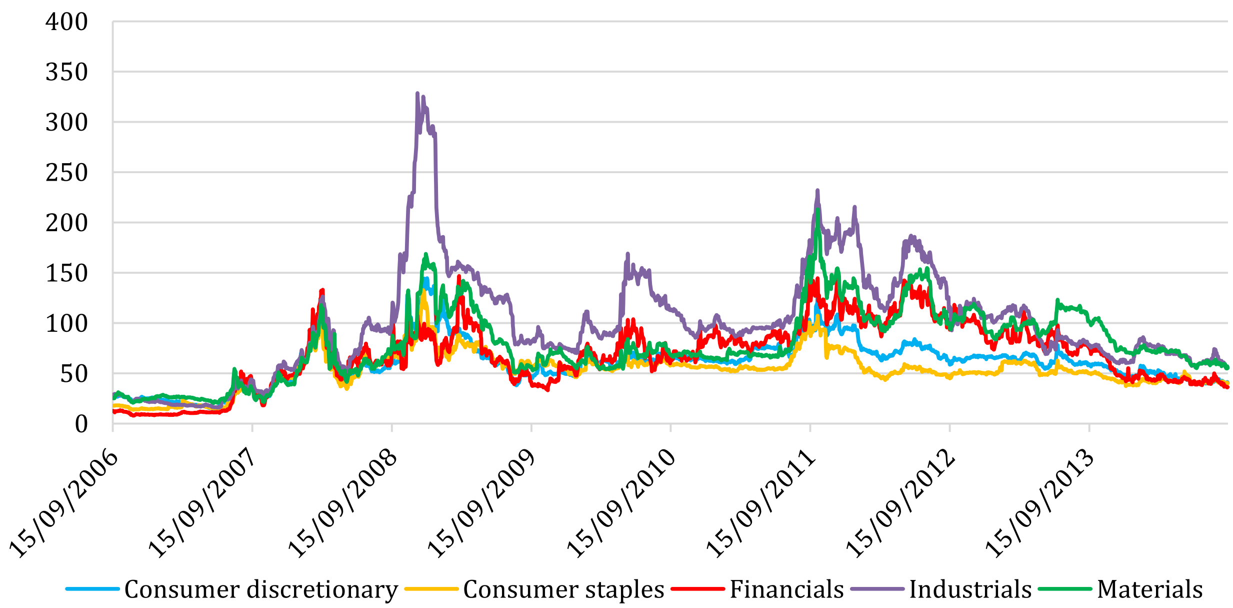


Figure 12

Median stock price of iTraxx companies by industry class (2006-2014)

The graph shows the median price in EUR for five European industries over the last eight years. Note: the y axis is in a different scale due to the high stock price of British American Tobacco (BATS:LSE) and Diageo (DGE:LSE).

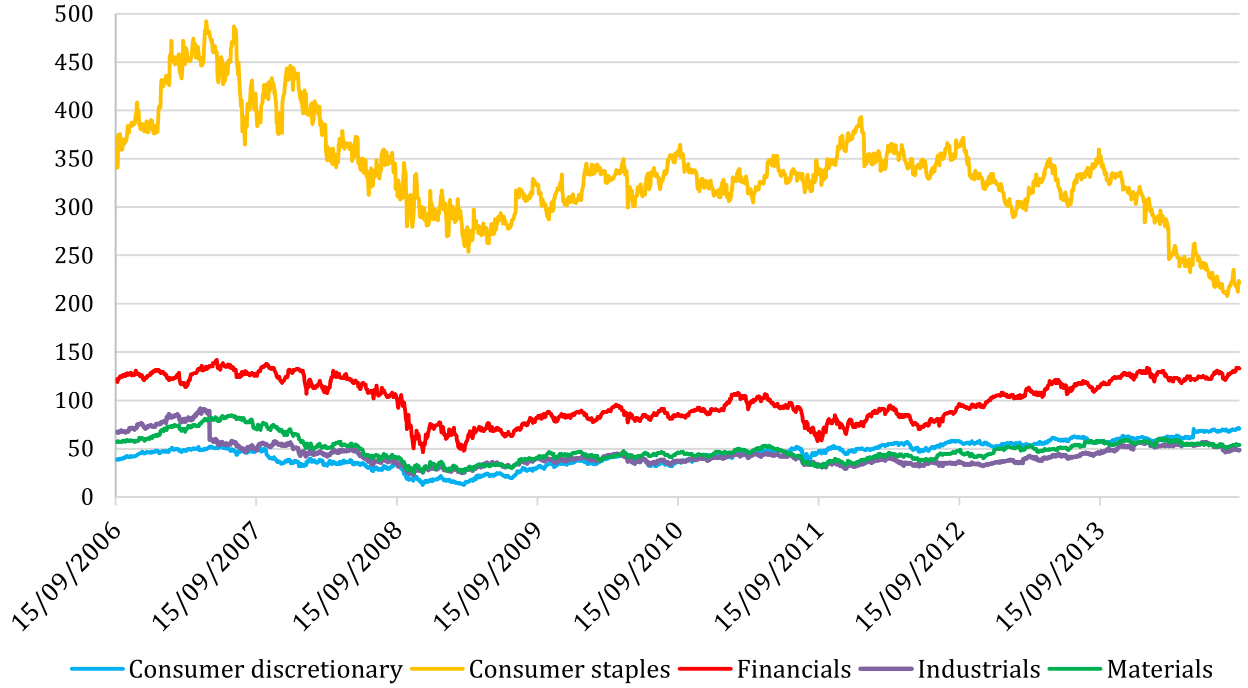


Figure 13

Median CDS spread and stock price of iTraxx consumer discretionary firms (2006-2014)

