

Three Essays on Credit Risk with a Special Focus on the Subprime Financial Crisis

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1 Preface

Crises of different magnitude have been part of the financial services industry since its origin. However, only few crises, if any, have had the impact of the recent subprime financial crisis. After a stage of cheap money pursued by the US Federal Reserve that resulted in a massive rise of US housing prices, the burst of the consequent bubble triggered widespread distress throughout banks and insurance companies, which finally distorted the world's economy as a whole. The current sovereign debt crisis can also be regarded as a direct consequence of the subprime financial crisis. Many governments have initiated rescue programs to assist troubled banks and insurance companies or to prevent their economy from falling into a recession. Due to their enormous extent, these countermeasures had an massive impact on national budgets. Additionally, the global economic cooling had a negative effect on national budgets as well.

Besides its enormous impact, what makes the subprime financial crisis stand out, is its fast transition over different sectors and countries. Having its origin in the US housing market, the crisis spread quickly and was by no means exclusive to the US or the housing sector. To give an example, between 01/07/2007 and 04/31/2009, the S&P 500 index dropped by 42% and the Eurostoxx 50 index, a well-diversified index in Europe, dropped by almost 49 %. The growing interdependence of financial markets as a consequence of the ongoing globalization is one of the reasons for this observations. Others argue that innovations in the financial services industry itself favored the quick transition of the crisis throughout different sectors. Among these innovations, the market for credit risk and credit derivatives are particularly under suspicion.

Credit markets and especially credit derivatives are widely believed to have acted as accelerants during the subprime financial crisis. The market for credit risk had grown rapidly before the crisis emerged. It allows to separate the origination of credit risk and bearing the exposure to such risks, by transferring the risk to a third party. This can be achieved in several ways. One way is by means of true sale transactions. A bank that grants loans to private persons or companies, can directly sell the loans to a third party. Another way is by means of a securitization transaction. In this kind of transaction an originator or a third party that bought loans in a true sale transaction, pools the loans together and sells securities that are contingent on the cash flows, the pooled loans generate. A third possible way to transfer credit risk to a third party is by means of credit derivatives. A bank granting a loan to a large company can e.g. transfer the credit risk to a third party by insuring against the default of the company via a credit default swap (CDS) contract or other forms of credit derivatives.

Not only can an originator of credit risk eliminate its exposure to it, third parties with no expertise in the lending business can obtain exposure to credit risk by the aforementioned techniques. This is one of the reasons why the subprime financial crisis was not exclusive to US

Savings and Loans Associations, as one might expect, but infected the global financial services industry as a whole. Additionally, this circumstance has had an amplifying effect. Since a broader base of investors had been able to obtain exposure to credit risk, the demand for such exposure increased significantly. Therefore, the volume of originated loans and mortgages increased as well. Nevertheless, as the originators did not have to bare the risk of these loans, they were not overly concerned with the creditworthiness of their borrowers. This is one of the reasons why the subprime market grew so rapidly.

Another important issue concerning the recent financial crisis is the fact that many market participants underestimated the inherent risks of securitization transactions and credit derivatives, especially for portfolio products, such as *n*th-to-default baskets and collateralized debt obligations (CDOs). These products share the common feature that they promise payments, which are contingent on the solvency of a pool of reference assets. By construction, such products are very sensitive towards systemic risk, i.e. the joint default of several entities in their respective reference pool. On the other hand, the pricing models of such products rely on a joint distribution of defaults for several borrowers, which is highly sensitive towards the assumptions concerning default dependence. Therefore, underestimating the systemic risk component, i.e. the default dependence between the reference entities under consideration will lead to misleading results concerning the risks of portfolio products. Furthermore, the high complexity of standard models for credit portfolio risk, hampered the assessment of the risks of structured products, leaving some investors unaware of the actual risk they were exposed to.

Given the aforementioned setting, it seems natural to investigate the interdependence between credit markets, credit derivatives and the recent subprime financial crisis. This investigation is at the core of this dissertation. In particular, it is dedicated to the following research questions:

- What are the causes of the subprime financial crisis?
- Which role did credit markets and credit derivatives play during the crisis?
- How might the crisis be resolved?
- What is the impact of the crisis on market participants perception of credit risk?
- How can complex credit derivatives be modeled in a way that allows an understanding of their inherent risk?

These research questions are addressed in three self-contained essays. The first essay, co-authored by Niklas Wagner, is dedicated to examine the causes of the subprime financial crisis

and possible conclusions that can be drawn from it. We discuss instruments such as credit markets and credit derivatives and how they fostered the instability of the financial system and show how the collapse of the financial system was eventually triggered. Additionally, we discuss possible means of government intervention in order to resolve the crisis within the financial system. We propose a resolution by means of government sponsored purchase programs for troubled assets. This way of recapitalizing the financial system has the appealing feature that it creates a setting, where illiquid, but otherwise solvent, banks are separated from insolvent banks. Consequently, we address the lessons learned from the subprime financial crisis by discussing possible consequences for the design, as well as the regulation of the financial system in the future.

The essay adds to the literature on the recent subprime financial crisis by providing a thorough discussion of the causes and consequences of the crisis. We put a special focus on the role of credit markets and credit derivatives as accelerants. Furthermore, we add to the literature on government intervention by providing a formal illustration of how the design of government bailout programs can influence decision making among financial institutions. For this purpose, we set up a simple and intuitive model, which helps to illustrate the effects of typical government bailout programs rather than providing informal arguments in favor of a certain design. With the help of the model, it can be shown that bailout programs can be designed in a way such that illiquid but solvent banks behave differently from insolvent banks. While not favoring solvent banks in the short run, this provides a valuable signal to outsiders, including investors as well as government agencies.

The second essay, co-authored by Niklas Wagner, addresses the question how the recent subprime financial crisis has altered market participants' perceptions concerning the determinants of credit risk, i.e. has the crisis had an impact on the market for credit risk itself? As the crisis has clearly shown the large vulnerability of the financial system to systemic risk, one would expect that market participants have altered their assessment of systematic risk when pricing credit derivatives. This effect should be particularly pronounced for portfolio products such as credit indices, as these are, by construction, vulnerable to systemic risk.

To analyze this, we conduct an empirical investigation of the iTraxx Europe index universe with the recent financial crisis in focus. We have a special focus on three different issues. First, we analyze the determinants of iTraxx spread changes to learn about the drivers of aggregate credit risk. We investigate whether the determinants have changed as a consequence of the recent financial crisis. If this would have been the case, this would suggest that investors have adjusted their models of credit risk and have reassessed their assumptions concerning the systemic component of aggregate credit risk. Second we perform a quantile regression to

analyze whether the determinants of iTraxx spreads are suited to explain spread changes in the upper and lower tail of the empirical distribution, i.e. whether extreme spread changes are subject to the same factors as changes around the mean or median of the empirical distribution. Third, we are concerned whether market participants use the iTraxx index as a source of (additional) information regarding systemic risk. Therefore, we investigate the lead-lag relationship between the iTraxx index market and equity markets. In case the iTraxx index market provide valuable information concerning systemic risk, iTraxx spread changes should not be led by stock market returns.

In order to address the issues outlined above we structure our empirical investigation as follows. First we examine the determinants of iTraxx spread changes by regressing daily spread changes of iTraxx Europe index family members on a rich set of explanatory variables. The set of independent variables comprises factors implied by structural models of credit risk, a set of liquidity factors and macroeconomic variables. We examine the determinants of the iTraxx Europe benchmark index, as well as the determinants of the different subindices of the benchmark index. In order to examine possible changes of the determinants as a consequence of the recent subprime financial crisis, we repeat our analysis for different subsamples. Our overall sample ranges from 06/16/2004 to 08/06/2010 and spans the crisis period, as well as a pre- and a post-crisis period. Hence, we can examine the evolution of credit spread determinants throughout the financial crisis. First we estimate our econometric model for the overall sample and then repeat the estimation for the pre-crisis, crisis and post-crisis subsamples to detect changes in the set of spread drivers.

In a next step we reestimate our econometric model via a quantile regression. Therefore, we can examine the performance of our set of explanatory variables in the upper and lower quantiles of the empirical distribution of spread changes, i.e. to check for the robustness of our OLS-regression results in different quantiles of the empirical distribution of spread changes. The quantile regression is conducted for all subindices and all subsamples. This allows us to study the determinants of spread changes in upper and lower quantiles of the empirical distribution, as well as changes in the determinants in the course of the financial crisis.

Consequently, to examine whether market participants rely on the iTraxx index as a source of additional information concerning systemic risk, we examine the lead-lag relationship between the market for credit risk and stock markets. For this purpose we estimate a vector autoregressive model with exogenous variables (VARX-model). The exogenous variables used in the VARX-model are supposed to jointly determine credit spread changes, as well as stock returns on a portfolio constructed out of the iTraxx index constituents. We estimate the VARX-model for all subindices and all respective subsamples to investigate whether the lead-lag relationship

has been altered by the recent financial crisis.

The essay contributes to the existing literature in several ways. First we investigate the explanatory power of a rich set of independent variables, including proxies for liquidity and macroeconomic factors. Second, to the best of our knowledge, this is the first empirical investigation of the behavior of iTraxx index spreads of the benchmark index and all subindices with a special focus on changes on credit spread determinants in the course of the recent subprime financial crisis. Third, our empirical paper provides deeper insights into the mechanics of iTraxx spreads by explicitly examining the behavior of credit spread changes at the upper and lower quantiles of the empirical distribution. Finally, we contribute to the existing literature by examining the evolution of lead-lag relationships between the iTraxx and stock returns in the course of the recent financial crisis, while controlling for several exogenous variables.

In the third essay I address the issue of complexity within portfolio products and credit derivatives such as n th-to-default baskets and CDSs subject to counterparty risk. During the recent financial crisis many of the assumptions behind standard pricing models for portfolio products proved to be myopic. Obviously, many market participants underestimated the systemic risk component, i. e. the risk associated with the joint default of several entities, inherent in these portfolio products. Approaches such as the Gaussian copula, which is applied in latent variable models, do not account for extreme default dependence, i.e. a clustering of defaults. However, this clustering is a common feature of distressed financial markets and was also observed during the recent subprime financial crisis. Therefore, the market's perception concerning the inherent risks of portfolio products were not adequate, as common models of dependent defaults are highly sensitive with respect to assumptions regarding the dependence structure (Frey and McNeil (2003)).

Models of portfolio credit risk allowing for extreme (possibly asymmetric) dependence of default are available. However, they are complex and difficult to implement. In this light there is a pronounced need for concepts allowing to stress test prices of portfolio products, possibly leading to bounds within the prices (spreads) of such products have to lie in the absence of arbitrage opportunities and that hold regardless of the actual dependence structures within the portfolio members. Such concepts allow for a decent understanding of the inherent risk of portfolio products, as they provide insights concerning the impact of default correlation and systemic risk on the pricing of such products.

The essay addresses the problem outlined above by introducing the method of maximum implied default correlation. It contributes to the existing literature by showing that, given the markets's perception of the stand-alone credit risk of two entities under consideration, it is possible to derive bounds for the default correlation between them. These bounds hold, as

long as no arbitrage opportunities exists. In turn, these bounds can be used to derive upper and lower bounds for the prices of securities that are subject to credit risk and sensitive to default correlation via numerical methods. Examples of such securities are credit default swaps (CDSs) subject to counterparty risk and n th-to-default baskets.

I apply the method of maximum implied default correlation to derive bounds for the prices of these two types of securities using an intuitive and easy to implement Monte Carlo simulation algorithm, which is based on a simple intensity model of default. The algorithm involves several steps. First, implied upper bounds for the default correlation of certain entities are calculated based on observed market data. Next, the implied upper default correlations are converted into a variance-covariance matrix of the respective default processes. In a succeeding step I model the default processes relying on the overlapping sums (OS) method. This involves expressing the default process of each entity under consideration as a sum of independent idiosyncratic as well as common default processes. For each entity its respective sum of default processes is calibrated to match the implied variance-covariance matrix of its default process. Consequently, the default times of each entity under consideration are simulated, allowing to derive the upper bound for securities with sensitivity to the default of the entity under consideration. The respective lower bound can be simulated by assuming that defaults are independent, i.e. that no default correlation is present. In addition to calculating upper and lower bounds for n th-to-default baskets and CDSs subject to counterparty risk, I analyze the sensitivity of the respective spreads concerning changes in the correlation structure of the underlying entities to provide a better understanding of the potential impact of default correlation.

The proposed approach allows for the comparison of market spreads for credit derivatives with model-implied maximum and minimum spreads, without extensive modeling of default correlations. In the absence of arbitrage opportunities, market quotes have to lie in between the implied bounds, regardless of the underlying default correlation structure between the entities contributing to the risk of the security under consideration. Hence, this paper provides further insights on the impact of default correlation on spreads of credit derivatives sensitive to default correlation and the efficiency of the credit derivatives market as a whole.

2 Government Intervention in Response to the Recent Financial Crisis: The Good into the Pot, the Bad into the Crop

Government Intervention in Response to the Subprime Financial Crisis: The Good into the Pot, the Bad into the Crop

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Abstract

The recent global financial crisis represents a major economic challenge. In order to prevent such market failure, it is vital to understand what caused the crisis and what are the lessons to be learned. Given the tremendous bailout packages worldwide, we discuss the role of governments as lenders of last resort. In our view, it is important not to suspend the market mechanism of bankruptcy via granting rescue packages. Only those institutions which are illiquid but solvent should be rescued, and this should occur at a significant cost for the respective institution. We provide a formal illustration of a rescue mechanism, which allows to distinguish between illiquid but solvent and insolvent banks. Furthermore, we argue that stricter regulation cannot be the sole consequence of the crisis. There appears to be a need for improved risk awareness, more sophisticated risk management and an alignment of interest among the participants in the market for credit risk.

Keywords: financial crisis, government intervention, bailout, risk management, credit risk, credit derivatives, securitization;

2.1 Introduction

The ongoing credit crisis has been of major economic policy concern for over a year. It not only vastly affects the financial system, but is also likely to have severe consequences for the global economic development. The extent of the crisis is enormous. According to the Bank of England (2008), the total volume of government support packages for the financial system amounted to approximately EUR 5.55 trillion as of October 2008. Due to the growing globalization and complexity of the financial system, the contagion effect of the current crisis throughout financial markets is unprecedented. The crisis clearly reveals the vulnerabilities of the financial system in its current form. Hence, it is of particular importance to understand what actually triggered the collapse of the financial system, and how such a collapse can be prevented in the future.

Our purpose here is to explain what led to the current crisis, and which conclusions can be drawn from it.¹ We describe the instruments fostering the instability of the financial system and show how the collapse of the financial system was eventually triggered. We then comment on the different possible means of government intervention, which aim at limiting the damage to the financial system. We show formally that only rescue packages including a purchase program for distressed assets create a setting where illiquid, but otherwise solvent, banks are separated from insolvent banks. Furthermore, we provide an overview of the possible consequences for the design, as well as the regulation of the financial system in the future.²

So far, the amount of literature commenting on how bailout plans for the current crisis should be arranged is scarce. Hoshi and Kashyap (2008) investigate government intervention during the recent Japanese financial crisis. Given this experience, the authors draw conclusions for the design of the Troubled Asset Relief Program (TARP) in the United States. They argue that buying distressed assets is an appropriate way to recapitalize banks. Nevertheless, they conclude that the Japanese program lacks efficiency, as assets cannot be purchased for more than their economic value and hence, the total amount of assets purchased remains low. Therefore, no capital is rebuilt and the system remains undercapitalized. Hence, the authors propose that besides buying distressed assets, government assistance should also be conducted via direct equity injections. Bebchuk (2008) comments on the design of the TARP emergency legislation. He agrees that asset purchases are suitable to cope with the financial crisis,

¹Other reviews of the subprime financial crisis include Batten and Hogan (2009), Pflleiderer and Marsh (2009), and Allen and Carletti (2010), among others. Batten and Hogan (2009) focus mainly on monetary and fiscal action in response to the crisis. Pflleiderer and Marsh (2009) examine the role of misaligned incentives and lacking transparency in financial markets, which eventually triggered the crisis. Allen and Carletti (2010) discuss long-term consequences for international financial markets which can be drawn from the subprime financial crisis.

²A first sketch of the ideas discussed in this paper is also presented in Breitenfellner and Wagner (2010).

nevertheless he proposes a redesign of the legislation in order to achieve the targets of the program, i.e. restoring stability in the financial system, while limiting costs to taxpayers. He argues that the possibility to overpay for certain assets is not in the interest of taxpayers. In order to prevent undercapitalization, he rather advocates allowing the purchase of securities newly issued by troubled institutions. Additionally, he argues that financial firms should be required to raise additional capital from their existing shareholders. A potential design of a government funded asset purchase program is presented by Bebchuk (2009). The author argues that, rather than setting up a single "Bad Bank", there should be several privately managed funds which acquire the assets. Their capital should be provided by the government and by private investors. The fact that several funds compete for the troubled assets assures that the market for these assets is restored.

Closest to our paper are the papers of Freixas (1999), Gorton and Huang (2004), Diamond and Rajan (2005), Acharya and Yorulmazer (2008) and Wilson (2010a).

Freixas (1999) compares the costs and benefits associated with a bailout of a bankrupt bank. It is shown that the optimal bailout policy is determined by the amount of unsecured debt issued by the respective bank. Nevertheless, the author shows that in equilibrium the lender of last resort, i.e. the government, will not rescue all banks which have a certain amount of unsecured debt outstanding, since rescues are costly. Some of these costs are due to moral hazard at the bank management due to the fact that managers anticipate the chance of being bailed out. Instead, the lender of last resort optimally follows a mixed bailout strategy, where she decides case by case whether to rescue a specific bank or not.

Gorton and Huang (2004) claims that the benefits of government bailouts depend on the type of liquidity shock faced by banks. The authors distinguish liquidity shocks from capitalization shocks. A liquidity shock is an event where banks suddenly need new resources. In contrast, capitalization shocks stem from a shock to the value of assets on a banks balance sheet. Government bailouts may be a counterproductive response to banks facing liquidity shocks as shown by Diamond and Rajan (2002). In case banks face a capitalization shock, Gorton and Huang (2004) show that government bailouts via asset purchases are feasible, when the number of assets to be sold is too large to be absorbed by private investors. In this case the provision of liquidity by the government increases overall welfare.

Acharya and Yorulmazer (2008) provide a formal illustration of the optimal resolution of bank failures. They show that, in case a sufficiently large number of banks fail, government intervention is superior to a private sector resolution of failed banks in terms of social welfare. They argue that the best way for the government to intervene is through the provision of liquidity to surviving banks. These funds in turn are used by surviving bank to acquire the

assets of failed banks. In contrast to our model, they assume that solvent and insolvent banks can be separated *ex ante*. Therefore, their model does not incorporate a mechanism to distinguish illiquid but solvent and insolvent banks.