The graph shows the median spread and price of five European companies within the consumer discretionary sector over the last eight years.

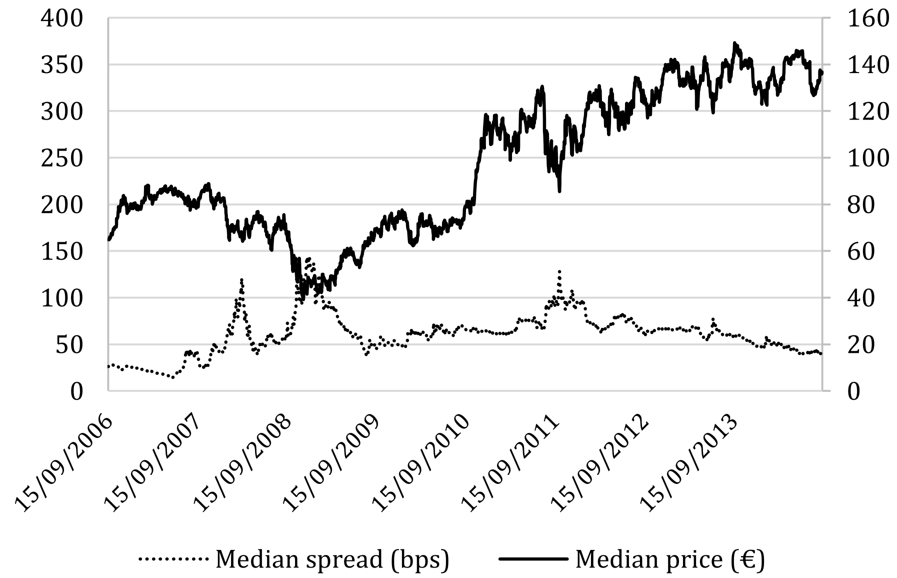


Figure 14
Median CDS spread and stock price of iTraxx consumer staples firms (2006-2014)

The graph shows the median spread and price of five European companies within the consumer staples sector over the last eight years. Note: the y axis is in a different scale due to the high stock price of British American Tobacco (BATS:LSE) and Diageo (DGE:LSE).

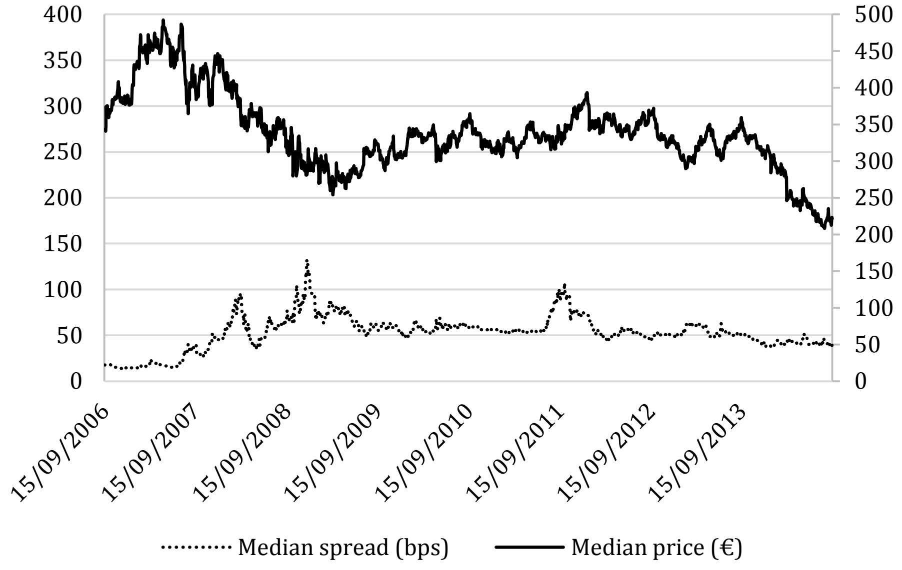


Figure 15
Median CDS spread and stock price of iTraxx financials firms (2006-2014)

The graph shows the median spread and price of five European companies within the financial sector over the last eight years.

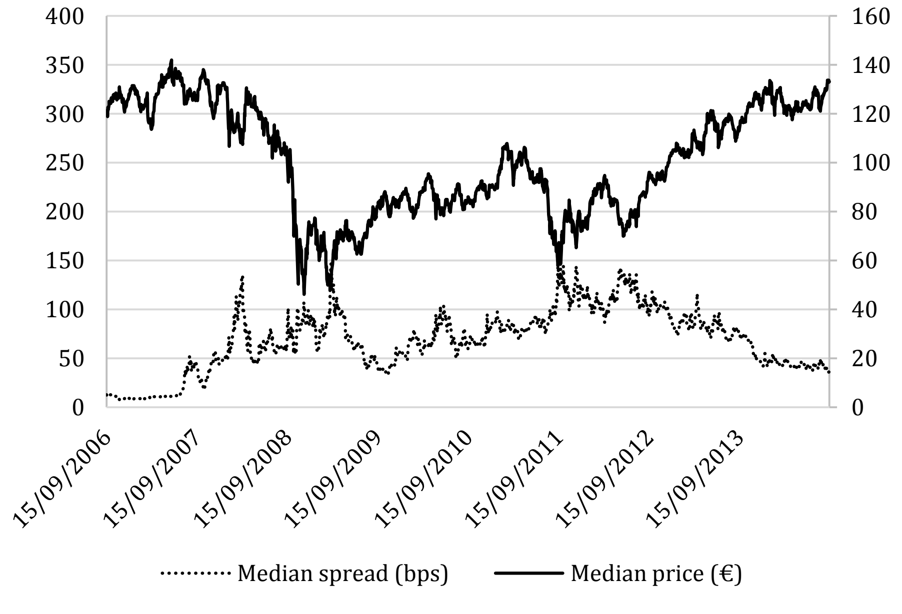


Figure 16
Median CDS spread and stock price of iTraxx industrials firms (2006-2014)

The graph shows the median spread and price of five European companies within the industrial sector over the last eight years.

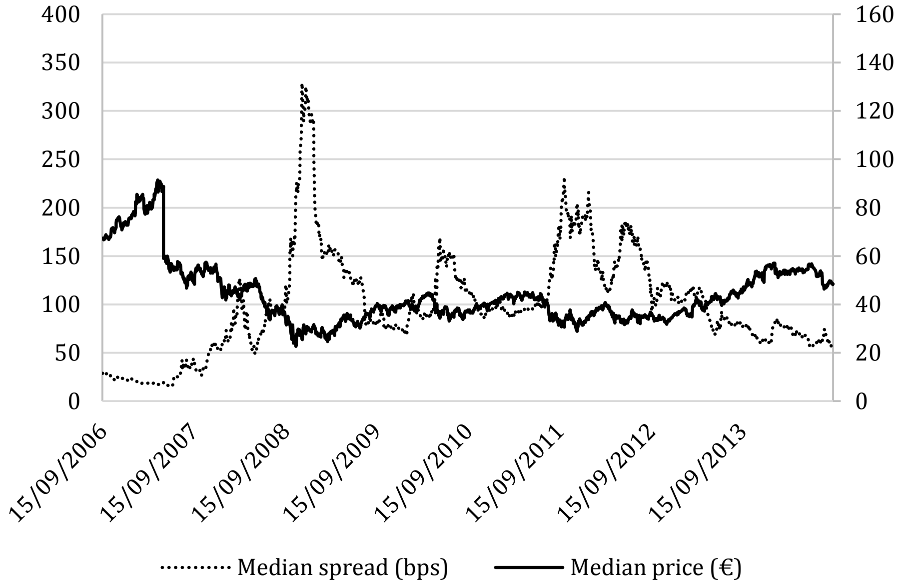


Figure 17
Median CDS spread and stock price of iTraxx materials firms (2006-2014)

The graph shows the median spread and price of five European companies within the materials sector over the last eight years.

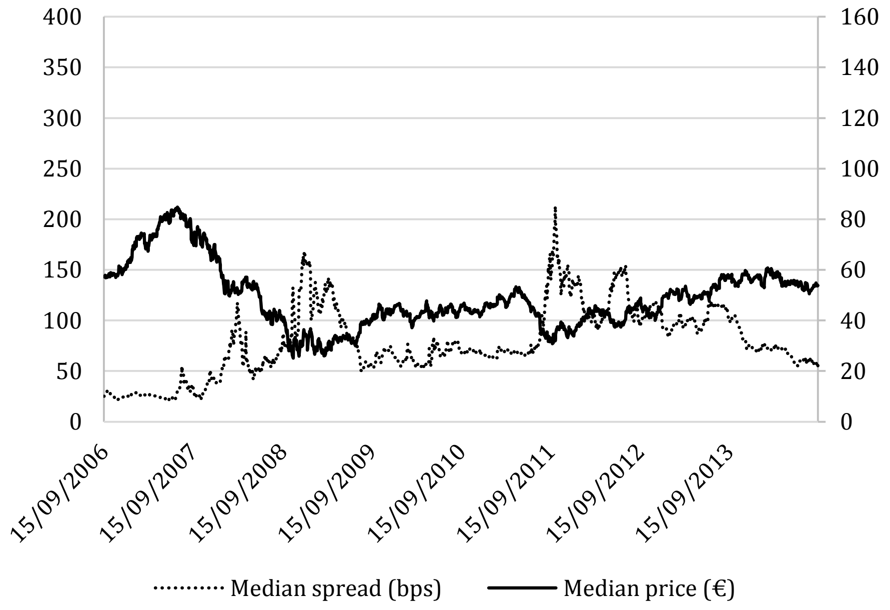


Figure 18
Median CDS spread of CDX companies by industry class (2006-2014)

The graph shows the median spread in bps for five North American industries over the last eight years.