A similar approach to ours is followed by Wilson (2010a). The author examines the Public Private Investment Partnership (PPIP) plan relying on option pricing arguments. In contrast to our findings, he concludes, that only solvent banks will be willing to sell distressed assets.³ The reason for the different result lies in the fact that the author does not impose an exigent liquidity need on the banks. Hence, there is no need for the banks to chose the refinancing option which is most favorable for them, as it is the case in our model.

We add to the literature on government intervention by providing a formal illustration of how the design of government bailout programs can influence decision making among financial institutions. As such, rather than providing informal arguments in favor of a certain design, we set up a simple and intuitive model, which helps to illustrate the effects of typical government bailout programs. We show that bailout programs can be designed in a way such that illiquid but solvent banks behave differently from insolvent banks. This provides a valuable signal to outsiders, including investors as well as government agencies.

The remainder of this paper is organized as follows. Section 2.2 briefly describes recent developments in the market for credit risk, which eventually led to the crisis. In Section 2.3, we discuss why the financial system broke down and how the crisis spread throughout the system. Some considerations referring to the use of government bailout programs and our model are presented in Section 2.4. The lessons learned from the current crisis are discussed in Section 2.5. Section 2.6 concludes the paper.

2.2 The Tale of Unlimited Risk Transfer

Once upon a time there was a world where banks did not have to bear any risks, as they could get rid of them in no time. This is an appropriate introduction for a tale about the market for credit risks. Unfortunately, this is not a tale.

The market for credit risk has grown rapidly since the early 1990's. It seemed to be one of the biggest success stories in the history of financial intermediation. The new paradigm was that underwriting and bearing credit risk could be perfectly separable. As such, credit risk could be transferred with hardly any constraints by banks to those seeking exposure in certain credit risks. On the other hand, any player in the financial system was able to gain exposure

³Wilson (2010b) shows that in some cases even solvent banks might be reluctant to sell toxic assets, as their shareholders possess an implicit option to put the bank in case of default, which is more valuable if the bank's asset volatility is large.

in the credit risk of certain entities, without direct involvement with the respective entity or even without upfront capital outlays.

The tools for credit risk transfer are numerous, among which Residential Mortgage Backed Securities (RMBSs) and Credit Default Swaps (CDSs) are the most prominent. The economic reasoning behind risk transfer is obvious. Financial institutions are able to specialize on certain segments of the banking landscape. For example, institutions with no expertise in the lending business are able to gain exposure in any kind of credit risk. On the other hand, originators are able to eliminate large positions from their books by passing them through to other market participants. In turn, the relieved capital can be used to grant additional loans. This development paves the way for new cash flows to credit markets, allowing the whole economy, as well as the public to profit from eased funding opportunities, which would not have existed without the risk transfer. From an economic perspective, it might be questionable whether securitization actually generates additional cash flows to credit markets. Nevertheless, it fosters an optimal allocation of resources in the credit market, as banks with expertise in the lending business are best suited to allocate scarce financial resources among those in need of external funding.

2.2.1 Securitization

The classic way of transferring credit risk is by means of securitization. In a typical securitization transaction, the originator of a credit portfolio sells his credit portfolio to a special purpose vehicle (SPV), which is refinanced via capital markets. Although the assets transferred to the SPV do no longer occur on the originator's balance sheet, the ties between the originator and the SPV are manifold, e.g. through swap agreements or guarantees. Securitization transactions have many advantages for the originator. The proceeds from selling the loan portfolio can readily be used to grant new loans. Therefore, securitization can be regarded as a form of refinancing. Among the other advantages are the transfer of credit risk to the SPV (and eventually to investors), and lower regulatory capital requirements for the originator.⁴

Overall, securitization transactions clearly augment lending capacities in the financial system and improve allocational efficiency of financial markets concerning both, funds and exposures. In turn, optimal allocation of resources helps to reduce the cost of credit (see e.g. Duffie (2007)). Unfortunately, the number of high quality obligors in the system will be limited. Hence, the overall proportion of low quality lenders will increase with the volume of lending. At this point, a disadvantage of securitization becomes obvious. As the originator may eliminate

⁴Gorton and Souleles (2005) provide a detailed overview of such transactions.

all the credit risk associated with the loan portfolio,⁵ he will not be overly concerned with the quality of his obligors. Consequently, there will be loans included in the portfolio, which would not have been granted by the originator, if he still had to account for them. This is a classic adverse selection problem. The deterioration of the average loan quality is further amplified by the incentive schemes within the lending business, where employee compensation largely depends on lending volume rather than on risk-adjusted return (see e.g. Mills and Kiff (2007)).

Additionally, SPVs will typically try to obtain maximal funding from selling securities on the capital market. In turn, the proceeds are transferred to the originator as a compensation for acquiring the loan portfolio. Hence, SPVs have an incentive to overstate the quality of their loan portfolio, again a moral hazard problem, as the investors buying SPV bonds and commercial papers will typically have an information disadvantage concerning the quality of the loans contained in the portfolio. The complexity of many securitization transactions adds to this information asymmetry. The overall quality of the loans underlying the securitization transaction declines with every new transaction, as the amount of high quality borrowers in the financial market is limited. However, the capital inflow due to the securitization transaction, will tempt the originator to grant further loans, despite the lower quality of obligors seeking debt financing via loans. These loans are then in turn securitized, creating some sort of “vicious circle”.

2.2.2 The Market for Credit Protection

Another segment of the market for credit risk is the market for credit protection. As shown in Figure 2.2.2, the market for credit protection has grown rapidly in recent years. As of June 2008, it amounted to a total volume of about USD 57.3 trillion of notional principal. Unlike securitization and credit insurance, buying and selling credit protection in the credit derivatives market does not require owning the underlying asset. In other words, credit protection is a synthetic transaction allowing market participants to gain exposure in credit risk with no initial cash outlay, or without owning the underlying asset.

Among the most common products of the credit protection industry are CDSs and Collateralized Debt Obligations (CDOs).⁶ Such products compensate the protection buyer for her losses associated with a credit event related to the underlying asset of the transaction. Due to the absence of an upfront payment, or the need to actually own the underlying asset,

⁵At least, this seems to be the case in the first place. Nevertheless, this is not quite adequate as we discuss later.

⁶Details on credit derivatives can e.g. be found in Scheicher (2003), who also includes some early warnings on financial stability.

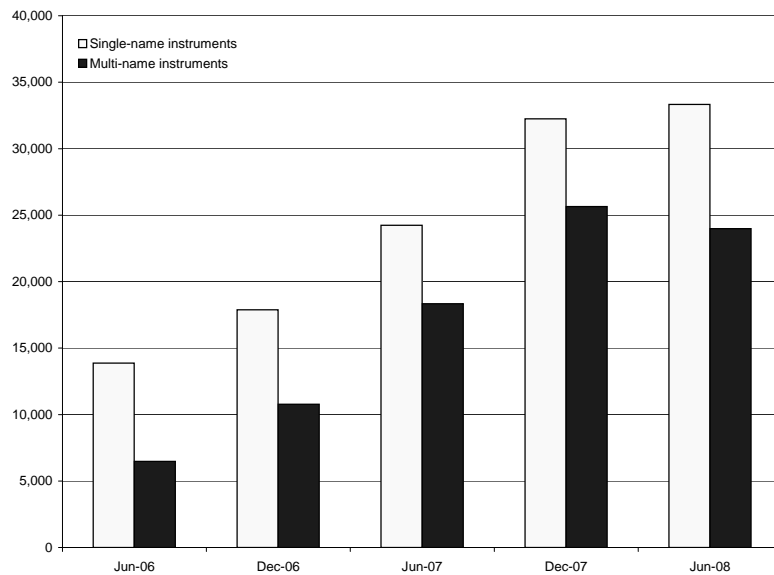


Figure 2.1: Notional amounts of credit default swaps outstanding in USD billion. Data source: Bank for International Settlements.

credit protection can be regarded as a convenient and widely used instrument for investors to gain exposure to various kinds of credit risk. This is clearly favorable from a diversification perspective. Additionally, credit protection can be used as a hedging instrument for exposures in the credit market, as given for example by corporate bond portfolios. Hedging by means of credit protection also has an effect on the regulatory equity cushion as required by the Basel II accord. Credit exposures which are hedged via credit protection transactions are no longer subject to regulatory capital requirements. Only the swap itself is accounted for, which reduces regulatory capital requirements as long as the swap carries a lower risk weighting than the underlying (see Basel Committee on Banking Supervision (2004)).

2.3 A Rude Awakening

2.3.1 The Collapse of Credit Markets

So far, we argued that the market for credit risk is to the benefit of the economy. So why did we experience such a devastating crisis? The answer is quite simple. There has been a lack

of risk awareness and overconfidence⁷ among market participants.

As stated above, securitization transactions were widely used by originators to eliminate credit portfolio risk from their balance sheets. An explanatory hypothesis would be that the notion was that loans which are off-balance sheet do not contribute to the institution's risk profile. This proved to be rather myopic. With the increasing number of securitization transactions, the quality of the loan portfolios declined. Those who invested in the tranches of the securitization transactions often were unaware of the inherent risk and relied on the external assessments of rating agencies, which in many cases were overly optimistic. After the burst of the housing bubble⁸ in the United States, more and more loans defaulted. Consequently, those who invested in securitization transactions incurred severe losses on their tranches, in particular on the first loss piece. Therefore, they had to write down their investments. This in turn put investors on the spot to liquidate their positions in order not to run into over-indebtedness. Additionally, the growing uncertainty concerning the actual risk profile of the securitization tranches led to an erosion of liquidity in the secondary market, resulting in enormous discounts on the tranches, if they were sellable at all. This created a vicious circle in the market for securitization tranches, which consequently collapsed. This collapse led to further write-downs on financial institutions' assets, which absorbed much of the financial system's liquidity. As a consequence, although exposures due to the loan portfolios securitized were not on the banks' balance sheets in the first place, they finally got there through the back door. Given increased illiquidity within the financial system, financial institutions ran into refinancing problems. The fact that many financial institutions heavily relied on short term refinancing, while being highly leveraged, further boosted the crisis. What made things even worse was the psychological effect of a loss of trust in the overall financial system. To avoid over-indebtedness, all kinds of assets had to be liquidated and the crisis spread throughout the system. The contagion effect was enormous throughout institutions, markets as well as regions.

2.3.2 The CDS-Domino-Effect

Of course, the crisis in financial markets also spilled over to the market for credit protection. Figure 2.3.2 illustrates the impact of the crisis, which led to significantly wider spreads in the market for credit risk. Here again, the contagion was fostered by the structure of the market. Most players in the market for credit protection hedge their exposures by an offsetting trans-

⁷Still in mid-2007, market participants believed that advances in credit risk modeling would prevent severe losses on highly rated tranches and credit derivatives, see e.g. Mills and Kiff (2007).

⁸See e.g. Shiller (2008) for a discussion of the role of bubbles in the subprime crisis.

action, thus exposures are passed on throughout the market. This seems perfectly reasonable as long as there is no counterparty risk. Unfortunately, this was actually not the case, as the market for credit protection is an over-the-counter (OTC) market. The financial turmoil at American International Group (AIG) clearly revealed the vulnerabilities of the market structure.

Given the setting in the market for credit risk described above, a CDS-Domino-Effect emerges as follows. In case a major player defaults, the CDS contracts it has written become virtually worthless. This leads to large unhedged positions at his swap counterparties. This may in turn force them into default, e.g. via increasing regulatory capital requirements, despite their given financial solvency. Again, exposures which seem to be perfectly hedged, instantly become a serious risk position, as they are not (fully) buffered by an equity cushion. The result is a domino-effect spreading throughout the market for credit protection, further destabilizing the overall financial system, caused by the failure to recognize the inherent counterparty risk in such credit protection contracts. In fact, the counterparty risk in a swap transaction does not solely depend on the respective direct counterparty, but it is rather determined by the weakest link (i.e. weakest protection seller) in the system, as the collapse of one major player may force the whole system into distress. This setting adds a major portion of systemic risk to the market for credit protection, which has to be accounted for.

2.3.3 The Drying Up of the Interbank Lending Market

As discussed above, disruptions, both in the market for securitization tranches and the market for credit protection, absorbed much of the liquidity in the global financial system. This effect was further emphasized by a loss of trust in the banking system. Rising uncertainty concerning the financial health of the banking system led to an increased reluctance among banks to lend money to each other in the wholesale market. This is illustrated by the behavior of LIBOR rates during the crisis as given in Figure 2.3.3. Even interventions by central banks were not able to offset the negative effects due to the loss of trust. Fears in the market were further fostered by the failure of Lehman Brothers. Unfortunately, many banks were highly dependent on wholesale funding as a consequence of major balance sheet expansions during the times of economic growth and business models based on high leverage. This failure of the interbank lending market was another cornerstone of the crisis. It forced many banks to liquidate large positions of liquid assets, leading to severe losses as for example in the equity markets.

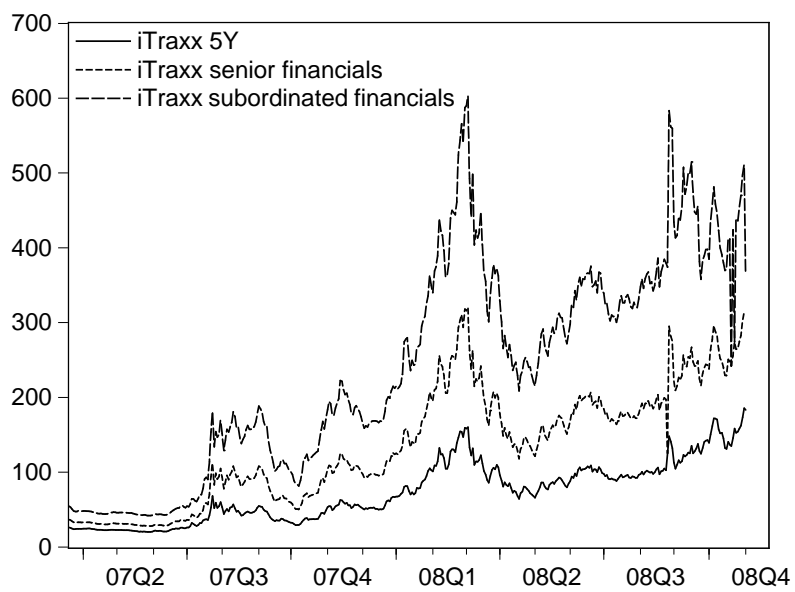


Figure 2.2: Spreads in bps for different members of the iTraxx Europe index universe, 03/20/2007 to 11/21/2008. Data source: International Index Company.

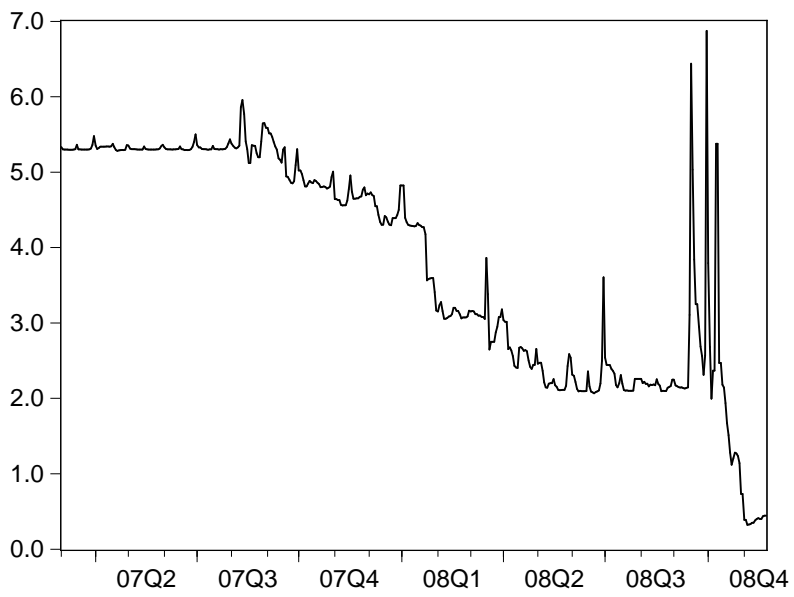


Figure 2.3: 3 month USD LIBOR quotes in percentage points, 03/01/2007 to 11/21/2008.
Data source: Thomson One Banker.

2.4 Stabilizing the Financial System - Short Term Government Intervention

There is no doubt that immediate action has to be taken in order to cope with a crisis of such magnitude. Otherwise, severe consequences for the financial system, as well as for the global economy would be inevitable. Due to the dimension of the subprime crisis, governments seem to be the only players which can achieve a significant impact from their interventions. The general reason behind government intervention and fiscal policy is subject to ongoing debate and beyond the scope of this paper. In this section, we focus on the design of short term government intervention, which aims at stabilizing the financial system.⁹

2.4.1 Are Rescue Packages Appropriate?

Governments worldwide have structured rescue packages to support financial institutions in distress. This rises an important question: Should distressed financial institutions be rescued by the government and consequently by tax payers? On the one hand, rescue measures seem appropriate given that the bankruptcy costs for the economy would exceed the costs of the rescue.¹⁰ On the other hand, with a government as the lender of last resort, there is little incentive for financial institutions to pursue sophisticated risk management strategies. In contrast, the incentive would be to increase the overall risk profile of the institution in order to obtain a higher expected payoff for shareholders. With a lender of last resort, shareholders are equipped with a put option written by the government, generating an incentive to increase the risk profile of the firm at the cost of the government. This again is a classic moral hazard problem.

In this light, guarantees as sole instrument of government intervention do not seem to be the appropriate measure to rescue banks. In case a rescue is inevitable, it should be perused with the help of capital injections rather than guarantees alone in order to avoid principal agent conflicts. Nevertheless, rescue packages should not be used arbitrarily. As stated above, the presence of a rescue package suspends the important market mechanism of bankruptcy. This mechanism ensures that only those financial institutions survive the crisis, which have pursued sound risk assessment and management. Those institutions with insufficient financial precautions, in the form of equity buffers, should fail in order to ensure

⁹A long term perspective of government intervention, i.e. deposit insurance, is discussed in Bryant (1980) and Diamond and Dybvig (1983) among others.

¹⁰Bankruptcy costs not only comprise direct costs associated with the bankruptcy of a single bank. Additionally, the indirect costs of contagion effects within the banking system have to be incorporated, as claimed by Goodfriend and King (1988).

the allocational efficiency of the financial system. Therefore, governments should not rescue financial institutions, as long as the bankruptcy costs born by the economy do not exceed the cost of rescue. In case the rescue of a certain financial institution is inevitable, these measures of assistance should come at a significant cost for the respective institution. Otherwise, the rescue packages could encourage institutions to rely on them as a cheap source of funding.

Given the above, an adequate design of rescue packages appears to be of particular importance. Among the possible means of government intervention are:

- Government guaranteed debt issuance programs,
- Direct equity injections,
- Purchases of distressed asset by the government.

In general, the design of a government rescue package for the financial services industry largely depends on its targets. Among those targets are the stabilization of the financial system via recapitalization, taxpayer protection, separation between good and bad management performance, to name just a few. Unfortunately, some of these targets work in opposite directions (like recapitalization and tax payer protection). Furthermore, the costs associated with bank failure are hard to quantify, making it difficult to measure an exact trade-off.