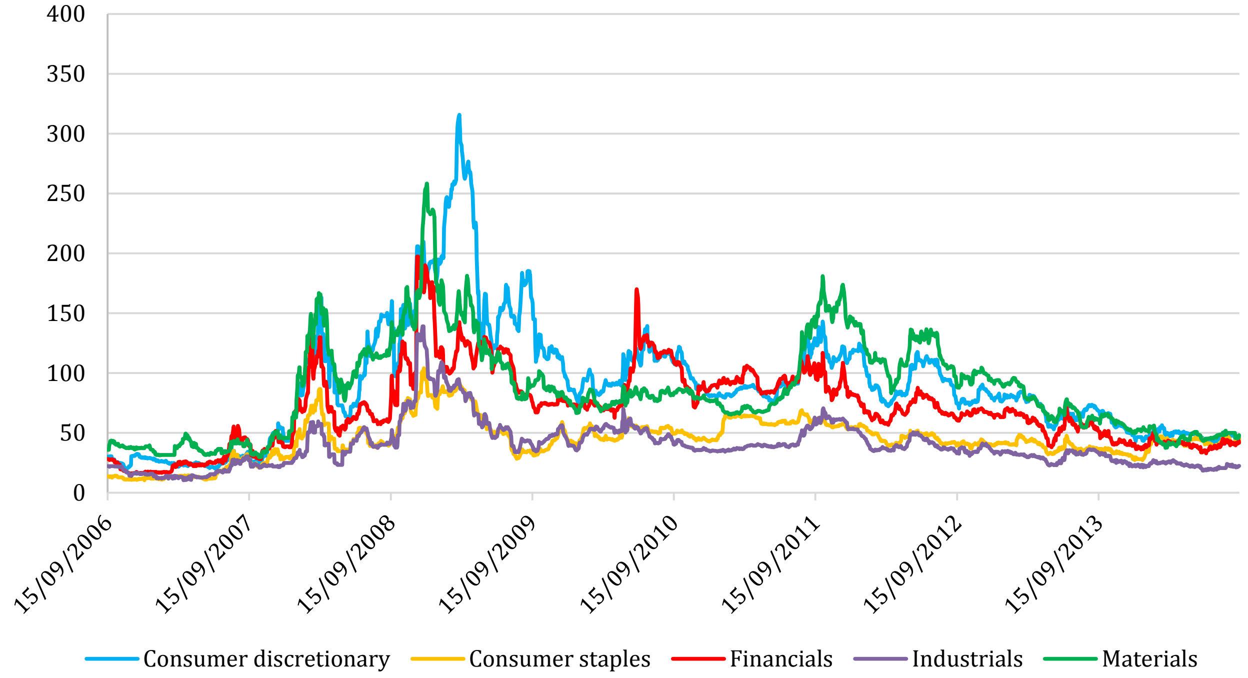


Figure 19
Median stock price of CDX companies by industry class (2006-2014)

The graph shows the median price in USD for five North American industries over the last eight years.

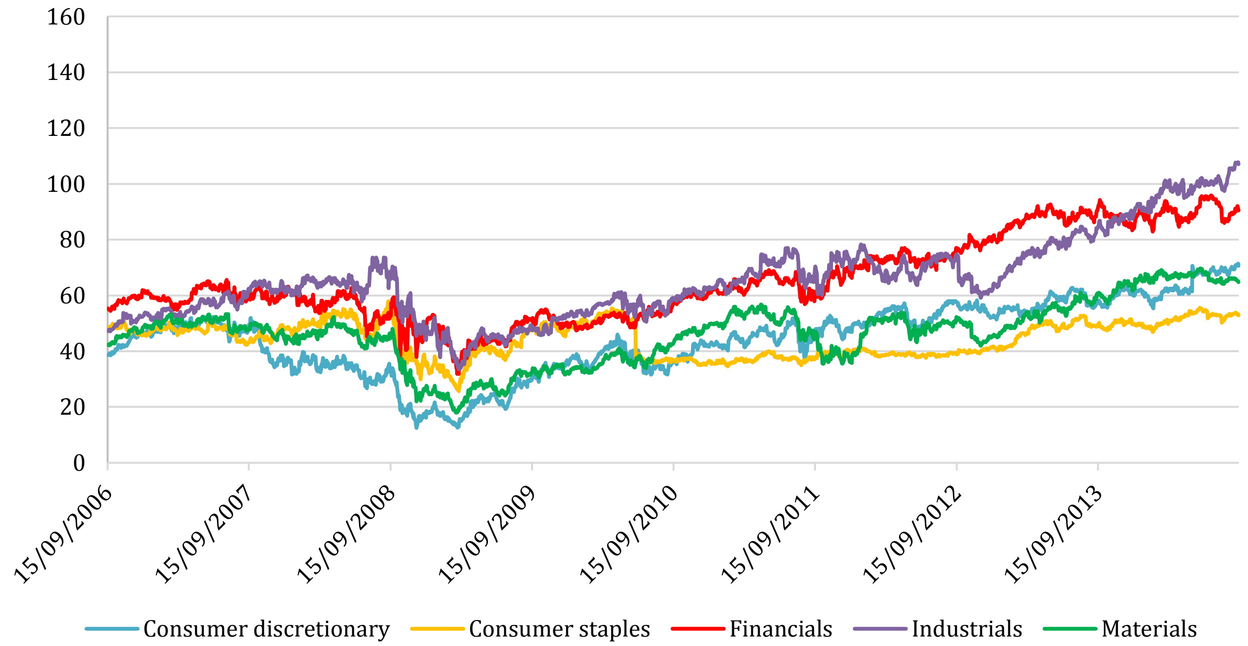


Figure 20
Median CDS spread and stock price of CDX consumer discretionary firms (2006-2014)

The graph shows the median spread and price of five North American companies within the consumer discretionary sector over the last eight years.

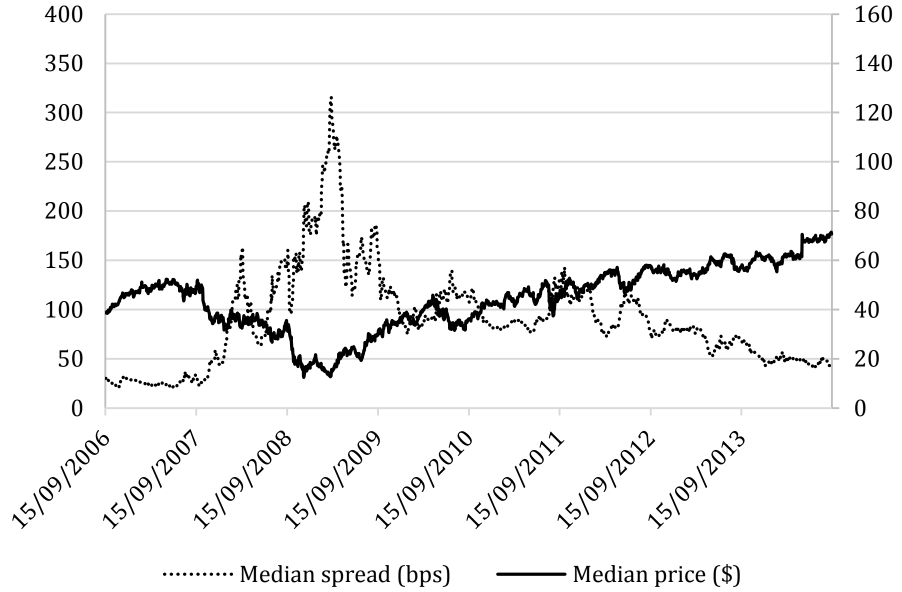


Figure 21
Median CDS spread and stock price of CDX consumer staples firms (2006-2014)

The graph shows the median spread and price of five North American companies within the consumer staples sector over the last eight years.

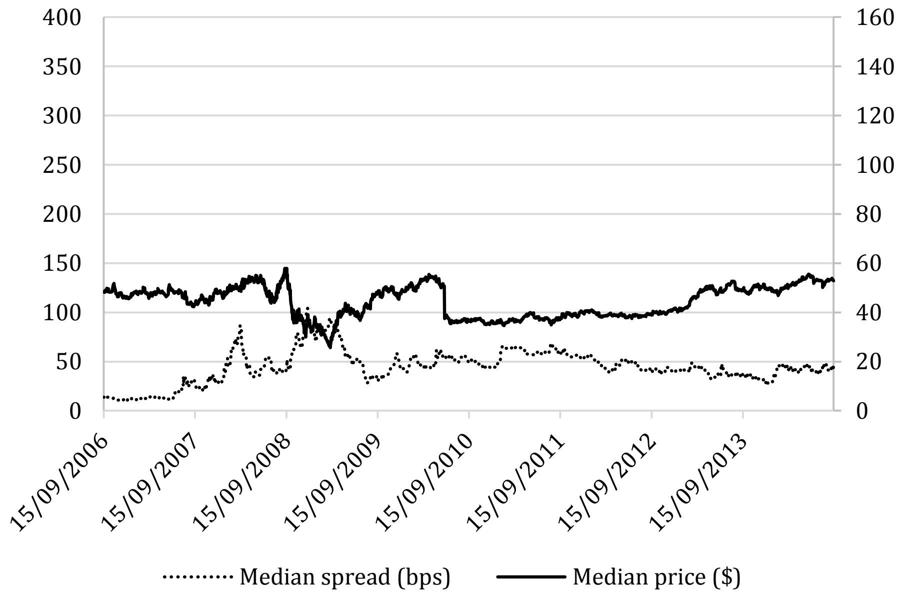


Figure 22
Median CDS spread and stock price of CDX financials firms (2006-2014)

The graph shows the median spread and price of five North American companies within the financial sector over the last eight years.