An appropriate rescue package avoids principal agent conflicts, while providing immediate liquidity to institutions which are in the state of distress. Furthermore, the package should only be to the benefit of banks which are illiquid but solvent, or of systemic relevance. At a first glance, a superior method to rescue banks is via asset purchases, where financial institutions sell with a discount to the economic value of the assets. As the economic value of many of those assets is above their current market value, this strategy has two major advantages. On the one hand, only those financial institutions with severe liquidity problems will be willing to sell undervalued assets. On the other hand, the government itself can profit from the expected higher payoffs from those assets in the future. Nevertheless, banks which need to be rescued due to their systemic relevance, might not be able to sell distressed assets. Therefore, combinations of different means of recapitalization seem to be necessary.

2.4.2 A Formal Illustration of Different Means of Government Intervention

In this section we formally show how different means of government intervention can influence decision making within the financial sector. Our purpose is to illustrate the design of a rescue package, which allows to distinguish between illiquid but solvent versus insolvent banks.

Although this focus might not be in the very best interest of taxpayers in the short run, at least it allows to identify and reward good management performance. In the long run, this separation is inevitable for the design of incentive mechanisms, which reward good management performance. This in turn can prevent future misconduct within the financial services industry.

In order to illustrate how the different means of government rescue packages can influence decision making among the financial services industry, suppose the following setting. There are two periods. In period $t = 0$ financial institutions face a liquidity shortage and decide how their liquidity need has to be refinanced. In $t = T$ the liquidity need vanishes and the capital obtained in period $t = 0$ matures. Furthermore, the present value, $V_{0,i}$, of a future claim is given by

$$V_{0,i} = E_0[V_{T,i}]e^{-r_i T}, \quad (2.1)$$

where r_i is the continuously compounded risk adjusted discount rate for asset i and $E_0[V_T]$ is the time zero expected cash flow due to the claim at maturity.

We next assume that there are two types of banks in the financial system, good banks and bad banks, which differ in their default risk. The different risk profiles of the two types of banks largely stem from the quality of their balance sheets. Outside investors, including government authorities, cannot distinguish between the two types, due to information asymmetries.¹¹ The risk adjusted cost of external funding for good banks is r_g and the one for bad banks is r_b , where $r_g < r_b$.

Given the probability of ending up with a good bank is p_g , $0 < p_g < 1$ investors will require a rate of

$$r_l = p_g r_g + (1 - p_g) r_b \quad (2.2)$$

for debt capital invested in a bank. Note that, due to asymmetric information, good banks suffer from losses due to higher than necessary refinancing costs. To overcome this problem, they could provide a signal to outside investors and profit from lower refinancing rates. However, as long as bad banks can imitate the signal without incurring significant costs, the signal of being either a good or a bad bank is worthless.

Guaranteed Debt Issuance Programs

Suppose now that both types of banks suffer from liquidity problems due to a system-wide financial crisis and are in need of external debt capital. Both banks can acquire a guarantee for their debt issuance programs, allowing them to borrow at the risk-free rate r_f , where $r_f < r_g$.

¹¹This is not a overly restrictive assumption in case the financial system is in distress. In this case, the focus of the government is more on providing immediate liquidity rather than assessing the risk profile of banks in need of funding.

The guarantee comes at a cost at the rate of s , which is the same for both types of lenders, as the government cannot distinguish between them.¹² In this setting, the rate at which a bank can be refinanced is given by

$$\min[p_g r_g + (1 - p_g)r_b, r_f + s]. \quad (2.3)$$

Banks of both types will rely on the government guarantee as long as the risk-free rate plus the fee s is lower than their initial refinancing costs. This is always true for both banks, since the good banks cannot provide a credible signal of being in the good cohort. As a consequence, government support packages will equally favor both types of banks or none of them. In this case state guarantees are not suited to create a setting where good banks can be separated from bad ones.

Government assistance in the form of guaranteed debt issuance programs has another important drawback. As the fee s charged for the state guarantee is a compensation for the risk of default of the guarantee taker, the government will incur a loss as long as s is too low relative to the default risk of the guarantee taker. In fact, the government faces the problem of any other outside investor. Consequently, the fair spread it should charge is given by

$$s = [p_g r_g + (1 - p_g)r_b] - r_f. \quad (2.4)$$

The risk-adjusted fee, s , charged for the guarantee is given by the risk-adjusted cost of debt capital less the risk-free rate. In this setting, the guarantee is either ineffective, as it does not lower the cost of capital for the bank, or it will result in a loss for the government, as the fee it charges does not cover the expected losses.

Direct Equity Injections

Another way to support distressed financial institutions is by means of direct equity injections. This can e.g. be conducted via an increase in share capital, either in the form of common or preferred stock. The risk adjusted rate of return for preferred stock is r_p^g for a good bank and r_p^b for a bad bank, where $r_p^g < r_p^b$, due to the higher default risk associated with a bad bank. Accordingly, a good bank is charged a rate of r_c^g for common equity, and a bad bank is charged r_c^b , where $r_c^g < r_c^b$. As equity capital has a lower seniority than debt capital, $r_g \leq r_p^g \leq r_c^g$ and $r_b \leq r_p^b \leq r_c^b$ must hold. Suppose that the government is willing to obtain preferred or common shares of a bank. The rate it charges for the equity injection is $r_f + i_p$ and $r_f + i_c$,

¹²Merton (1977) derives entity specific prices for guarantees using option pricing arguments. However, this approach does not seem appropriate for banks, due to the dynamic structure of their assets.

respectively, where i represents the risk premium. Again, investors cannot distinguish between good and bad banks. Thus, any bank can be refinanced via preferred shares at a rate of

$$\min[p_g r_c^g + (1 - p_g) r_p^b, r_f + i], \quad (2.5)$$

regardless of its risk profile.

The choice between refinancing via debt or equity largely depends on the structure of the respective bank's balance sheet. In general, equity capital is chosen in case the bank aims at increasing its core capital ratio. In case a bank only seeks for liquidity, as it is otherwise healthy, it will rather chose to refinance via debt capital. Nevertheless, comparing the two possible cases, it is obvious that the problem faced by banks and investors is nearly the same in both of them. Both types of banks can refinance at the same conditions, regardless of their risk profile. Additionally, intervention in both cases will either result in a loss for the government (as long as the risk premium it charges is lower than the expected losses) or, otherwise, it will be ineffective.

Purchases of Distressed Assets

Next suppose that the government, instead of providing guarantees on debt financing programs, aims at recapitalizing financial institutions by buying illiquid assets from their balance sheets. The purchase of the assets comes at a discount to the (pre-crisis) book value of the assets. The discount is given by d , $d \geq 0$, so the i 'th asset is purchased at the time zero price

$$P_i = X_i(1 - d), \quad (2.6)$$

where X_i is the book value of the asset.

Selling assets to the government has a similar effect on a bank's leverage as being recapitalized via an equity injection. Both means of intervention help to decrease the bank's leverage via increasing its core capital ratio. The difference between the two lies in the way through which this decreased leverage is achieved. Asset purchase programs result in reduced balance sheet totals at the banking sector, while this is not achieved via equity injections.

Combinations of Different Means

Most of the government bailout programs launched in the course of the subprime financial crisis are a combination of different means of government intervention.¹³ In this section we

¹³The TARP program is a combination of equity injections and asset distressed asset purchases, while most European bailout programs combine government guaranteed debt issuance programs with direct equity

focus on a combination of debt issuance programs and asset purchases. Nevertheless, our results generally apply to other combinations as well.

Assume that $V_{0,i}$ is the present value of the expected payoff from asset i at maturity. As long as $V_{0,i} \leq P_i$ it is rational to sell the asset from the bank's perspective. Furthermore, for banks with a need for liquidity, selling assets instead of obtaining debt financing can be rational even if $V_{0,i} \geq P_i$. In any case, the costs of obtaining funding via selling an asset are given by

$$V_{0,i} - P_i.$$

The costs for obtaining external debt financing amount to

$$P_i \left(e^{\min[p_g r_g + (1-p_g)r_b, r_f + s]T} - 1 \right). \quad (2.7)$$

In both case we assume a liquidity need of P_i .¹⁴ For any bank it is now rational to sell assets as long as

$$V_{0,i} - P_i \leq P_i \left(e^{\min[p_g r_g + (1-p_g)r_b, r_f + s]T} - 1 \right). \quad (2.8)$$

It follows from equation (2.8) that the form of refinancing chosen by a bank in our world depends on the quality of its assets as well as the time horizon of the refinancing transaction. The willingness of the bank to sell assets will decline with a better quality of its assets and a shorter time horizon of its liquidity needs.

Equilibrium Conditions I

As assumed above, the different risk profiles of the two types of banks largely stem from the quality of their balance sheet. The quality of assets held by good banks is likely to be better than the one of bad banks' assets. Let assets owned by good banks be denoted by the subscript j and let the ones owned by bad banks carry the subscript k . All banks suffer a liquidity shock and have to obtain liquid funds in order not to default. Both types of banks face the problem characterized by equation (2.8). Nevertheless, in this setting, the two banks will behave differently. As the good banks own high quality assets, they will be reluctant to sell them and rather chose to be refinanced via external debt capital. In contrast, the banks of the bad cohort will sell a large fraction of their assets.

Furthermore, as the illiquidity of the good banks is caused by a market shock, it is likely to vanish shortly after its occurrence. Therefore, the time horizon for which good banks have to

injections.

¹⁴In the special case that the fee equals the fair risk premium, the cost at which any bank may obtain external funding amounts to $P_i(e^{r_i T} - 1)$.

obtain external capital is short (as they are only subject to the liquidity shock, but otherwise are solvent). The reverse holds for the bad banks, as their illiquidity is not only due to the market shock, but also a result of structural issues within the bank.

Therefore, we may assume that $T_g \leq T_b$. As long as

$$V_{0,j} - P_j > P_j \left(e^{\min[p_g r_g + (1-p_g)r_b, r_f+s]T_g} - 1 \right), \quad \forall j, \quad (2.9)$$

good banks will not sell any assets. This is a robust signal for market participants of being a good bank, as long as it is irrational for bad banks to mimic. If this is the case, good banks can obtain external funding at a rate of r_g , as long as we assume that $r_g < r_f + s$, and $r_f + s$ otherwise. Hence, the two types of banks can be distinguished as long as bad banks sell some of their assets. From a bad bank's perspective, this is rational as long as

$$\sum_{k=1}^n (V_{0,k} - P_k) < \sum_{k=1}^n P_k \left(e^{\min[p_g r_g + (1-p_g)r_b, r_f+s]T_b} - 1 \right), \quad (2.10)$$

supposing that their funding need amounts to $\sum_{k=1}^n P_k$. For inequalities (2.9) and (2.10) to hold, the discount d must satisfy

$$d > 1 - \frac{V_{0,j}}{X_j e^{\min[p_g r_g + (1-p_g)r_b, r_f+s]T_g}}, \quad \forall j \quad (2.11)$$

and

$$d < 1 - \frac{\sum_{k=1}^n V_{0,k}}{\sum_{k=1}^n X_k e^{\min[p_g r_g + (1-p_g)r_b, r_f+s]T_b}}. \quad (2.12)$$

If the discount is chosen according to equations (2.11) and (2.12), government bailout programs including possible asset purchases generate a separating equilibrium between good banks and bad banks through a self-selection mechanism¹⁵. The good banks are able to borrow money at their risk adjusted cost of external capital and they are better off than in a situation where the government intervention is conducted via guaranteed debt funding programs only.¹⁶ As long as long as $V_{0,i} > P_i$, the government can profit from the rescue packages, as it acquires assets for less than their economic value. In sum, all three parties are better off than with

¹⁵We thank an anonymous referee for noting that the self-selection mechanism might fail if the discount offered is either chosen to be large or to small. For the mechanism to work a prudent choice of the discount is of paramount importance.

¹⁶As long as $r_f + s > r_g$.

government guarantees only.

Equilibrium Conditions II

In the setting described above, good banks do not hold any assets for which,

$$V_{0,j} - P_j > P_j (e^{\min[p_g r_g + (1-p_g)r_b, r_f + s]T_g} - 1). \quad (2.13)$$

Putting it differently, we assume that good banks do not hold any distressed assets, which is a rather restrictive assumption. Nevertheless, this assumption can be relaxed, while we still are able to separate good and bad banks. This is achieved, as long as selling illiquid assets and obtaining external debt capital are mutually exclusive.¹⁷ In this case, banks are not allowed to obtain external funding, given that they have sold distressed assets to the government. Good banks, having a funding need of $\sum_{j=1}^m P_j$, will not sell any assets as long as

$$\sum_{j=1}^m (V_{0,j} - P_j) > \sum_{j=1}^m P_j (e^{\min[p_g r_g + (1-p_g)r_b, r_f + s]T_g} - 1). \quad (2.14)$$

Banks will retain assets for which inequality (2.8) holds and they will incur a loss by retaining assets for which selling is rational. Nevertheless, this loss is outweighed by the loss they would incur by not being able to rely on external funding, due to the mutual exclusiveness of the two funding sources. The lower bound for the discount d , for which good banks will be reluctant to sell any assets, implied by inequality (2.14) is given by

$$(2.15)$$

The upper bound as given by (2.12) remains unchanged. Hence, it can be seen that good and bad banks still behave differently in this setting.

A Numerical Example

To illustrate our findings we provide a small numerical example. Suppose $p_g = 0.5$, $r_f = 5\%$, $r_g = 8\%$, and $r_b = 16\%$. There are two banks, one of either type, which both have a liquidity need of 100 over the next two months. In the first case, suppose government assistance

¹⁷This can be ensured by restrictive covenants in the purchase agreement. From the government's perspective, this is clearly desirable. Otherwise, banks could use rescue packages as a "dump" for worthless assets, regardless of their solvency.

comes in the form of a guarantee at the cost of $s = 5\%$. Hence, the cost of obtaining external capital via state guaranteed lending for both banks is

$$(100 \cdot (e^{(0.05+0.05) \cdot \frac{2}{12}} - 1)) = 1.68.$$

Next, suppose government assistance comes in the form of a purchase of illiquid assets by state authorities. The good bank owns two assets. Each asset has a book value of 60. The first asset has a present value of 60 and the second asset has a present value of 45. The bad bank also owns two assets, each with book value of 60. The first asset has a present value of 60 and the second has a present value of 41. Further suppose that the discount is $d = 16.67\%$. For both the good and the bad bank, debt capital can be acquired at a cost of

$$100 \cdot (e^{(0.5 \cdot 0.08 + 0.5 \cdot 0.16) \cdot \frac{2}{12}} - 1) = 2.02.$$

The cost of obtaining capital via selling assets for the good bank are

$$(60 + 45) - 2 \cdot [60 \cdot (100\% - 16.67\%)] = 5.$$

Therefore, it will chose to obtain fresh capital via external debt funding. The bad banks cost of obtaining capital via an asset sale is

$$(60 + 41) - 2 \cdot [60 \cdot (100\% - 16.67\%)] = 1.$$

Therefore, the bad bank will decide to sell the assets instead of relying on external funding. This provides a signal for outsiders allowing the good bank to lend at its risk adjusted rate of 8%. Hence, it is better off than in the state guarantee case. In this simple example, we showed that all three parties are better off when the government's rescue package comes in the form of asset purchases. A drawback of this situation is that the bad bank is able to lend money at a lower rate than the good bank (5.97% compared to 8%). Nevertheless, the two types can be separated, allowing to reward good banks in the future.

2.5 Consequences in the Long Term - Lessons Learned

Given the above, several questions arise: What are the lessons learned from the current crisis? What has gone wrong and how can such failures be prevented in the future? Is there a need

for stricter regulation in the financial system? It appears straightforward to blame the financial services industry for the crisis and to ask for stricter regulation, but unfortunately, the answer is not quite as simple as that.

2.5.1 The Future Role of Securitization

In the public discussion, securitization is often blamed to be “the root of all evil”, leading to the melt-down in the financial system. Given this, what consequences should the crisis have for the securitization market? Is there still room for securitization transactions, or do the drawbacks of securitization outweigh the advantages discussed above?

The advantages of securitization transactions do warrant the risks inherent in securitization transactions. However, the system has to undergo certain changes to avoid a collapse like the one we see today. As argued by the International Monetary Fund (2003) and Franke and Krahen (2008), there currently is a misalignment of the incentives of the different counterparties in typical securitization transactions. As the originator can eliminate the whole credit portfolio from her balance sheet, she has little incentive to assure certain minimum quality requirements for loans contained in the securitized portfolio, which is confirmed empirically by Amiyatosh (2009).¹⁸ This can easily be prevented by requiring the originator to retain a certain share of the transaction, preferably a fraction of the first-loss-piece, on her books. This would ensure that no “toxic waste” is contained in the loan portfolio, since the originator is directly exposed to its inherent credit risk. Furthermore, the originator should be required to publicly declare the share and the tranches of the transaction she retains. This signal can be used by investors to assess the risk associated with a certain transaction. The optimal size of the share of the transaction the originator is required to hold is subject to further research. On the one hand, if the share is too small, the alignment of incentives is not accomplished. On the other hand, if the share is too large, the whole securitization transaction becomes unattractive for the issuer, since other forms of refinancing, e.g. the issuance of covered bonds become more rewarding. This terminates the positive effects of securitization transaction for the economy. Requiring the originator to retain a certain share of the transaction has another positive effect, as it also limits the overall volume of loans granted. In case the originator retains a certain share of the transaction, she expends her balance sheet, which would not be the case if she fully passes on all the tranches of the transaction. This automatically limits the number of loans she can grant as she cannot (at least she should not) exceed a certain level of leverage. This assures

¹⁸Gorton (2009) disagrees with the opinion that securitization transactions lead to a decline in the quality of mortgages originated. He argues that, despite the fact that the credit risk is eliminated from the originator's balance sheet, she still is exposed to the performance of the securitized mortgage portfolio, e.g. through servicing fees and warehousing risks.

that the quality of obligors does not decrease arbitrarily.

Another important issue, which led to the financial crisis is the enormous complexity of certain products in the market for credit risk. This complexity not only hampered investors' assessment of the risk associated with the products, even rating agencies were not able to specify and measure the risk underlying certain transactions. Unfortunately, many investors relied on external ratings, which were provided by overly optimistic rating agencies. Nevertheless, it is astonishing that investors relied on ratings and invested in products they obviously did not fully understand. The only explanation for this is that sophisticated risk assessment and management was sacrificed on the altar of irrational return expectations.

2.5.2 The Role of Internal Risk Management

The absence of proper risk awareness among market participants is surely among the basic causes of the current crisis. As argued above, market participants may assume that various risks can easily be eliminated through instruments like securitization and credit protection. What has been overseen is the fact that there are risks besides credit risk, which cannot be eliminated easily, including market risks, liquidity risks, and counterparty risks. The number of bad loans in the economy does by no means justify the enormous volume of financial products which are labeled as "toxic waste"¹⁹ during the recent period of market stress. The essential problem is that there no longer exists a market for these products, due to a lack of liquidity as well as due to a lack of trust in those products. This fact, in connection with the fair value accounting principle, causes serious write-downs on investments in those assets, although these write-downs might only in part be driven by a lack of quality of the product itself. The possibility of such an erosion of secondary markets has obviously not been taken into account. This is clearly a failure of internal risk management within financial institutions. In this light, one has to discuss the question, whether or not this failure can be prevented by stricter regulation. A possible solution may be to require financial institutions to hold an increased equity cushion in order to absorb losses due to market and liquidity risk.²⁰ On the other hand, it seems doubtful whether or not this is really an issue for regulators. Normally, those market participants which had not accounted properly for their exposure to market and liquidity risks would be wiped out, and those with appropriate risk management systems in

¹⁹According to Bank of England (2008) estimates, about 37% of the mark-to-market losses on US subprime RMBSs can be attributed to discounts for illiquidity and uncertainty rather than actual credit risk.

²⁰Admittedly, it is impossible to hold equity cushions to absorb any potential losses due to market and liquidity risk. The October 2008 market meltdown is clearly some tail event, which cannot be fully absorbed. Nevertheless, it seems doubtful that the situation would have spread the way it did, had market participants at least provided enough capital to absorb moderate losses due to market and liquidity risk.

charge would prevail. Unfortunately, this market mechanism was suspended by the rescue packages initiated by governments worldwide.

2.5.3 Long Term Profitability versus Short Term Cash Generation

The above discussion leads us to another trigger of the financial crisis, namely inappropriate management incentives. Typical performance measures (such as the Return on Equity (ROE), among others) do not seem to be sound target figures for financial institutions as they do not account for risk. Instead of rewarding sophisticated risk management, such measures rather induce managers to increase leverage and to pursue a more risky business model. This strategy may yield sound performance figures in the short run, but does not necessarily promote the long term stability of an institution. This corporate governance issue could be resolved via shareholders. Unfortunately however, the number of long term investors seems to be steadily decreasing in the markets. Instead, investors with a short term investment horizon, e.g. hedge funds, own significant shares in many financial institutions. Their focus is frequently on short term cash generation rather than sustainable growth. This clearly plays a supporting role in a failure of internal control mechanisms of publicly listed companies. Rather than assuring that the management acts in the sake of long term stability, via linking compensation to typical performance ratios, management is offered an incentive to increase short term profitability.

2.6 Conclusion and Outlook

The current turmoils in the global financial system are unprecedented. They highlight the need for massive structural changes in the financial services industry. In our view, stricter regulation is not the sole answer to the problem. In the future, financial institutions need to focus on appropriate risk management and risk assessment instead of maximizing short term profitability. In this light, government support packages granted to financial institutions have to be seen with prudence, as they may hinder the future development of sound risk management strategies. Rather than solely providing guarantees, government support should aim at appropriate capital ratios within the banking system.²¹ This recapitalization must come at a significant cost in order to provide accurate incentives.

An recent interesting issue is why banks seem to be reluctant to rely on government bailout programs. Most programs are designed in a way that allows financial institutions to lower their refinancing cost. Hence, it would seem reasonable to rely on government assistance from a

²¹On March 30, 2010, it was announced that the Irish National Asset Management Agency (NAMA) would buy of risky loans worth EUR 16 billion at a discount of 47%.

shareholder value perspective. Nevertheless, the restrictive covenants of the packages (e.g. caps on management salaries, as well as the stigma of being in need of state assistance), seem to tempt some managers to proceed without assistance. Furthermore, it remains questionable whether market participants have learned their lesson from the current crisis. The worldwide development of treasury bonds since the early 1980's indicates yet another bubble. Time will tell when and how the financial system will cope with its future potential crises.

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3 Explaining Aggregate Credit Default Swap Spreads

Explaining Aggregate Credit Default Swap Spreads

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Abstract

We examine risk factors that explain daily changes in aggregate credit default swap (CDS) spreads before, during and after the 2007-2009 financial crisis. Based on the European iTraxx index universe, we document time-variation in the significance of spread determinants. Before and after the crisis, spread changes are mainly determined by stock returns and implied stock market volatility. Global financial variables possess explanatory power during the pre-crisis and the crisis period. Liquidity proxy variables are significantly related to spread changes for financials, while unrelated for non-financials. Our examination of the risk factors' explanatory power for large spread changes, reveals weakened significance, indicating that additional factors are necessary for their explanation. Finally, we examine the lead-lag relationship between spread changes and stock returns. Stock market returns lead spread changes during the crisis period, while a bi-directional relationship emerges after the crisis period. This suggests that aggregate spread changes are informative for equity market participants, possibly measuring systemic risk.

Keywords: aggregate credit risk, credit default swaps, financial crisis, quantile regression, vector autoregression, iTraxx;

3.1 Introduction

In the light of the 2007-2009 global financial crisis, a more decent understanding of credit markets appears desirable. An important segment of the market for credit risk are credit derivatives, a recent financial market innovation, which have a huge impact on financial markets. Credit derivatives can be separated into single name products such as e.g. credit default swaps (CDSs) and portfolio products like collateralized debt obligations (CDOs) and credit indices.¹ From a researcher's point of view, credit derivatives provide an excellent laboratory for studying the mechanics of credit markets. Due to their pronounced liquidity compared to bonds they quickly process information, which is relevant for determining the creditworthiness of a company. Furthermore, portfolio products, such as credit indices, seem well suited to reflect relevant information concerning the creditworthiness of a sector or even an economy as a whole. Furthermore, as Longstaff and Rajan (2008) point out, credit derivatives are sensitive to the joint distribution of default risk. Hence, they are crucial for an understanding of systemic risk in financial markets.

We conduct an empirical investigation of the iTraxx Europe index universe with the recent financial crisis in focus. We address three different issues. First, we want to identify the determinants of iTraxx spread changes to learn about the drivers of aggregate credit risk which in turn can be regarded as systemic risk factors. We are particularly interested in whether the determinants have changed as a consequence of the recent financial crisis, i.e. whether investors have adjusted their models of credit risk and have reassessed their assumptions concerning the systemic component of spreads. Second, we investigate whether the determinants of iTraxx spreads are suited to explain spread changes in the upper and lower tail of the empirical distribution, i.e. whether extreme spread changes are subject to the same factors as changes around the mean or median of the empirical distribution. Third, we are concerned whether market participants use the iTraxx index as a source of (additional) information regarding systemic risk. Therefore, we investigate the lead-lag relationship between the iTraxx index market and equity markets. If the iTraxx market is used as a source of information regarding systemic risk by investors it should not be led by stock markets.

In order to address these three issues we proceed in the following way. In a first step we regress daily spread changes of iTraxx Europe index family members on a rich set of explanatory variables. It comprises variables implied by structural models of credit risk, a set of liquidity factors and global financial variables. We examine spread changes of the iTraxx Europe benchmark index, as well as spread changes of the different subindices of the benchmark index. We put a special focus on changes of credit spread determinants as a consequence of

¹A credit index can be regarded as a single tranche CDO.

the recent financial crisis. Our sample ranges from 06/16/2004 to 08/06/2010 and spans the crisis period, as well as a pre- and a post-crisis period. This allows us to examine the evolution of credit spread determinants throughout the financial crisis. First we estimate our econometric model for the full sample and then repeat the estimation for the pre-crisis, crisis and post-crisis subsamples to detect changes in the set of spread drivers.

In a next step we reestimate our econometric model via quantile regression. This allows us to examine the performance of our set of explanatory variables in the upper and lower quantiles of the empirical distribution of spread changes, i.e. to check for the robustness of our OLS-regression results in different quantile of the empirical distribution of spread changes. The quantile regression is conducted for all subindices and all subsamples. This allows us to study the determinants of spread changes in upper and lower quantiles of the empirical distribution, as well as changes in the determinants in the course of the financial crisis.

To examine whether market participants rely on the iTraxx index as a source of additional information we examine the lead-lag relationship between the market for credit risk and stock markets. For this purpose we estimate a vector autoregressive model with exogenous variables (VARX-model). The exogenous variables are supposed to jointly determine credit spread changes, as well as stock returns on a portfolio constructed out of the iTraxx index constituents. We estimate the VARX-model for all subindices and all respective subsamples to investigate whether the lead-lag relationship has been altered by the recent financial crisis.

Our paper contributes to the existing literature in several ways. First we investigate the explanatory power of a rich set of independent variables, including proxies for liquidity and global financial factors. Second, to the best of our knowledge, this is the first empirical investigation of the behavior of iTraxx index spreads of the benchmark index and all subindices with a special focus on changes on credit spread determinants in the course of the recent financial crisis. Third, our empirical paper provides deeper insights into the mechanics of iTraxx spreads by explicitly examining the behavior of credit spread changes at the upper and lower quantiles of the empirical distribution. Finally, we contribute to the existing literature by examining the evolution of lead-lag relationships between the iTraxx and stock returns in the course of the recent financial crisis, while controlling for several exogenous variables.

We find strong evidence of variation in the determinants of credit spread changes in the course of the recent financial crisis. This finding suggests that market participants have altered their models of credit risk as a consequence of the crisis. While the number of factors necessary to explain iTraxx spread changes varies throughout the sample period, the explanatory power of our set of independent variables rises. The predominant factor determining iTraxx spread changes for all subsamples and all subindices is the return on an equal-weighted stock

portfolio consisting of the iTraxx constituents. The performance of the other factors implied by structural models, i.e. the risk-free rate, stock market volatility and the shape of the risk-free curve, is significantly worse in all of the subsamples and for all subindices. Furthermore, in contrast to the results of Alexander and Kaeck (2008) we do not find empirical evidence that stock market volatility rather than stock market returns have a predominant influence on credit spread changes in crisis periods.

The explanatory power of our liquidity and global financial variables differs largely throughout the different subindices and subsamples. Global financial variables have a statistically, as well as economically significant influence on spread changes in the pre-crisis and in the crisis period for most subindices. Especially during the crisis, systemic risk, as measured by the returns on a global stock index has a significant influence on spread changes, highlighting the increased awareness of investors regarding systemic risk throughout the crisis. Equity market illiquidity is not significant except for the Senior Financials and the Subordinated Financials index, for which we observe a positive relationship between stock market illiquidity and spread levels. For those subindices, the effect is especially pronounced in the crisis period. This suggests that during the crisis investors were especially concerned with hedging their risk towards the financial sector. The illiquidity of the iTraxx index itself is not significant, except for the Non-Financials index. This comes as no surprise as the iTraxx Non-Financials index tends to be the most illiquid subindex of the iTraxx index universe.

Furthermore, we observe pronounced positive autocorrelation in iTraxx spread changes for all subindices, even after controlling for a rich set of explanatory variables. However, the effect is largest for the pre-crisis sample and declines steadily throughout our sample period. The declining autocorrelation of iTraxx spread changes suggests that the liquidity of the iTraxx index has constantly risen throughout our sample period.

The results of the quantile regression generally confirm the results of the OLS-regression analysis. However, there is strong empirical evidence that our set of explanatory variables performs worse in explaining spread changes in the upper and lower quantiles of the empirical distribution than at the median or the mean. Both spread widening and spread tightenings in the tail of the empirical distribution are systematically underestimated. Regression results reveal that a statistically significant systemic component of spread changes in the upper and lower quantile is not explained by our set of independent variables. This finding is not in line with structural models. Hence, adjustments to structural models of credit risk seem necessary. Additionally, the explanatory power of our set of variables varies throughout the different quantiles.

The results of the VARX-model provide empirical evidence for the existence of variation in

the lead-lag relationship between credit spread changes and stock returns. While the regression results for the full sample convey a two-sided relationship, the regression yields incomprehensive results for the different subsamples. In the pre-crisis sample no apparent lead-lag relationship between iTraxx spread changes and stock returns can be observed. In the course of the recent financial crisis, stock returns lead spread changes for almost all subindices. In contrast, we observe a two-sided relationship in the post-crisis sample for all subindices. The results for the Senior Financials and the Subordinate Financials index even suggest that spread changes tend to lead stock returns in the post-crisis period.

In general the results of the VARX-model provide strong evidence that both the market for credit risk and the stock market possess relevant information for market participants. There is no apparent lead-lag relationship favoring one market over the other, except for the pre-crisis period. Furthermore, the role of credit markets in processing information has changed in the course of the recent financial crisis, as it tends to lead stock markets in the post-crisis subsample, at least for financial entities. This result confirms the previous finding that the liquidity of the iTraxx index has increased significantly. We conclude that market participants rely on information of both markets when engaging in trading or hedging. Hence, the iTraxx index universe indeed provides additional information concerning the systemic risk of financial markets.

The rest of this paper is organized as follows. The literature related to our empirical investigation is reviewed in Section 3.2. We introduce CDS indices and the iTraxx index universe in Section 3.3. The theoretical aspects underlying our empirical investigation are discussed in Section 3.4. The data set used in the empirical analysis is introduced in Section 3.5. Our econometric model and the results are discussed in Section 3.6. Section 3.7 concludes the paper.

3.2 Literature Review

The pricing of credit derivatives has gained increasing attention in the literature recently. Currently there are two fundamental approaches available. On the one hand there are the structural models based on the seminal work of Merton (1974). In structural models the default process is explicitly modeled by assuming that an issuer defaults on its obligations when its firm value drops below a certain threshold. Although perfectly reasonable in the first place, structural models suffer from a considerable drawback. Major input data like the firm value, or its volatility cannot be observed directly and have to be approximated. This often causes a poor model fit to empirical data.

On the other hand there is the class of reduced form models. In this model class an issuer default is an unpredictable event driven by a random jump process characterized by the default intensity (see e.g. Duffie and Singleton (1999), Jarrow et al. (1997) and Lando (1998) among many others). Securities subject to credit risk can be priced with reduced-form models, by extracting default intensities from historical data. This provides more flexibility and mitigates some of the data problems inherent with structural models. Nevertheless, they suffer from the difficult calibration of the jump process modeling the issuer default.

Both approaches have been verified in numerous empirical studies. Many of them focus on the explanatory power of the variables implied by the framework instead of testing the model directly. This detour is sometimes necessary as major input data for structural models are unavailable, or because the extensive calibration of the default intensity in reduced form models yields unrealistic results. Benkert (2004) uses the structural framework to derive theoretical determinants of CDS spreads. The implied variables are used as explanatory variables in a panel regression to explain CDS spread levels. This approach was first introduced by Collin-Dufresne et al. (2001) who use the theoretical determinants of credit spreads implied by the structural framework to explain changes in corporate bond spreads. A similar access is also followed by Campbell and Taksler (2002). Benkert (2004) concludes that CDS spreads are to a large extent influenced by the determinants implied by structural models, especially by equity volatility.

Ericsson et al. (2004) examine the explanatory power of independent variables implied by structural models in explaining CDS spread levels, as well as spread changes. They find strong evidence that firm leverage, volatility, and the risk-free rate are statistically, as well as economically significant in the determination of CDS spreads. A principal component analysis of the residuals suggests that the structural framework explains a significant amount of variation in the data and that there is only weak evidence in favor of a missing common explanatory factor.

Among the first studies to examine the effect of illiquidity on CDS spreads is Tang and Yan (2007). They measure liquidity effects by constructing several illiquidity proxies to account for several aspects of illiquidity in CDS markets. They find evidence that both the liquidity level and liquidity risk have significant influence on CDS spreads, on average accounting for about 20% of CDS spreads. They conclude that there is an explicit need for a CDS pricing model taking liquidity effects into account. Das and Hanouna (2009) investigate the influence of equity market liquidity on credit spreads. Using a sample of single name CDS data the authors discover a statistically, as well as economically significant relationship between equity market liquidity and credit spreads. The influence is most likely to be due to investors' need to hedge

their credit exposure in equity markets.

While the aforementioned studies focus on single name credit risk, there is a growing amount of literature covering portfolio products such as CDS indices. In one of the first empirical papers with a focus on credit indices Byström (2005) analyzes the relationship between equity market returns, equity market volatility and iTraxx spreads. He finds strong evidence that current, as well as lagged stock returns explain much of the variation in CDS index spreads. Furthermore he discovers significant correlations between stock markets and CDS markets, whereas the stock market seems to lead the CDS market in the transmission of firm specific information. Alexander and Kaeck (2008) introduce a Markov switching model to examine the determinants of iTraxx Europe index spreads in two different regimes. They confirm the statistically significant explanatory power of the variables implied by the structural framework. Additionally, they find that CDS spreads are more sensitive to stock returns than stock volatility in normal market conditions. In times of turbulences, spreads are extremely sensitive to stock volatility. Scheicher (2008) analyzes to what extent the set of explanatory variables governing iTraxx CDX tranche spreads has changed during the recent global financial crisis. The author finds empirical evidence that a decreasing risk appetite of investors, as well as concerns about market liquidity have contributed to the rising spread levels during the crisis. Furthermore, the author discovers that the repricing of tranches during the crisis is more pronounced in the CDX than in the iTraxx index universe. Giammarino and Barrieu (2009) use an adaptive nonparametric modeling approach to explain iTraxx spreads by tradeable market factors. Their model allows for dynamic factor sensitivities. The authors find empirical evidence for significant variation in factor sensitivities. During crises, factor sensitivities may be subject to sudden jumps while showing pronounced time consistency in calm periods.

Lead-lag relationships between the market for credit risk and stock markets have been addressed in several empirical studies. For example Norden and Weber (2009) analyze the relationship between CDS, bond and stock markets with a vector autoregressive model. The authors find empirical evidence that stock markets lead CDS and bond markets, while CDS spread changes lead bond spread changes. The co-movement between CDS spreads and bond returns is especially pronounced for companies with low credit quality or large bond issues. Fung et al. (2008) examine the relationship between the U.S. stock market and the CDS markets. The authors discover that the stock market leads the CDS index market in price discovery. However, CDS markets have a crucial role in the volatility spillover between the two markets. The authors conclude that both markets provide relevant information for market participants.

3.3 Characteristics of CDS Contracts and CDS Indices

A CDS can be regarded as an insurance against the default of a certain issuer of debt capital, called reference entity, at the cost of a periodic fee, called spread. In case of an issuer default, the protection buyer is compensated for his losses due to the default by the protection seller. Therefore, CDS spreads can be regarded as a measure for the credit risk of the reference entity, as they represent the compensation an investor has to be offered in order to be willing to obtain exposure to the reference entity's default risk. In contrast to a classical insurance contract, an engagement in a CDS contract does not require owning the reference asset.

Credit indices are among the major financial innovations in the new millennium. In contrast to single name CDSs they allow to insure a whole portfolio of single name credit risk with a single transaction. The outcome is similar to buying protection on each of the names in the portfolio. Hence credit indices can be regarded as an aggregation of single name CDSs.