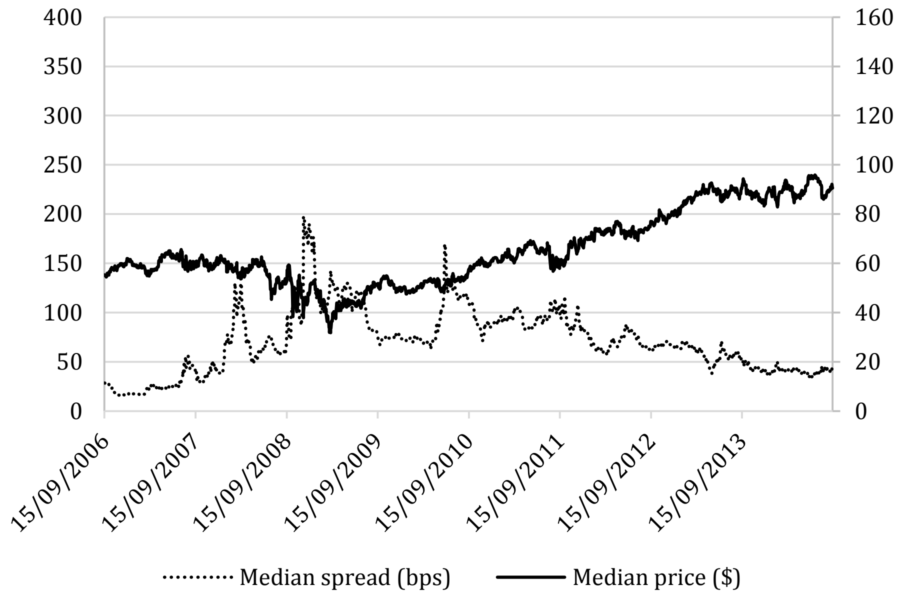


Figure 23
Median CDS spread and stock price of CDX industrials firms (2006-2014)

The graph shows the median spread and price of five North American companies within the industrial sector over the last eight years.

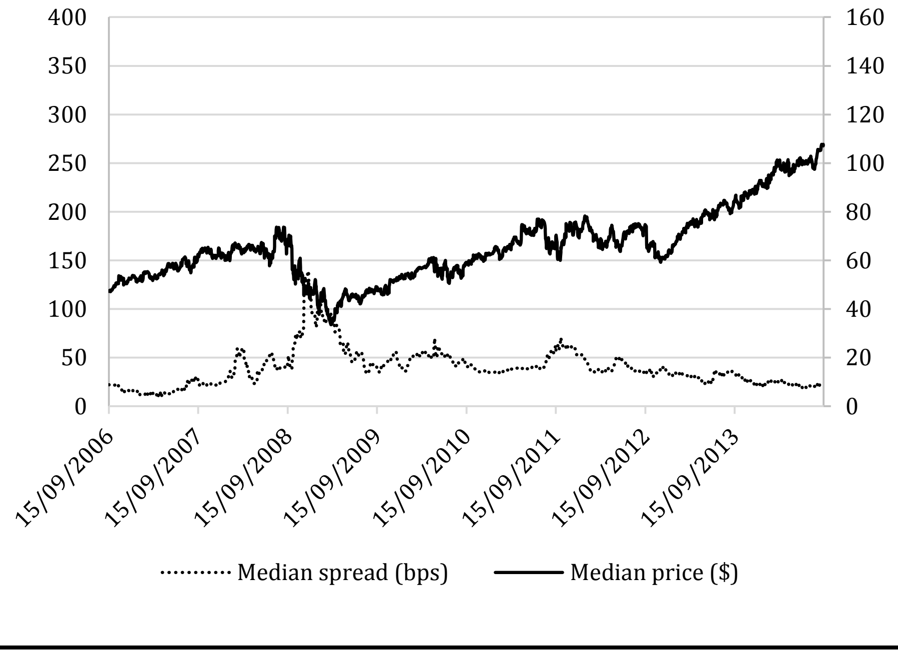
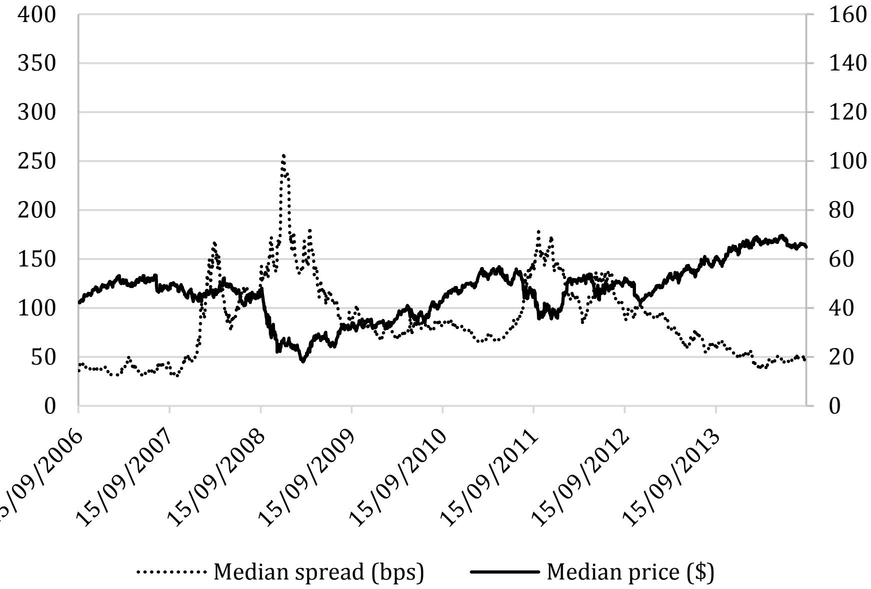