3.3.1 The iTraxx Europe Index Family

Up to date there exist two major families of credit indices, the Dow Jones CDX index universe, covering North America and emerging markets, and the iTraxx index universe, with a regional focus on Europe and Asia. The iTraxx Europe benchmark index consists of 125 European entities with an investment grade rating (Markit (2011)). Among the subindices of the iTraxx Europe benchmark index are the iTraxx HighVol, the iTraxx Senior Financials, the iTraxx Subordinated Financials and the iTraxx Non-Financials index.² The iTraxx Senior and Subordinated Financial indices comprise the same set of constituents, while offering protection on different (senior vs. subordinated) reference obligations. Within each index, the constituents are weighted equally. The indices are rolled twice a year. At each roll date the constituents of the respective index are determined according to a liquidity poll, ranking entities based on the trading volume in the CDS market in the previous six months.³ The sectoral breakdown of the final 125 index constituents is as follows:

- 30 Autos & industrials,
- 30 Consumers,
- 20 Energy,

²The iTraxx index family was formed as a result of the merger of the iBoxx and Trac-X indices in June 2004. Each iTraxx index family consists of a benchmark index and further subindices. There had been further sectoral indices in the past, which are no longer rolled.

³For further details regarding the membership determination details refer to Markit (2011).

- 20 TMT (Technology, Media and Telecommunication),
- 25 Financials.

In case one of the index constituents is subject to a credit event, the entity is removed from the index. The notional of the index is reduced accordingly. The credit event triggers a payout from the protection seller to the protection buyer. The settlement can either be physical or in cash.

3.3.2 Index Pricing

Markit calculates both quoted and theoretical index prices and levels. The procedures are described in Markit (2010b). Quoted index prices and spreads are calculated as the arithmetic average of prices and spreads quoted by market makers. The calculated spread has to be based on quotes of at least three different market makers. The highest and the lowest quotes are discarded and do not enter the calculation in order to eliminate outliers.

In addition to the quoted spreads, theoretical spreads are calculated as a benchmark of the pricing accuracy of market participants. The calculation is based on spread data for each of the index constituents. The spread data is used to construct a spread curve for each constituent. Spreads for terms which are not traded are obtained via linear interpolation. The spread curves are used to calculate the survival probabilities at each coupon payment date for each index constituent. Then the present value (PV) and the accrued interest (AI) for each index constituent is calculated.⁴ These are aggregated to the index PV (\overline{PV}) and accrued interest (\overline{AI}) by calculating the weighted averages of the constituents' PVs and accrued interest. The index price is then calculated as

$$P_{index} = 1 + \overline{PV} - \overline{AI}. \quad (3.1)$$

The theoretical index spread is obtained by solving for the flat curve that gives \overline{PV} .

3.4 Background

3.4.1 Spread Modeling

The theoretical framework we rely on for our empirical analysis is based on the findings of Lando (1998) and the reduced form pricing framework of Duffie and Singleton (1999). Reduced form

⁴An example of how the PV of an constituent is calculated is give in Markit (2010a).

models treat default as an unpredictable event driven by a hazard process λ_t . The mean loss rate at time t is given by $\lambda_t L_t$, where L_t is the expected fractional loss of market value in case of a default at time t . Given that the mean loss rate process $\lambda_t L_t$ is exogenous, standard term structure models are applicable to the pricing of default risky claims, by parameterizing the risk-adjusted short rate process $R_t = r_t + \lambda_t L_t$ instead of the short rate process r_t (see Lando (1998)).

This finding is used by Duffie and Singleton (1999) to price contingent claims subject to credit risk as follows. Suppose an arbitrage-free setting where all claims are priced under the equivalent martingale measure Q . Next, suppose that a contingent claim is a pair (Z, τ) , where Z is a random variable representing a payment and τ is the time when Z is paid. The price process V of a given contingent claim (Z, τ) is given by

$$V_t = E_t^Q \left[\exp \left(- \int_t^\tau R_t dt \right) Z \right], t < \tau, \quad (3.2)$$

where E_t^Q represents the risk neutral, conditional expectation at date t given the information filtration \mathcal{F} .

Some empirical studies like Berndt et al. (2005) and Pan and Singleton (2005) observe actual CDS spreads which are systematically higher than those implied by reduced-form pricing models. In the arbitrage-free setting of this framework we would expect these mispricings to be fully arbitrated away, which is obviously not the case. A possible explanation for this puzzle are frictions due to illiquidity effects, which in turn hamper arbitrage.

In order to account for illiquidity effects in the reduced-form pricing framework for contingent claims subject to credit risk, Duffie and Singleton (2003) propose that an liquidity premium should directly be applied in terms of a price discount for the valuation of contingent claims, such as CDS. Therefore, the risk-adjusted short-rate process is expressed as

$$R_t = r_t + \lambda_t L_t + \ell_t, \quad (3.3)$$

where ℓ_t represents an liquidity premium, which can be interpreted as the risk-neutral expected fractional loss due to illiquidity effects.

3.4.2 Implications for our Empirical Investigation

As outlined in the previous section, specifying the risk-adjusted short rate process R_t is essential for pricing claims subject to credit risk, such as bonds and CDS. Given that a credit index

has to be priced, the claim is contingent on the solvency of a portfolio of obligors. Hence, R_t has to reflect the risk of the portfolio of index constituents. Nevertheless, as the index PV is calculated as the weighted average of the constituents's PVs, there is no fundamental difference between the pricing of the iTraxx index and a e.g. a single name CDS. In the remainder we are concerned with identifying the determinants of R_t . The variables implied by structural models of credit risk are natural candidates. However, since R_t cannot be fully explained by these variables, additional factors determining R_t , such as illiquidity components have to be incorporated.

3.5 Data

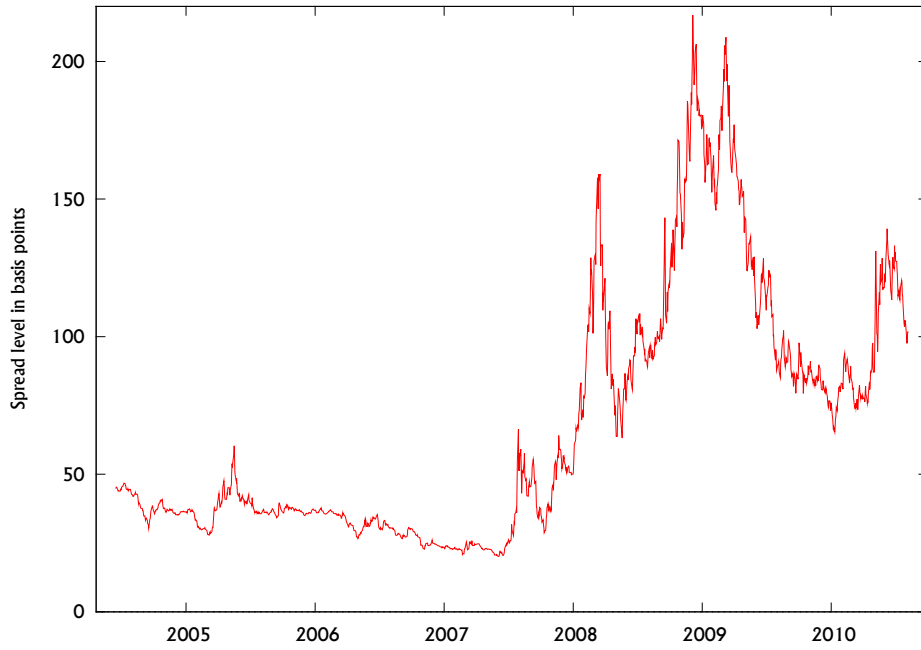
In this section we introduce the data set used for our empirical analysis. The iTraxx data is described in Section 3.5.1 and the independent variables used are introduced in Section 3.5.2.

3.5.1 iTraxx Spread Data

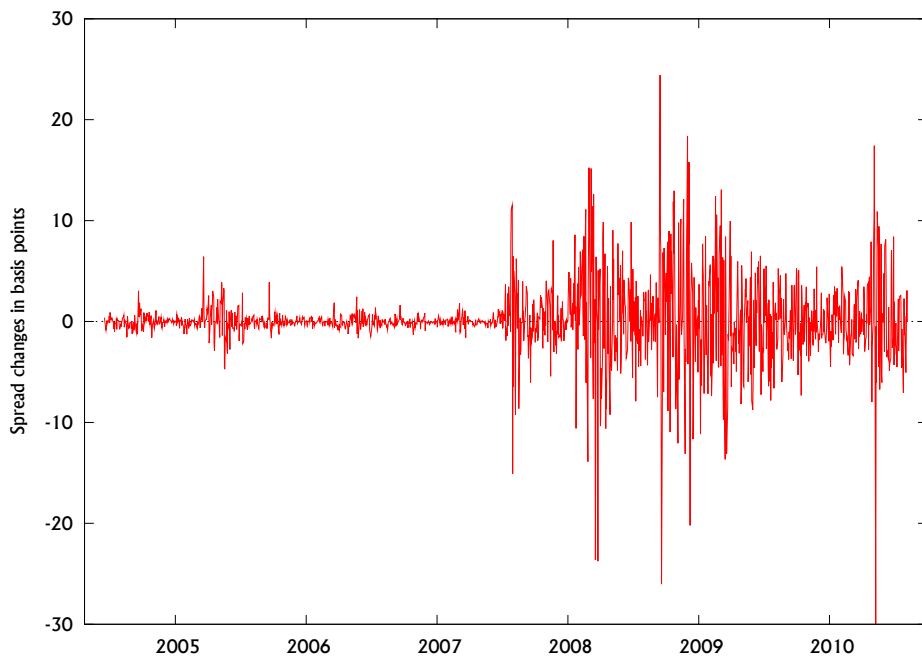
Our dataset consists of daily bid and ask quotes of the first 13 series of the iTraxx Europe benchmark index, as well as the subindices of the iTraxx Europe universe. We chose a tenor of five years as this is the most liquid maturity available. The sample ranges from June 16th 2004 to August 6th 2010 and comprises 1603 trading days. The sample is also split into three subsamples. Sample lengths are chosen according to the results of a Chow-breakpoint test with 5% significance level. Rather than analyzing every roll of the index on its own, we aggregate the single iTraxx series to form a single time series of iTraxx spreads for each (sub)index. This may lead to distortions, i.e. jumps in the index levels, as the index constituents change with every roll. However, the number of changes is moderate, thus there are no large spread differences between the single roll dates. The current index mid-spread is calculated as the arithmetic mean of the bid and ask quotes. The data set is obtained from Open Bloomberg. We analyze daily spread changes in order to have sufficient observations to obtain robust results, despite the large amount of independent variables and the fact that the sample is divided into subsamples. In the empirical analysis we focus on spread changes rather than on spread levels, since spread levels are non-stationary, as confirmed by a unit root test. A time series plot for both iTraxx spread levels and spread changes is shown in Figure 3.1.

The upper panel of Figure 3.1 illustrates the massive impact of the global financial crisis on the iTraxx Europe benchmark index. Since the first series of the iTraxx Europe index the mid-spread had declined steadily, besides a peak at May 2005 at about 60 basis points (bps) when Ford and general Motors were downgraded, from about 45 bps in June 2004 to the all-time

Figure 3.1: Time series plots of iTraxx Europe mid-spread levels (upper panel) and mid-spread changes (lower panel) throughout the entire sample ranging from 06/16/2004 to 08/06/2010 measured in basis points.



(a) iTraxx Europe spread levels



(b) iTraxx Europe spread changes

Table 3.1: Descriptive statistics

This table provides descriptive statistics for both, iTraxx Europe spread levels and spread changes between 06/16/2004 and 08/06/2010. spread levels and changes are measured in basis points.

	spread levels	spread changes
Mean	67.643	0.035
Median	44.000	-0.054
Minimum	20.159	-29.996
Maximum	216.870	24.427
Standard deviation	45.108	3.575
Skewness	1.069	-0.513
Excess kurtosis	0.20865	11.759

low of 20.159 bps in June 2007. After the outburst of the financial crisis in the second half of 2007, mid-spreads had risen massively and peaked at 216.870 bps in December 2008. Since then, the mid-spread had declined to about 100 bps at the end of our sample. Nevertheless, they ranged well above the levels between June 2004 and June 2007.

The lower panel of Figure 3.1 indicates that our sample comprises different volatility regimes throughout the sample. After a calm period between June 2004 and June 2007, we observe a period of very volatile spreads between the second half of 2007 and early 2009 as a result of the recent financial crisis. Since early 2009, spread volatility declined again but remained well above pre-crisis levels. This observation will be accounted for in our empirical investigation, by splitting the full sample into three subsamples. This is done to investigate whether the determinants of spread changes differ among the subsamples.

Summary statistics for both iTraxx Europe spread levels and spread changes are provided in Table 3.1. Neither iTraxx Europe spread levels, nor spread changes are normally distributed. Spread levels are skewed to the right and exhibit moderate excess kurtosis. Spread changes are skewed to the left and are subject to significant excess kurtosis. The mean spread level throughout our sample is 67.643 bps and the median spread level is 44 bps. Since spread levels change massively throughout the sample, with values ranging from 20.159 to 216.687 bps, the standard deviation of spread levels is quite high at 45.108 bps. The mean spread change throughout the sample is close to zero at 0.035 bps. Nevertheless, spread changes are highly volatile with a standard deviation of 3.575 bps. The high volatility is emphasized by the large gap between the minimum and the maximum spread change (-29.996 bps vs. 24.427 bps).

3.5.2 Independent Variables

The set of independent variables used is based on the theoretical methodology outlined in Section 3.4. Natural candidates to use for the regression analysis are the variables implied by structural models. Unfortunately not all factors implied by structural models are observable and therefore have to be proxied by observable factors. Furthermore, additional variables seem necessary, as variables implied by structural models fail to capture all the variation in credit spreads. Hence, we augment the set of variables used with liquidity, as well as global financial variables. In the remainder of this section we introduce the independent variables used for the empirical analysis and explain their theoretical influence on iTraxx Europe spread levels.

Variables implied by structural models

Structural models are appealing when it comes to explain the mechanics behind the default process of a company. Since the factors implied by structural models have a theoretical underpinning, it is straightforward to include them in an empirical investigation on spread determinants. The variables included in our econometric models are discussed below.

The risk-free rate

According to structural models the effects of the risk-free rate are twofold. On the one hand, an increasing risk-free rate leads to an increasing drift rate of the company value. The higher the drift rate, the more likely the company value is to remain above the default boundary and thus default risk decreases. On the other hand, a higher risk-free rate refers to a higher discount rate, which decreases the present value of future cash flows. This effect devalues the put option of the company's owners. Both effects imply that a rising risk-free rate should lead to a decrease in credit spreads. In the empirical analysis we use the one year Euribor rate as a proxy for the risk-free rate.

The company value

Another important factor in structural models is the company value. An increasing company value raises the distance-to-default of the respective entity. The distance-to-default measures the number of standard deviations the firm value lies above the default barrier. The higher the distance-to-default the more unlikely the entity is to hit the barrier, i.e. the lower the credit risk. Thus, an increasing company value theoretically leads to lower credit spreads. As the company value is not directly observable and we investigate spread changes rather than spread levels, we refer to stock returns as a proxy for changes in the company value.

To examine the effect of stock returns on iTraxx Europe spread changes we form equal weighted stock portfolios for every iTraxx series. The portfolio constituents comprise the constituents of the respective iTraxx series. If an iTraxx constituent has no traded stock or no stock data is available for the respective entity it is removed from the portfolio and the portfolio weights are adjusted accordingly. If the iTraxx constituent has no traded equity but is a subsidiary of a parent with traded equity, the parent is included into the portfolio. All equity prices are converted to Euro currency to avoid biases due to exchange rate effects. We calculate the log-return of the portfolios on a daily basis and aggregate the portfolio returns to a single time series to match the iTraxx time series. The equity data set is obtained from Thomson One Banker.

The volatility of the company value

Since structural models of credit risk rely on option pricing arguments, the volatility of the company value is another important driver of credit spreads. The higher the volatility the more valuable is the put option of the company owners and the less valuable is the value of the firms debt. Therefore, rising equity volatility leads to an increase of the respective company's spreads.

As the volatility of the company value is not directly observable stock volatility is used as a proxy. Therefore we calculate the standard deviation of the equity portfolios described above using a rolling window containing the preceding 20 return observations. The volatilities then are aggregated to a time series matching the iTraxx Europe time series.

The slope of the risk-free term structure

When the risk-free rate is assumed to be time-varying, an increasing slope of the yield curve implies a higher spot rate in the future. This is because an increasing slope causes forward rates to increase, which are similar to expected future spot rates. Hence, an increasing slope of the risk-free curve should lower credit spreads. We calculate the slope of the risk-free curve as the difference between the one year Euribor and the Eonia overnight rate.

Liquidity variables

In the empirical analysis we account for two possible sources of illiquidity effects. On the one hand illiquidity in the iTraxx Europe index itself could have a significant influence on the spreads. On the other hand equity market illiquidity is another possible factor priced.

Liquidity in the market for credit risk

We use the quoted bid-ask spread changes of the iTraxx Europe index as a proxy for illiquidity in the market for credit risk. Bid-ask spreads are widely used as liquidity proxies in empirical studies. Wider bid-ask spreads are a sign for growing illiquidity in the market. This in turn may be interpreted as a sign of growing market uncertainty and therefore rising risks in the market, which causes spreads to widen. Additionally, if investors demand a risk premium for illiquidity, the factor should be priced in iTraxx spreads and growing illiquidity should cause spreads to widen. Bid and ask quotes for the iTraxx Europe index are obtained from Open Bloomberg. The spread is calculated as the difference between the quoted bid and ask spread of the respective index.

Equity market illiquidity

Equity market illiquidity is another factor, which is believed to be priced in credit spreads. Das and Hanouna (2009) argue that equity market liquidity is priced in the market for credit risk due to hedging activities. If investors hedge their positions in the market for credit risk via equity markets, growing illiquidity causes hedges to be more expensive. This in turn will cause spreads to rise. Unfortunately, equity market liquidity, especially on a market or portfolio level, is not directly observable and difficult to proxy. To date several methods to measure market liquidity have been proposed. We employ the liquidity measure of Amihud (2002)

The measure of Amihud (2002) is based on the idea that in a perfectly liquid market, large trades should have no impact on prices as long as the trade is not induced by price relevant information. Therefore, equity market liquidity is expressed by the *AILLIQ*-measure, which relates price changes to trading volume. It is calculated as

$$AILLIQ_t = \frac{1}{N_t} \sum_{i=1}^{N_t} \frac{|R_{i,t}|}{VOLD_{i,t}}, \quad (3.4)$$

where N_t is the number of stocks at time t , $R_{i,t}$ is the time t return of stock i , and $VOLD_{i,t}$ is the daily trading volume in Euro currency (EUR) of stock i at time t .⁵ Since the *AILLIQ*-measure typically yields very small values, we multiply it by 10^6 to make it more manageable for our regression analysis.

Global financial variables

⁵Note that we do not take a time average of the ratio $\frac{|R_{i,t}|}{VOLD_{i,t}}$ as it is done by Amihud (2002) to dampen the effect of outliers. In our case this is achieved by taking the average over our stock portfolio.

We include several global financial variables, which account for macroeconomic effects into the econometric model. The recent financial crisis has shown that credit spreads do not seem to be solely driven by firm-specific data.

The state of the global economy

As a consequence of the globalization the state of the world economy is of rising importance for companies. A global recession will result in growing default rates around the world and will lead to higher credit spreads. To proxy for the state of the world economy we include the MSCI World log index returns as an explanatory variable in our econometric model. The data is obtained from Thomson One Banker.

Global market risk

Rising perceptions of global market risk, measured by implied stock market volatility, can be regarded as a sign of growing uncertainty in financial markets. This in turn will lead to higher spreads in credit markets, as defaults are more likely in times of market stress. We include the VStoxx implied volatility index as a measure of market risk. Besides measuring market risk, the VStoxx index has additional appeal for our empirical analysis, as it can be regarded as a proxy for the implied volatility of iTraxx constituents. Although we calculate the volatility of the equity portfolio including the members of the iTraxx index, this measure might not capture the perceptions of future volatility, which is the case for the VStoxx index.

Crisis indicator

In times of market distress many investors seek to curtail their risk exposure and invest in safe assets. A classical, so called safe harbor, is gold. Therefore we include gold price changes as a proxy for changes in the risk appetite of investors and the stability of financial markets. In times of distress, the risk appetite of investors and the stability of the market declines and investments such as gold become more popular, leading to rising gold prices. In times of crisis, defaults are more likely, so rising gold prices should lead to rising iTraxx spread levels. We employ daily gold price quotes from the London afternoon fixing and calculate daily log-returns of the gold price. The data is download from the website of Deutsche Bundesbank (www.buba.de).

Table 3.2: Independent variables included in the econometric model
 The table contains the explanatory variables used in the empirical analysis as well as the signs of regression coefficients as predicted by theory.

Explanatory Variable	Description	Predicted Sign
$\Delta Euribor$	Change in the Euribor rate	-
R_P	Return on the stock portfolio comprising iTraxx index constituents	-
ΔVol_P	Change of the trailing volatility of the stock portfolio comprising iTraxx index constituents	+
$\Delta Steep$	Change in the steepness of the risk-free curve	-
$\Delta Spread$	Change of the bid-ask spread of the iTraxx index	+
$\Delta AILLIQ$	Change in the Amihud-Liquidity measure for the stock portfolio comprising iTraxx index constituents	+
R_{MSCI}	Return on the MSCI World index	-
$\Delta VStoxx$	Change in the VStoxx volatility index	+
R_{Gold}	Return on the gold price	+
$\Delta iTraxx_{t-1}$	Lagged change of the iTraxx spread	+/-

Summary

Table 3.2 gives an overview of all variables included in the econometric model and signs of the regression coefficients predicted by theory.

3.6 Empirical Analysis

Our empirical analysis seeks to find answers to five research questions:

- What are the determinants of aggregate credit spread changes and consequently systemic risk?
- How do the determinants evolve throughout the recent financial crisis?
- Do the determinants differ for the single subindices?
- Do the determinants of aggregate credit spread changes differ within the various quantiles of the empirical distribution?
- Do market participants use information provided by aggregate credit spreads as a measure of systemic risk?

For this purpose we conduct our empirical analysis in the following way. First we examine the determinants of iTraxx spread changes and their evolution throughout the recent financial crisis by estimating an OLS-regression model. We analyze the iTraxx Europe benchmark index, as well as all of its subindices. Our goal is to achieve a better understanding of the drivers of systemic risk in financial markets and their underlying dynamics. The results are presented in Section 3.6.1. In order to check for the robustness of the OLS-regression results and to examine the performance of our set of independent variables in the upper and lower quantiles of the empirical distribution of spread changes, we additionally provide results for a quantile regression in Section 3.6.2. Finally, we investigate the lead-lag relationship between the market for credit risk and the stock market by estimating a VARX-model to assess whether the systematic risk component contained in iTraxx spreads is actually priced by market participants. If it is, iTraxx spread changes should not be led by stock returns. The results for the VARX-model are discussed in Section 3.6.3.

Using daily spread changes leaves us with sufficient observations under a division of our sample into subsamples. We split the sample into three subsamples based on the results of a Chow (1960) breakpoint test. Our analysis reveals that the null hypothesis of no structural break at a given date can be rejected at the 5 percent significance level and with a p-Value of 0.000 for July 2, 2007. The same holds for May 1, 2009 with a p-Value of 0.035. Given these results and the historical setting as outlined in Section 3.5.1, we label the first subsample as "pre-crisis" (June 16, 2004 to July 2, 2007), the second subsample as "crisis" (July 3, 2007 to May 1, 2009) and the final subsample as "post-crisis" (May 2, 2009 to August 6, 2010) period.

3.6.1 OLS-Regression Results

In this section we investigate the determinants of iTraxx spread changes. We check for the explanatory power of a large set of independent variables. Additionally, we investigate the evolution of spread determinants throughout the recent financial crisis. We perform the investigation for the whole sample period, as well as for three subsamples. These comprise a pre-crisis sample a crisis sample and a post-crisis sample. The sample lengths are chosen according to a Chow-breakpoint test with a significance level of 5%. We repeat the analysis for the benchmark index, as well as all subindices of the iTraxx index family. For this purpose we

estimate an OLS-model of the form

$$\begin{aligned} \Delta iTraxx_t = & \beta_0 + \beta_1 \Delta Euribor_t + \beta_2 R_{P,t} + \beta_3 \Delta Vol_{P,t} \\ & + \beta_4 \Delta Steep_t + \beta_5 \Delta Spread_t + \beta_6 \Delta AILLIQ_t \\ & + \beta_7 R_{MSCI,t} + \beta_8 \Delta VStoxx_t + \beta_9 R_{Gold,t} + \beta_{10} \Delta iTraxx_{t-1} + \epsilon_t, \end{aligned} \quad (3.5)$$

where $iTraxx_t$ is the level of the mid-iTraxx-spread at time t and ϵ_t is the error term.⁶ In order to account for possible heteroskedasticity and autocorrelation in the error term, we calculate Newey-West heteroskedasticity and autocorrelation consistent estimators.

The model described by equation (3.5) is estimated for the whole sample period, as well as for the single subsamples. Furthermore, we analyze spread changes of the iTraxx Europe benchmark index, as well as spread changes of the different subindices, i.e. the iTraxx HighVol, the iTraxx Senior Financials, the iTraxx Subordinated Financials and the iTraxx Non-Financials indices.

Regression results for the benchmark index

Table 3.3 contains the regression results for the benchmark index. In the first column the results for the full sample are summarized. As expected, the log return on the equal weighted stock portfolio comprising the constituents of the respective iTraxx series has a statistically, as well as economically significant influence on iTraxx spread changes. This is in line with results of previous empirical studies investigating the determinants of credit spreads. In contrast to other studies, neither the past volatility of the equity portfolio nor implied equity volatility has a statistically significant influence on credit spread changes. In general, the variables implied by structural models perform rather poor in explaining spread changes, besides equity returns. Neither the interest rate factors nor the volatility factors have a statistically significant influence. The same holds for the liquidity proxies.

The results for the global financial variables are mixed. The state of the global economy, as proxied by the return on the MSCI World index, is statistically significant at the 5% level. As expected, the regression coefficient is negative confirming theoretical arguments. Returns on gold and the Vstoxx index do not have a statistically significant influence in the full sample.

The AR(1) term is significant at the 1% level, suggesting that there is pronounced positive autocorrelation in spread changes of the benchmark index. This can be interpreted as under-reaction due to a lack of liquidity. The adjusted R-squared of the econometric model is quite

⁶The dependent variable in our regression model is spread changes rather than spread levels, as a Dickey-Fuller unit root test cannot reject the null of a unit root in iTraxx spread levels, which suggests non-stationarity in the spreads.

Table 3.3: OLS-regression results for the benchmark index

This table provides the regression coefficients and t-values of the OLS-model for the iTraxx Europe benchmark index. T-values are given in parentheses. Coefficients which are statistically significant differently from zero are marked with asterisks. * refers to a 10%, ** refers to a 5% and *** refers to a 1% level of significance. The results for the full sample period are given in the first panel. The second panel contains the results for the pre-crisis subsample, the third panel contains the results for the crisis subsample and the fourth panel contains the results for the post-crisis period.

	iTraxx Europe 5Y			
	Full sample	Pre-crisis	Crisis	Post-crisis
<i>const</i>	0.0247 (0.39)	0.0067 (0.26)	-0.0617 (-0.30)	-0.0039 (-0.03)
$\Delta Euribor_t$	-5.4489 (-1.16)	-1.1756 (-0.96)	-18.2117 (-2.19)**	25.4492 (1.42)
$R_{P,t}$	-128.0807 (-6.22)***	-25.8476 (-4.23)***	-160.8244 (-5.30)***	-145.2223 (-4.02)***
$\Delta Vol_{P,t}$	-230.4598 (-1.21)	-69.8637 (-0.76)	-96.8877 (-0.45)	-193.8085 (-0.62)
$\Delta Steep_t$	0.5357 (0.70)	-0.2205 (-0.91)	1.7187 (1.07)	-0.6719 (-0.49)
$\Delta Spread_t$	0.1482 (0.57)	0.7148 (1.33)	-0.0557 (-0.11)	0.3557 (1.56)
$\Delta AILLIQ_t$	0.0132 (0.20)	-0.0226 (-0.80)	-0.6809 (-0.14)	6.0326 (0.83)
$R_{MSCI,t}$	-42.0082 (-2.53)**	-2.7386 (-0.39)	-48.0169 (-2.09)**	-23.0503 (-0.60)
$\Delta VStoxx_t$	0.1280 (0.77)	0.2005 (3.12)***	-0.1178 (-0.64)	0.4411 (3.78)***
$R_{Gold,t}$	-11.2684 (-1.62)	-2.6852 (-1.71)*	-20.3185 (-1.47)	-7.6853 (-0.61)
$\Delta iTraxx_{t-1}$	0.0829 (3.33)***	0.2528 (5.62)***	0.0872 (2.33)**	0.0573 (1.50)
Adj. R ²	0.46	0.25	0.47	0.55

high at 0.46, hence our set of covariates is able to explain a significant part of the variation in iTraxx spread changes.

The results for the different subsamples provide some further insights into the mechanics behind credit spread changes. For the pre-crisis subsample the results differ from the full sample in many respects. Nevertheless, the autocorrelation is even more pronounced in the pre-crisis sample than in the full sample. Additionally, gold price changes have a statistically, as well as economically significant influence on iTraxx spreads. However, the regression coefficient is negative rather than positive implying that rising gold prices are accompanied by declining spreads. This contradicts the theoretical arguments discussed in Section 3.4. In contrast to the full sample results the implied volatility is significant at the 1% level for the pre-crisis period. The return on the stock portfolio is again significant at the 1% level. However, the absolute value of the regression coefficient is lower for the full sample (-128.0807 vs. -25.8476), suggesting that the sensitivity of spread changes to stock returns is less pronounced in the pre-crisis period. The adjusted R-squared of the model is significantly lower for the pre-crisis sample than for the full sample at 0.25.

Within the crisis sample the influence of the equity return is much more pronounced than within the pre-crisis period. The regression coefficient is more than six times higher than in the pre-crisis sample. None of the two volatility factors has a significant influence on iTraxx spreads during the crisis period. The Euribor rate is significant at the 5% level. The macroeconomic variables do not have a statistically significant influence on spread changes, except for the MSCI world index. The autocorrelation is still significant but less pronounced in the crisis period than in the pre-crisis period. Overall, the independent variables are able to explain about 47% of the variation in iTraxx spread changes during the crisis, almost twice than in the pre-crisis period. However, the level of determination is largely driven by stock returns.

For the post-crisis sample, the dominant factors are the ones implied by structural models, i.e. equity returns and equity volatility, although the realized equity volatility again has no significant influence. This may be attributed to the backward-looking manner the volatility is calculated. The AR(1) term is no longer significant at common confidence levels. The level of determination for the post-crisis sample is the highest of all subsamples with an adjusted R-squared of 0.55%.

The main results for the benchmark index can be summarized as follows. Equity returns are the predominant factor in iTraxx spread changes. The return of the equity portfolio underlying the iTraxx Europe index is highly significant, both statistically and economically, throughout all subsamples. The results for the other variables implied by structural models are less convincing. Implied equity volatility is significant in two of the three subsamples, but not during the recent

financial crisis. Liquidity variables do not play a role in the determination of spread changes of the benchmark index, regardless of the respective subsample. Global financial variables are significant in the pre-crisis and crisis period. Nevertheless, compared to stocks, they explain only a small share of the variation in iTraxx spread changes. The variables generally show mixed results and are insignificant in many cases. The same is true for the interest rate factors. Hence, variables other than equity volatility and equity returns have a limited influence on spread changes.

Our analysis provides strong evidence that the determinants of iTraxx spread changes are varying through time. The factor sensitivities of iTraxx spread changes vary significantly throughout the different subsamples. Furthermore, there is evidence that the factors priced change throughout our sample period. Although fewer factors seem to be priced in the post-crisis period than in the pre-crisis period, the level of determination is much higher for the post-crisis period. This suggests that market participants alter their models of aggregate credit risk when economic conditions change. In general, stock returns and stock market volatility explain most of the variation, especially in the pre- and the post-crisis sample. In the crisis sample, volatility has no significant influence on the spreads. In contrast, the influence of stock returns is even more pronounced in the crisis sample than in the other subsamples, while both volatility factors are not significant at common levels. Admittedly, this finding might be a specific feature of the recent financial crisis, which was characterized by a large systemic impact leading to high correlations of different segments of financial markets. MSCI world returns, are economically, as well as statistically significant in the crisis period, suggesting that concerns about global stability play a dominant role. The autocorrelation within the spread changes declines throughout the sample, suggesting that the liquidity of the benchmark index is generally rising.

Variables other than equity volatility and equity returns have a limited influence on the spreads of the benchmark index. Liquidity effects are not priced throughout all subsamples. The global financial variables show mixed results and are not significantly different from zero in many cases. The same is true for the interest rate factors.

Subindices

In a next step, we repeat the analysis conducted for the benchmark index for the different subindices. The results for the iTraxx HighVol and the iTraxx Senior Financials index are presented in Table 3.4. The results for the iTraxx Subordinated Financials and the Non-Financials index are presented in Table 3.5.

Table 3.4: OLS-regression results for the HighVol and the Senior Financials index

This table provides the regression coefficients and t-values of the OLS-model for the iTraxx Europe HighVol and the iTraxx Europe Senior Financials index. T-values are given in parentheses. Coefficients which are statistically significant differently from zero are marked with asterisks. * refers to a 10%, ** refers to a 5% and *** refers to a 1% level of significance. The results for the full sample period are given in the first and fifth panel. The second and sixth panel contain the results for the pre-crisis subsample, the third and seventh panel contain the results for the crisis subsample and the fourth and eighth panel contain the results for the post-crisis period.

	iTraxx Europe HighVol 5Y				iTraxx Europe Senior Financials 5Y			
	Full sample	Pre-crisis	Crisis	Post-crisis	Full sample	Pre-crisis	Crisis	Post-crisis
<i>const</i>	0.0237 (0.18)	0.0312 (0.55)	0.1937 (0.56)	-0.3028 (-1.19)	0.0418 (0.52)	-0.0046 (-0.34)	-0.1019 (-0.43)	0.0824 (0.41)
$\Delta Euribor_t$	-13.9927 (-1.20)	-3.6756 (-1.50)	-41.3795 (-2.24)**	64.3964 (1.11)	-3.2747 (-0.68)	-0.2933 (-0.39)	-13.1108 (-1.49)	8.3095 (0.41)
R_{Pt}	-231.7083 (-4.18)***	-49.4120 (-3.73)***	-249.8677 (-2.76)***	-314.7903 (-4.33)***	-117.4986 (-4.98)***	-3.6326 (-1.15)	-150.8209 (-4.56)***	-119.1615 (-3.11)***
ΔVol_{Pt}	-176.7083 (-0.86)	-86.6292 (-0.56)	-71.6415 (-0.24)	-272.3710 (-0.87)	-220.2770 (-1.01)	15.0110 (0.38)	-181.2451 (-0.80)	-167.0226 (-0.61)
$\Delta Steep_t$	1.6331 (1.22)	-0.5031 (-1.40)	2.7280 (0.96)	1.7639 (0.67)	1.0188 (1.08)	0.0154 (0.09)	3.0351 (1.56)	0.4671 (0.32)
$\Delta Spread_t$	0.0556 (0.26)	1.8832 (1.64)	0.2386 (0.37)	0.0578 (0.32)	0.2699 (0.92)	0.1748 (1.09)	0.3499 (0.68)	0.3381 (0.97)
$\Delta AILLIQ_t$	1.6457 (0.90)	45.1582 (1.03)	0.4980 (0.26)	426.4036 (0.65)	2.8417 (4.98)***	36.4261 (0.50)	2185.0000 (1.83)*	2.6084 (2.31)**
$R_{MSCI,t}$	-93.7207 (-1.95)*	-4.4299 (-0.32)	-137.2518 (-1.91)*	-5.9316 (-0.07)	-68.8336 (-3.93)***	1.3777 (0.44)	-47.5143 (-2.11)**	-118.1084 (-2.86)***
$\Delta VStoxx_t$	-0.0267 (-0.10)	0.3827 (2.95)***	-0.3405 (-0.96)	0.3143 (1.01)	0.0132 (0.06)	0.0948 (2.73)***	-0.3077 (-1.75)**	0.4996 (2.49)**
$R_{Gold,t}$	-34.3170 (-2.29)**	-7.4279 (-2.39)**	-58.3959 (-1.92)*	-28.9966 (-1.24)	-2.2281 (-0.25)	-2.3193 (-2.87)***	-4.9422 (-0.32)	4.7680 (0.21)
$\Delta iTraxx_{t-1}$	0.1372 (3.51)***	0.2745 (7.06)***	0.1112 (2.99)***	0.1396 (1.91)*	0.1015 (2.51)**	0.2457 (4.26)***	0.1282 (2.20)**	0.0526 (0.95)
Adj. R ²	0.42	0.25	0.46	0.47	0.33	0.13	0.31	0.47

Table 3.5: OLS-regression results for the Subordinated Financials and the Non-financials index

This table provides the regression coefficients and t-values of the OLS-model for the iTraxx Europe Subordinated Financials and the iTraxx Europe Non-financials index. T-values are given in parentheses. Coefficients which are statistically significant differently from zero are marked with asterisks. * refers to a 10%, ** refers to a 5% and *** refers to a 1% level of significance. The results for the full sample period are given in the first and fifth panel. The second and sixth panel contain the results for the pre-crisis subsample, the third and seventh panel contain the results for the crisis subsample and the fourth and eighth panel contain the results for the post-crisis period.