Figure 24
Median CDS spread and stock price of CDX materials firms (2006-2014)

The graph shows the median spread and price of five North American companies within the materials sector over the last eight years.



Appendix 9: Additional Results for the Robustness Tests

Table 46
Risk metrics for iTraxx firms with *RR* = 0.6 (2010-2014)

The table shows the main VaR and ETL measures for the European sample. The first column reports results for the four-year full sample, while column 2 and 3 report results for biannual subsamples.

	2010-2014		2010-2012		2012-2014	
	CDS	Equity	CDS	Equity	CDS	Equity
99% VaR	0.46%	4.31%	0.49%	4.43%	0.34%	3.96%
Std. Dev. 99% VaR	0.33%	1.16%	0.39%	1.08%	0.26%	3.77%
ETL 99% VaR	0.60%	5.73%	0.62%	5.37%	0.46%	5.17%
# Obs. in the 1% tail	11	11	6	6	6	6
# Total obs.	117746	117746	58986	58986	58647	58647

Table 47
Risk metrics for CDX firms with *RR* = 0.6 (2010-2014)

The table shows the main VaR and ETL measures for the North American sample. The first column reports results for the four-year full sample, while column 2 and 3 report results for biannual subsamples.

	2010-2014		2010-2012		2012-2014	
	CDS	Equity	CDS	Equity	CDS	Equity
99% VaR	0.29%	4.99%	0.34%	4.68%	0.21%	3.98%
Std. Dev. 99% VaR	0.24%	2.29%	0.28%	1.91%	0.32%	1.51%
ETL 99% VaR	0.48%	7.04%	0.45%	6.76%	0.35%	5.54%
# Obs. in the 1% tail	11	11	6	6	6	6
# Total obs.	96906	96906	48546	48546	48267	48267

Appendix 10: Additional Figures

Figure 25
99% VaR distribution for iTraxx firms (2006-2014)

The graph shows the frequency distribution of 99% CDS and equity VaR for European firms.

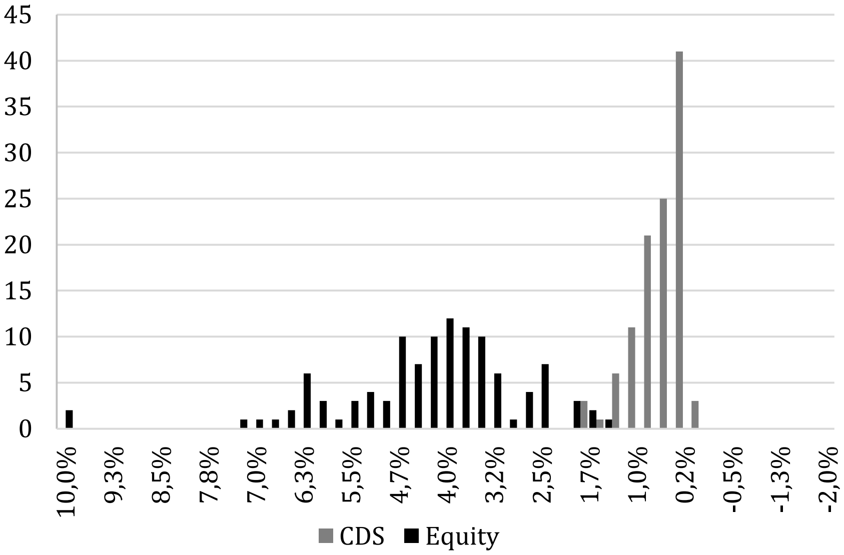


Figure 26
99% VaR distribution for CDX firms (2006-2014)

The graph shows the frequency distribution of 99% CDS and equity VaR for North American firms.

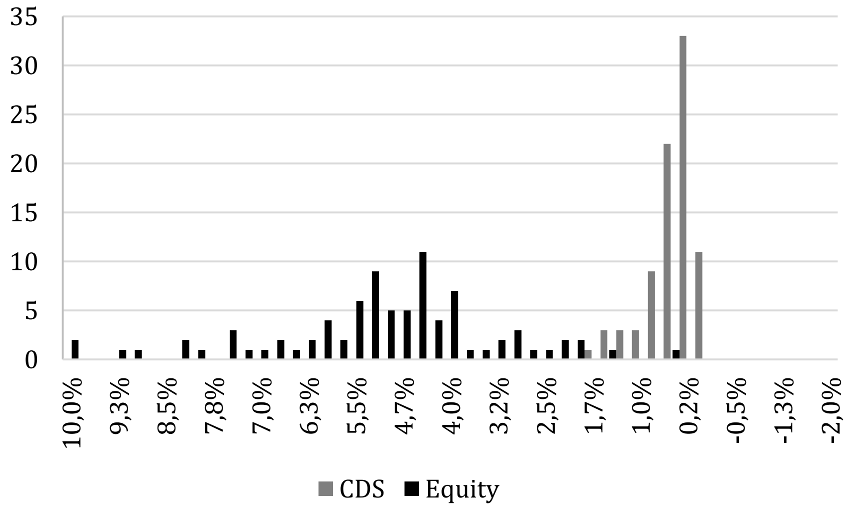


Figure 27
Trading volumes for investment grade indices (2011-2014)

The graph shows weekly trading volumes for the iTraxx Europe and the CDX North American IG indices from February 2011 and September 2014. Data is expressed in USD bln. Source: DTCC (2014).

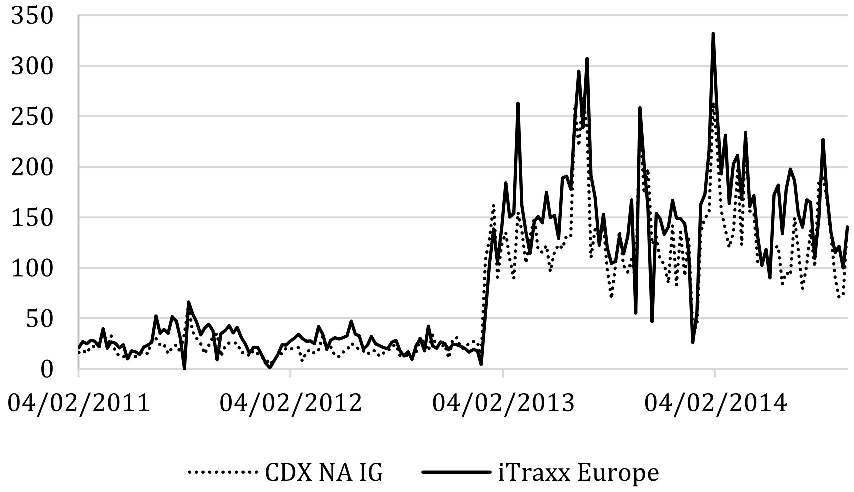


Figure 28
Trading volumes for high yield indices (2011-2014)

The graph shows weekly trading volumes for the iTraxx Europe Crossover and the CDX North American HY indices from February 2011 and September 2014. Data is expressed in USD bln. Source: DTCC (2014).

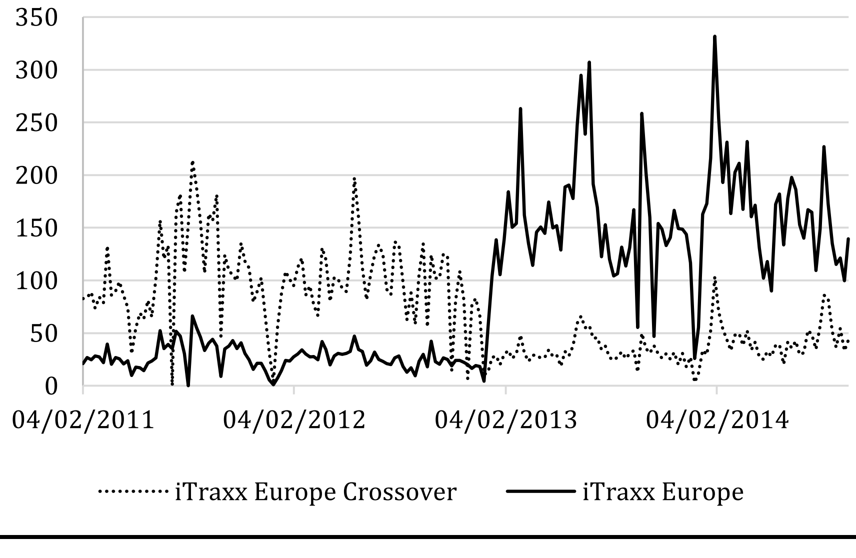


Figure 29
Median CDS spread and stock price for American International Group (2006-2014)

The graph shows the median spread and price for the multinational insurance organization headquartered in New York.