	iTraxx Europe Subordinated Financial 5Y				iTraxx Europe Non-Financial 5Y			
	Full sample	Pre-crisis	Crisis	Post-crisis	Full sample	Pre-crisis	Crisis	Post-crisis
<i>const</i>	0.0077 (0.05)	-0.0067 (-0.29)	-0.2677 (-0.56)	0.2458 (0.64)	0.0283 (0.40)	-0.0017 (-0.06)	0.3997 (1.34)	-0.0656 (-0.51)
$\Delta Euribor_t$	-3.2978 (-0.41)	-0.9031 (-0.85)	-20.5518 (-1.39)	46.6983 (0.95)	-10.8026 (-1.52)	-1.9411 (-1.50)	-26.6957 (-1.77)*	28.9645 (1.97)*
R_{Pt}	-215.6733 (-4.45)***	-5.6689 (-0.99)	-197.7773 (-3.40)***	-275.6367 (-2.85)***	20.7902 (0.30)	-16.0898 (-2.21)**	112.6188 (0.93)	-88.0182 (-2.53)**
ΔVol_{Pt}	-435.4552 (-1.28)	36.1936 (0.45)	-912.2576 (-1.90)*	-96.8945 (-0.25)	301.5863 (0.78)	-18.9163 (-0.22)	601.0763 (1.23)	-296.7918 (-0.83)
$\Delta Steep_t$	1.3676 (0.95)	-0.1317 (-0.77)	4.0659 (1.17)	1.6422 (0.64)	0.6498 (1.08)	-0.0840 (-0.32)	0.9967 (0.72)	1.0408 (0.70)
$\Delta Spread_t$	0.9736 (2.00)**	-0.1500 (-0.82)	1.5040 (2.34)**	0.6884 (1.21)	-0.0228 (-0.41)	0.5600 (14.14)***	-0.3311 (-0.41)	-0.0110 (-0.21)
$\Delta AILLIQ_t$	9.0370 (5.18)***	34.0135 (0.25)	3923.0051 (2.11)**	6.4415 (2.79)***	0.0040 (0.01)	0.0898 (-0.30)	-4.6283 (-0.53)	0.3537 (0.05)
$R_{MSCI,t}$	-123.9216 (-3.22)***	-3.5077 (-0.49)	-106.2147 (-2.59)**	-207.6965 (-1.90)*	-78.2387 (-1.83)*	1.6114 (0.19)	-126.8721 (-1.93)*	-29.3002 (-0.65)
$\Delta VStoxx_t$	0.0410 (0.14)	0.1697 (2.58)**	-0.0856 (-0.32)	0.4654 (1.34)	0.3212 (1.37)	0.2003 (3.35)***	0.3899 (1.14)	0.4378 (3.23)***
$R_{Gold,t}$	22.7619 (1.24)	-2.6440 (-2.01)**	60.8879 (1.79)*	10.6363 (0.22)	0.9236 (0.05)	-1.6713 (-1.03)	25.6385 (0.71)	-21.9907 (-0.90)
$\Delta iTraxx_{t-1}$	0.1152 (2.59)***	0.3142 (6.80)***	0.1273 (1.64)	0.0798 (1.79)*	0.0180 (0.38)	0.2364 (5.09)***	-0.0044 (-0.06)	0.0253 (0.59)
Adj. R ²	0.34	0.17	0.34	0.45	0.11	0.27	0.09	0.38

The results obtained from the regression analysis for the different subindices of the iTraxx Europe benchmark index are in many respects similar to the ones of the benchmark index. There is empirical evidence that stock returns are the major determinant of iTraxx spread changes. Stock market returns prove to be statistically significant in twelve out of 16 regressions for the different subindices. The other factors implied by structural models do not play such an important role as the stock market factor. Changes in the Euribor rate are significant in only three out of 16 cases. The steepness of the risk-free curve has no statistically influence for all subsamples and subindices. Implied equity volatility has a statistically significant influence in seven out of 16 cases. Again, previous findings of related empirical studies that credit spreads are especially sensitive towards volatility in times of crises are not confirmed.

Illiquidity effects are more pronounced for the subindices than for the benchmark index. Equity market illiquidity is priced in the Senior Financials index, as well as in the Subordinated Financials index. In contrast, equity market illiquidity has no statistically significant influence on the HighVol and the Non-Financials index. This results suggest that hedging needs of investors are especially pronounced when credit risk of financial institutions is borne. In line with the theoretical arguments provided by Das and Hanouna (2009), rising illiquidity in equity markets causes credit spreads to rise, as it makes hedging more expensive. The influence of equity market illiquidity is stronger within the crisis and post-crisis sample than in the pre-crisis sample, suggesting that illiquidity had a crucial role in the recent financial crisis. The fact that the sensitivity of iTraxx spread changes towards stock market liquidity is even more pronounced after the crisis suggests that market participants have altered their perception of the impact of stock liquidity on aggregate credit risk and have therefore altered their models as a consequence of the crisis. Illiquidity in the market for credit risk, as measured by the bid-ask spread of the respective index, does not have a significant influence except for the iTraxx Non-Financials index. This confirms that the iTraxx Non-financials index is generally the most illiquid of the subindices.

The results for the other independent variables are in line with the results for the benchmark index. Both the state of the global economy, as measured by the MSCI World index returns and gold price changes, are significantly related to credit spread changes. However, the effect of gold price changes is most pronounced during the pre-crisis period. In general, the additional explanatory power of the global financial variables is small compared to the stock returns and volatility and the gain from including them into a model of aggregate credit risk, which already accounts for stock returns, is minor.

Similar to the benchmark index the degree of autocorrelation in spread changes declines throughout the sample for all subindices. In the pre-crisis period, all subindices show statis-

tically significant positive autocorrelation. This suggests that the subindices underreact to new information, which can be interpreted as a lack of liquidity in the early years of the index family, which steadily declines as the iTraxx matures. During the post-crisis period only the iTraxx HighVol index shows significant autocorrelation. This suggests that the efficiency of the iTraxx index universe has risen significantly since the start of the index in 2004.

The results for the different subindices confirm the presence of variation in the determinants of iTraxx spread changes. As observed for the benchmark index, the degree of determination rises throughout the different subsamples, reaching the highest levels for the post-crisis period. In contrast, the number of factors necessary to explain spread changes seems to decline through time. In the post-crisis samples most of the variation in iTraxx spreads is explained by stock returns and implied stock market volatility, while other factors have limited or no influence.

3.6.2 Quantile Regression Results

In order to assess the robustness of the results obtained in the OLS-regression analysis in the upper and lower quantiles of the empirical distribution of spread changes we perform a quantile regression.⁷ This approach allows us to assess the performance of our set of explanatory variables in predicting spread changes in upper and lower quantiles of the empirical distribution. In other words, we analyze whether our set of explanatory variables is suited to predict large spread changes, either positive or negative. For our purpose we estimate the linear model described by equation (3.5) via quantile regression for the 0.25, the 0.50 and the 0.75 quantile of the empirical distribution. The results for the different subindices and subsamples are presented in Tables 3.6 to 3.10.

The results of the quantile regression are in many respects similar to the results of the OLS-regression. The return on the stock portfolio of index constituents is the predominant determinant of iTraxx spread changes. This result is robust for all quantiles and all subindices and subsamples, and statistically highly significant in almost every case. The regression coefficient generally is the highest for the upper 0.75 quantile, i.e. large spread widenings, except for the post-crisis period. This finding suggests that the dependence between asset classes has asymmetric features and is especially pronounced in downturns.

The results of the quantile regression confirm the results of the OLS-regression concerning the presence of varying determinants within the complete sample. Comparing the post-crisis sample results to the ones for pre-crisis sample, there is empirical evidence that different

⁷This approach was introduced by Koenker and Bassett (1978). According to Koenker and Hallock (2001) quantile regression models are models which express quantiles of the conditional distribution of the dependent variable as a function of observed covariates.

Table 3.6: Quantile regression results for the benchmark index

This table contains the regression coefficients and t-values of the quantile regression for the benchmark index. The regression is performed for the 0.25, the 0.50 and the 0.75 quantile (τ) of the empirical distribution. Coefficients which are statistically significantly different from zero are marked with asterisks. * refers to a 10%, ** refers to a 5% and *** refers to a 1% level of significance. The results for the full sample period are given in the first panel. The second panel contains the results for the pre-crisis subsample, the third panel contains the results for the crisis subsample and the fourth panel contains the results for the post-crisis period.

	τ	Full sample		Pre-crisis		Crisis		Post-crisis	
		coefficient	t-value	coefficient	t-value	coefficient	t-value	coefficient	t-value
const	0.25	-0.852	-13.69***	-0.261	-11.54***	-1.816	-5.90***	-1.503	-7.88***
	0.5	0.053	1.39	-0.002	-0.11	0.042	0.26	0.016	0.11
	0.75	1.005	15.77***	0.251	10.00***	1.739	7.78***	1.544	8.82***
$\Delta Euribor_t$	0.25	3.911	1.99**	-0.947	-1.02	-18.443	-1.78*	46.490	2.92***
	0.5	-2.051	-1.29	-2.240	-2.53**	-17.300	-3.05***	-8.007	-0.53
	0.75	-8.868	-4.64***	-2.413	-5.24***	-23.697	-3.52***	-26.360	-1.20
$R_{P,t}$	0.25	-85.882	-10.35***	-28.341	-5.26***	-136.375	-4.53***	-95.395	-3.84***
	0.5	-89.192	-17.49***	-27.646	-6.11***	-144.588	-8.31***	-127.206	-6.34***
	0.75	-113.896	-13.34***	-32.302	-6.36***	-163.178	-7.49***	-128.713	-5.08***
$\Delta Vol_{P,t}$	0.25	-114.847	-1.98**	-60.438	-1.87*	69.974	0.43	369.280	1.40
	0.5	131.754	3.53***	43.914	1.21	116.326	0.81	226.696	1.47
	0.75	313.335	4.70***	58.645	1.14	272.783	1.73*	-77.183	-0.39
$\Delta Steep_t$	0.25	0.578	1.16	-0.338	-1.32	1.179	0.48	-0.625	-0.38
	0.5	0.610	1.73*	0.024	0.12	2.496	2.21**	-0.388	-0.30
	0.75	0.862	1.65*	0.125	0.64	2.700	2.61**	-2.785	-1.71*
$\Delta Spread_t$	0.25	0.021	0.37	-0.041	-0.15	-0.330	-0.86	0.135	0.50
	0.5	0.059	1.04	0.114	0.39	-0.207	-0.93	0.037	0.15
	0.75	-0.104	-1.19	0.853	5.84***	-0.226	-0.93	0.143	0.61
$\Delta AILLIQ_t$	0.25	0.011	0.04	0.018	0.92	7.929	0.35	14.796	1.61
	0.5	-0.056	-0.55	-0.042	-1.47	-0.123	-0.02	-2.384	-0.35
	0.75	-0.088	-0.53	-0.047	-1.07	1.125	0.71	-4.442	-0.36
$R_{MSCI,t}$	0.25	-46.574	-5.08***	-3.038	-0.55	-59.413	-3.05***	-58.733	-2.29**
	0.5	-37.745	-7.08***	-1.318	-0.28	-70.342	-4.49***	-29.865	-1.42
	0.75	-49.893	-5.89***	0.039	0.01	-72.059	-3.18***	-17.517	-0.66
$\Delta VStoxx_t$	0.25	0.235	6.21***	0.084	2.31**	-0.090	-0.54	0.397	3.02***
	0.5	0.163	4.61***	0.048	1.47	-0.273	-2.47**	0.430	3.95***
	0.75	0.100	1.84*	0.060	1.56	-0.285	-1.75**	0.471	4.44***
$R_{Gold,t}$	0.25	-11.018	-2.90***	-4.204	-2.84***	-35.570	-2.40**	-15.376	-1.17
	0.5	-3.887	-1.48	-1.422	-1.01	-16.887	-1.98**	-19.957	-2.70***
	0.75	-4.198	-0.99	-0.390	-0.23	1.427	0.12	-18.871	-1.39
$\Delta iTraxx_{t-1}$	0.25	0.119	9.85***	0.210	22.86***	0.129	3.08***	0.031	0.73
	0.5	0.134	15.72***	0.214	10.04***	0.105	3.96***	0.064	2.00**
	0.75	0.107	9.69***	0.242	9.86***	0.100	3.10***	0.100	2.55**

Table 3.7: Quantile regression results for the HighVol index

This table contains the regression coefficients and t-values of the quantile regression for the HighVol index. The regression is performed for the 0.25, the 0.50 and the 0.75 quantile (τ) of the empirical distribution. Coefficients which are statistically significantly different from zero are marked with asterisks. * refers to a 10%, ** refers to a 5% and *** refers to a 1% level of significance. The results for the full sample period are given in the first panel. The second panel contains the results for the pre-crisis subsample, the third panel contains the results for the crisis subsample and the fourth panel contains the results for the post-crisis period.

	τ	Full sample		Pre-crisis		Crisis		Post-crisis	
		coefficient	t-value	coefficient	t-value	coefficient	t-value	coefficient	t-value
const	0.25	-1.407	-10.45***	-0.533	-10.19***	-2.804	-5.76***	-2.942	-8.82***
	0.5	0.089	1.31	0.003	0.09	0.262	1.05	-0.049	-0.17
	0.75	1.650	12.65***	0.546	9.73***	2.832	5.92***	2.675	9.24***
$\Delta Euribor_t$	0.25	4.639	1.87*	-0.659	-0.30	-30.135	-2.63***	126.727	2.76***
	0.5	-4.107	-1.44	-4.937	-2.86***	-35.923	-4.35***	28.005	0.56
	0.75	-22.630	-5.11***	-3.355	-1.67*	-40.169	-3.13***	-74.359	-2.15**
$R_{P,t}$	0.25	-161.499	-9.46***	-51.452	-3.98***	-147.386	-2.96***	-267.562	-5.25***
	0.5	-149.488	-18.95***	-67.489	-7.94***	-182.999	-6.16***	-188.481	-4.56***
	0.75	-180.661	-11.50***	-72.269	-5.82***	-245.426	-5.93***	-246.485	-12.56***
$\Delta Vol_{P,t}$	0.25	-326.665	-2.48**	-40.710	-0.46	-90.255	-0.22	-198.050	-0.92
	0.5	81.943	1.42	73.540	1.09	103.162	0.58	-357.365	-2.67***
	0.75	50.714	0.51	-17.550	-0.17	175.187	0.72	-746.537	-2.85***
$\Delta Steep_t$	0.25	0.091	0.09	-0.798	-2.28**	3.091	1.03	0.916	0.29
	0.5	0.585	1.29	-0.325	-1.48	3.610	1.79*	-0.403	-0.13
	0.75	2.280	2.96***	-0.423	-0.71	0.356	0.10	-2.996	-1.02
$\Delta Spread_t$	0.25	0.093	1.10	-0.156	-0.42	-0.078	-0.19	0.182	1.02
	0.5	-0.063	-0.95	0.141	0.46	-0.198	-0.72	0.107	0.62
	0.75	-0.032	-1.08	0.865	2.19**	-0.336	-0.74	0.150	0.56
$\Delta AILLIQ_t$	0.25	0.819	0.42	93.569	0.32	-1.768	-0.25	1124.860	1.49
	0.5	2.999	2.65***	468.983	1.97*	-0.411	-0.08	617.821	1.47
	0.75	0.682	1.16	560.193	1.73*	8.406	1.61	-1049.740	-2.08**
$R_{MSCI,t}$	0.25	-112.421	-7.57***	-7.705	-0.65	-213.530	-4.71***	-59.643	-1.07
	0.5	-98.199	-10.22***	-3.779	-0.40	-165.019	-5.90***	-135.779	-3.10***
	0.75	-91.951	-6.72***	14.740	1.08	-182.507	-3.21***	-67.207	-2.70***
$\Delta VStoxx_t$	0.25	0.047	0.60	0.200	2.12**	-0.266	-0.91	0.319	1.43
	0.5	-0.037	-1.19	0.064	1.04	-0.371	-2.99***	0.703	5.30***
	0.75	0.078	0.86	0.158	1.78*	-0.698	-3.10***	0.637	5.01***
$R_{Gold,t}$	0.25	-9.940	-1.64	-10.441	-4.25***	-38.878	-1.87*	-43.470	-1.59
	0.5	-7.157	-2.02**	-6.784	-2.89***	-8.968	-0.64	-7.682	-0.33
	0.75	-10.889	-1.89*	-2.377	-0.64	-10.404	-0.55	-29.362	-1.50
$\Delta iTraxx_{t-1}$	0.25	0.110	6.87***	0.260	9.45***	0.107	3.86***	0.148	3.26***
	0.5	0.144	29.73***	0.251	11.61***	0.145	6.25***	0.151	4.01***
	0.75	0.143	8.61***	0.307	9.48***	0.181	4.40***	0.063	2.21**

Table 3.8: Quantile regression results for the Senior Financials index

This table contains the regression coefficients and t-values of the quantile regression for the Senior Financials index. The regression is performed for the 0.25, the 0.50 and the 0.75 quantile (τ) of the empirical distribution. Coefficients which are statistically significantly different from zero are marked with asterisks. * refers to a 10%, ** refers to a 5% and *** refers to a 1% level of significance. The results for the full sample period are given in the first panel. The second panel contains the results for the pre-crisis subsample, the third panel contains the results for the crisis subsample and the fourth panel contains the results for the post-crisis period.

	τ	Full		Pre-crisis		Crisis		Post-Crisis	
		coefficient	t-value	coefficient	t-value	coefficient	t-value	coefficient	t-value
const	0.25	-0.851	-12.28***	-0.128	-11.34***	-2.052	-6.12***	-1.566	-5.43***
	0.5	0.057	1.47	-0.016	-2.05**	-0.190	-1.00	0.212	1.18
	0.75	1.067	11.80***	0.099	7.88***	1.970	6.59***	2.056	8.67***
$\Delta Euribor_t$	0.25	1.994	0.95	0.136	0.30	-14.675	-1.57	26.048	1.37
	0.5	-0.157	-0.09	-0.663	-1.76*	-18.351	-3.28***	-17.753	-0.87
	0.75	-8.770	-3.12***	-1.070	-2.35**	-15.588	-1.93*	-10.584	-0.65
$R_{P,t}$	0.25	-86.028	-10.26***	-4.435	-1.77*	-127.329	-3.59***	-114.974	-3.59***
	0.5	-62.981	-13.42***	-4.314	-2.10**	-120.621	-8.07***	-116.150	-4.48***
	0.75	-88.579	-7.91***	-7.467	-2.97***	-160.522	-4.66***	-99.557	-4.22***
$\Delta Vol_{P,t}$	0.25	-160.057	-4.49***	-8.806	-0.51	-260.076	-1.36	-14.456	-0.14
	0.5	-50.452	-1.08	20.205	1.29	-227.885	-1.67*	34.049	0.37
	0.75	113.954	1.73*	48.311	5.51***	222.916	1.67*	-141.372	-1.59
$\Delta Steep_t$	0.25	0.843	1.70*	-0.206	-1.99**	0.503	0.20	0.392	0.16
	0.5	0.436	1.45	0.072	0.76	3.288	3.70***	-0.381	-0.23
	0.75	0.491	0.89	0.062	0.41	0.940	0.41	-2.843	-1.86*
$\Delta Spread_t$	0.25	-0.042	-0.37	0.041	0.66	-0.242	-0.73	-0.132	-0.34
	0.5	-0.153	-1.99*	0.125	2.26**	0.095	0.35	-0.037	-0.13
	0.75	-0.117	-0.98	0.107	1.72*	0.263	0.57	0.332	1.11
$\Delta ALLIQ_t$	0.25	2.426	0.13	13.257	0.48	1579.460	1.11	-1.025	-0.03
	0.5	4.896	15.28***	-4.096	-0.14	362.955	0.37	3.252	1.54
	0.75	2.177	0.09	12.090	0.22	-866.668	-0.66	3.135	0.22
$R_{MSCI,t}$	0.25	-62.165	-9.24***	-2.015	-0.84	-66.968	-2.10**	-102.772	-3.10***
	0.5	-50.909	-13.33***	-0.600	-0.28	-59.870	-3.71***	-90.555	-3.24***
	0.75	-63.743	-6.33***	3.380	1.17	-63.284	-2.57**	-56.883	-2.02**
$\Delta VStoxx_t$	0.25	-0.013	-0.28	0.016	0.90	-0.393	-2.83***	0.209	1.39
	0.5	0.071	2.56**	-0.001	-0.06	-0.104	-1.05	0.232	2.60**
	0.75	0.093	1.76*	0.025	1.45	-0.383	-3.25***	0.683	6.01***
$R_{Gold,t}$	0.25	-6.928	-2.04**	-1.664	-2.35**	-15.177	-0.92	-17.850	-0.87
	0.5	-0.560	-0.22	-1.418	-2.07**	1.130	0.17	-14.746	-1.08
	0.75	0.935	0.21	-1.928	-2.22**	6.449	0.44	-13.791	-0.92
$\Delta iTraxx_{t-1}$	0.25	0.129	14.03***	0.167	6.43***	0.146	3.22***	0.114	3.00***
	0.5	0.091	13.06***	0.203	9.06***	0.055	1.96*	0.109	4.72***
	0.75	0.066	3.83***	0.254	11.28***	0.016	0.40	0.068	2.09**

Table 3.9: Quantile regression results for the Subordinated Financials index

This table contains the regression coefficients and t-values of the quantile regression for the Subordinated Financials index. The regression is performed for the 0.25, the 0.50 and the 0.75 quantile (τ) of the empirical distribution. Coefficients which are statistically significantly different from zero are marked with asterisks. * refers to a 10%, ** refers to a 5% and *** refers to a 1% level of significance. The results for the full sample period are given in the first panel. The second panel contains the results for the pre-crisis subsample, the third panel contains the results for the crisis subsample and the fourth panel contains the results for the post-crisis period.

	τ	Full		Pre-crisis		Crisis		Post-Crisis	
		coefficient	t-value	coefficient	t-value	coefficient	t-value	coefficient	t-value
const	0.25	-1.415	-11.65***	-0.205	-10.49***	-3.256	-5.91***	-2.970	-6.50***
	0.5	0.114	1.55	-0.020	-1.41	-0.114	-0.36	0.300	1.10
	0.75	1.761	12.57***	0.175	7.53***	2.881	6.74***	3.252	7.63***
$\Delta Euribor_t$	0.25	1.803	0.33	-0.279	-0.35	-31.460	-2.22**	63.642	1.65
	0.5	-0.434	-0.15	-0.661	-1.00	-17.332	-1.78*	26.374	1.21
	0.75	-14.381	-2.32**	-0.849	-1.23	-21.668	-1.78*	11.557	0.26
$R_{P,t}$	0.25	-127.845	-9.95***	-8.062	-2.00**	-237.462	-4.46***	-256.105	-4.69***
	0.5	-104.365	-10.47***	-8.240	-2.39**	-248.862	-8.84***	-168.582	-5.11***
	0.75	-131.944	-7.08***	-11.749	-2.53**	-249.115	-7.24***	-103.908	-2.03**
$\Delta Vol_{P,t}$	0.25	-459.121	-4.62***	24.531	1.51	-682.849	-2.57**	335.766	1.54
	0.5	-176.192	-1.72*	44.980	1.81*	-493.309	-3.63***	-186.497	-1.73*
	0.75	152.727	2.19**	87.175	2.12**	-349.383	-2.13**	-147.917	-1.00
$\Delta Steep_t$	0.25	1.312	2.21	-0.225	-1.13	5.225	1.41	2.437	0.70
	0.5	0.566	1.20	-0.005	-0.05	3.107	1.72*	-1.023	-0.59
	0.75	0.829	0.86	-0.032	-0.14	2.070	0.58	-3.284	-1.10
$\Delta Spread_t$	0.25	0.222	1.41	-0.033	-0.33	0.778	1.05	-0.118	-0.46
	0.5	-0.011	-0.48	-0.137	-1.98**	0.613	1.38	-0.160	-1.36
	0.75	-0.005	-0.04	-0.261	-2.72***	0.391	0.80	0.178	0.49
$\Delta AILLIQ_t$	0.25	10.703	0.37	-54.153	-0.60	2920.830	1.41	8.287	6.20***
	0.5	14.848	31.04***	1.971	0.06	1529.780	1.07	4.884	2.57**
	0.75	16.833	18.12***	-24.488	-0.24	910.995	0.57	17.626	0.34
$R_{MSCI,t}$	0.25	-79.033	-5.62***	-5.699	-1.68*	-46.143	-1.01	-205.545	-3.24***
	0.5	-77.186	-6.81***	-5.217	-1.51	-74.209	-2.72***	-212.227	-6.92***
	0.75	-127.047	-6.16***	-5.445	-1.13	-106.897	-3.80***	-231.760	-3.89***
$\Delta VStoxx_t$	0.25	0.431	3.83***	0.026	1.03	-0.391	-1.27	0.366	1.46
	0.5	0.342	7.41***	0.010	0.39	-0.426	-3.67***	0.975	5.70***
	0.75	0.211	1.76*	0.012	0.38	-0.615	-2.29**	1.025	3.21***
$R_{Gold,t}$	0.25	-0.634	-0.09	-1.233	-1.03	-0.684	-0.04	34.110	1.09
	0.5	-1.796	-0.41	-2.267	-2.03**	31.342	1.77*	19.103	0.96
	0.75	6.066	0.69	-3.576	-2.29**	41.014	2.68***	-6.666	-0.26
$\Delta iTraxx_{t-1}$	0.25	0.111	8.87***	0.230	10.77***	0.117	2.88***	0.078	3.54***
	0.5	0.124	25.73***	0.251	15.96***	0.100	4.09***	0.116	5.73***
	0.75	0.105	7.11***	0.324	11.41***	0.068	1.49	0.092	2.75***

Table 3.10: Quantile regression results for the Non-Financials index

This table contains the regression coefficients and t-values of the quantile regression for the Non-Financials index. The regression is performed for the 0.25, the 0.50 and the 0.75 quantile (τ) of the empirical distribution. Coefficients which are statistically significantly different from zero are marked with asterisks. * refers to a 10%, ** refers to a 5% and *** refers to a 1% level of significance. The results for the full sample period are given in the first panel. The second panel contains the results for the pre-crisis subsample, the third panel contains the results for the crisis subsample and the fourth panel contains the results for the post-crisis period.

	τ	Full sample		Pre-crisis		Crisis		Post-crisis	
		coefficient	t-value	coefficient	t-value	coefficient	t-value	coefficient	t-value
const	0.25	-0.627	-10.99***	-0.285	-11.77***	-0.424	-2.26**	-1.546	-8.34***
	0.5	-0.017	-0.62	-0.003	-0.16	0.000	0.00	0.061	0.38
	0.75	0.708	11.07***	0.269	10.67***	0.920	5.03***	1.597	8.15***
$\Delta Euribor_t$	0.25	0.622	0.26	-3.029	-2.61**	-2.520	-0.79	48.432	3.27***
	0.5	-3.017	-8.16***	-1.258	-1.37	0.000	0.00	23.742	1.37
	0.75	-9.637	-4.26***	-1.713	-1.50	-15.687	-2.61**	17.233	1.05
R_P	0.25	-21.038	-2.64***	-17.485	-3.09***	-9.305	-0.86	-106.970	-4.97***
	0.5	-19.116	-10.15***	-19.123	-4.17***	0.000	0.00	-102.571	-4.53***
	0.75	-47.072	-6.22***	-18.936	-3.20***	-23.864	-1.56	-63.581	-3.39***
$\Delta Vol_{P,t}$	0.25	106.945	2.91***	55.964	1.11	144.999	1.13	211.491	1.15
	0.5	116.130	6.72***	9.987	0.24	0.000	0.00	323.283	1.56
	0.75	316.136	5.60***	-3.465	-0.07	388.689	3.22***	67.629	0.27
$\Delta Steep_t$	0.25	-0.155	-0.39	0.097	0.50	0.029	0.03	0.632	0.89
	0.5	-0.157	-0.78	0.008	0.03	0.000	0.00	0.148	0.12
	0.75	0.580	1.54	-0.133	-1.24	1.241	1.06	0.919	1.33
$\Delta Spread_t$	0.25	0.006	0.37	0.472	15.02***	0.384	0.28	0.001	0.02
	0.5	-0.006	-0.46	0.508	14.30***	0.429	0.82	0.004	0.12
	0.75	-0.016	-0.93	0.538	13.03***	0.126	1.22	0.023	0.69
$\Delta AILLIQ_t$	0.25	0.012	0.10	-0.013	-0.54	-1.224	-0.25	8.916	1.48
	0.5	0.000	0.00	0.009	0.68	-0.014	0.00	-6.376	-1.05
	0.75	-0.079	-1.90*	-0.021	-0.58	1.721	0.26	-7.460	-2.00**
$R_{MSCI,t}$	0.25	-13.332	-2.25**	-8.927	-1.60	-8.080	-0.73	-31.426	-1.26
	0.5	-8.248	-2.81***	3.060	0.61	0.000	0.00	-26.049	-1.04
	0.75	-11.761	-1.82*	-1.250	-0.23	-21.846	-1.53	-25.540	-1.24
$\Delta VStoxx_t$	0.25	0.230	4.91***	0.052	1.22	-0.004	-0.06	0.224	1.81*
	0.5	0.143	8.58***	0.093	2.69***	0.000	0.00	0.243	1.98**
	0.75	0.176	3.91***	0.095	2.42**	0.048	0.58	0.414	3.50***
$R_{Gold,t}$	0.25	-11.874	-3.52	-3.798	-2.42	-6.648	-1.85	-6.921	-0.61
	0.5	-6.578	-4.56	-0.510	-0.34	0.000	0.00	-20.143	-1.62
	0.75	-8.436	-3.07	0.643	0.34	5.043	0.58	-36.005	-3.20
$\Delta iTraxx_{t-1}$	0.25	0.032	1.45	0.130	5.66***	-0.135	-8.93***	0.029	1.80*
	0.5	0.092	12.60***	0.201	9.63***	-0.037	-0.45	0.029	0.70
	0.75	0.117	7.52***	0.237	9.63***	0.081	1.12	0.071	2.04**

explanatory variables are significant in the single subsamples. This points to the fact that the pricing of the iTraxx by market participants has been reassessed in the light of the recent credit crisis.

In addition to confirming the major results of the OLS-regression, the quantile regression reveals some additional insights regarding the mechanics governing iTraxx spread changes. For example, the volatility of the stock portfolio shows some remarkable results for the quantile regression. When we look at the results for the full sample period (the first panel of Tables 3.6-3.10), there is a switch in the regression coefficient between the upper and the lower quantile. For the lower quantile the regression coefficient carries the wrong sign from a theoretical perspective. In general, the volatility is statistically significant for several quantiles and seems to be better suited in explaining large spread widenings than large spread tightenings. Hence, it provides valuable information for upper and lower quantiles of spread changes, although it is not significant in the OLS-regression.

The interest rate factor, proxied by the Euribor rate, shows some nonlinearities as well. The factor is statistically significant in the upper quantile in almost all cases, except for the post-crisis samples. In contrast, its predictive power is worse for the lower quantile, with the wrong sign of the regression coefficient in most cases. Just like the volatility of the equity portfolio, the Euribor rate has predictive power for large spread widenings, while showing inconsistent results for large spread tightenings.

The opposite is true for the gold price changes. Their statistical significance is generally higher in the lower quantile than in the upper quantile, i.e. gold price changes have higher explanatory power for large spread tightenings than large spread widenings. However, the sign of the regression coefficient is negative and not in line with theory.

The liquidity variables, especially the proxy for equity market illiquidity, perform best around the median of spread changes. Surprisingly, their predictive power in the upper and lower quantiles is statistically not significant, even for the subsamples and subindices where they have a statistical significant influence in the OLS-regression.

A look at the regression results for the constant reveals another interesting feature of iTraxx spread changes. In the preceding OLS-regression, the constant is not statistically different from zero for all subsamples and all subindices. In the quantile regression, the picture is different. The constant is statistically significantly different from zero at the 1%-level for all upper and all lower quantiles. This result is robust for all subsamples and all subindices. In contrast, the constant is not statistically significant different from zero for all median quantiles. It carries a negative sign for all lower quantiles and a positive sign for all upper quantiles. This suggests that our set of explanatory variables systematically underestimates large spread tightenings,

as well as large spread widenings.

This empirical finding leads to the conclusion that our set of explanatory variables is not able to explain a significant systematic fraction of spread changes in the upper and lower tail of the empirical distribution. Additional factors seem to be necessary to explain spread changes at the tails of the empirical distribution that are not implied by structural models. The liquidity variables, which seem to be natural candidates for predicting extreme spread movements fail to fulfill this task, having no statistically significant influence in the upper and lower quantiles.

3.6.3 The Lead-Lag Relationship Between the Market for Credit Risk and the Stock Market

In order to assess whether market participants use iTraxx Europe spreads as an additional source of information regarding systemic risk, we examine the lead-lag relationship between iTraxx spread changes and stock returns on the portfolio consisting of iTraxx constituents. For this purpose we estimate a VARX-model. The exogenous variables used in the model are supposed to jointly determine iTraxx spread changes, as well as stock returns. The set of exogenous variables used in the preceding OLS-regression are natural candidates. As these variables should in theory determine the creditworthiness of the index constituents, they in turn should drive stock returns as well. The same is true for the hedging arguments related to the liquidity variables. Using a VARX- instead of a simple VAR-model has the advantage that no biases due to omitted variables arise. The econometric representation of the VARX-model is of the form

$$\begin{aligned} \Delta iTraxx_t = & c_1 + \sum_{i=1}^4 \beta_{1,i} \Delta iTraxx_{t-i} + \sum_{i=1}^4 \gamma_{1,i} R_{P,t-i} + \lambda_{1,1} \Delta Euribor_t \\ & + \lambda_{1,2} \Delta Vol_{P,t} + \lambda_{1,3} \Delta Steep_t + \lambda_{1,4} \Delta Spread_t + \lambda_{1,5} \Delta AILLIQ_t \\ & + \lambda_{1,6} R_{MSCI,t} + \lambda_{1,7} \Delta VStoxx + \lambda_{1,8} R_{Gold,t} + \epsilon_{1,t} \end{aligned} \quad (3.6)$$

$$\begin{aligned} R_{P,t} = & c_2 + \sum_{i=1}^4 \beta_{2,i} \Delta iTraxx_{t-i} + \sum_{i=1}^4 \gamma_{2,i} R_{P,t-i} + \lambda_{2,1} \Delta Euribor_t \\ & + \lambda_{2,2} \Delta Vol_{P,t} + \lambda_{2,3} \Delta Steep_t + \lambda_{2,4} \Delta Spread_t + \lambda_{2,5} \Delta AILLIQ_t \\ & + \lambda_{2,6} R_{MSCI,t} + \lambda_{2,7} \Delta VStoxx + \lambda_{2,8} R_{Gold,t} + \epsilon_{2,t}. \end{aligned}$$

We choose a lag order of 4 lags, which is the model with the lowest value for the Hannan-

Table 3.11: VARX-regression results for the benchmark index

This table provides the regression coefficients and t-values of the VARX-model for the iTraxx Europe benchmark index. T-values are given in parentheses. Coefficients which are statistically significant differently from zero are marked with asterisks. * refers to a 10%, ** refers to a 5% and *** refers to a 1% level of significance. The results for the full sample period are given in the first panel. The second panel contains the results for the pre-crisis subsample, the third panel contains the results for the crisis subsample and the fourth panel contains the results for the post-crisis period.

	Full sample		Pre-crisis		Crisis		Post-crisis	
	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$
$\Delta iTraxx_{t-1}$	0.1405 (5.33)***	0.0000 (-0.11)	0.2611 (6.98)***	0.0001 (0.28)	0.1858 (3.42)***	0.0000 (-0.28)	0.0183 (0.36)	0.0001 (0.97)
$\Delta iTraxx_{t-2}$	-0.0904 (-3.38)***	0.0002 (2.50)**	-0.0617 (-1.57)	0.0002 (1.22)	-0.0449 (-0.81)	0.0001 (0.74)	-0.2134 (-4.12)***	0.0004 (2.96)***
$\Delta iTraxx_{t-3}$	-0.0651 (-2.39)**	0.0000 (0.47)	-0.0022 (-0.06)	-0.0003 (-1.50)	-0.1153 (-1.99)**	0.0001 (0.51)	-0.0497 (-0.97)	0.0001 (0.46)
$\Delta iTraxx_{t-4}$	-0.0858 (-3.17)***	0.0001 (1.12)	-0.0169 (-0.43)	0.0002 (1.20)	-0.0414 (-0.73)	0.0002 (1.37)	-0.1697 (-3.29)***	0.0000 (-0.25)
$R_{P,t-1}$	24.1083 (3.49)***	-0.0066 (-0.42)	-0.5533 (-0.13)	0.0003 (0.02)	44.8871 (2.98)***	-0.0207 (-0.65)	-11.7071 (-0.80)	0.0179 (0.53)
$R_{P,t-2}$	-25.4689 (-3.67)***	0.0555 (3.48)***	3.0922 (0.74)	0.0195 (0.91)	-20.2091 (-1.32)	0.0129 (0.40)	-61.7319 (-4.29)***	0.1363 (4.10)***
$R_{P,t-3}$	-11.5521 (-1.63)	-0.0021 (-0.13)	-2.0161 (-0.48)	0.0209 (0.98)	-8.5873 (-0.54)	0.0024 (0.07)	-24.1543 (-1.68)*	-0.0072 (-0.22)
$R_{P,t-4}$	-14.8114 (-2.10)**	0.0444 (2.73)***	1.5152 (0.36)	-0.0063 (-1.50)	3.7480 (0.24)	0.0727 (2.21)**	-54.5310 (-3.74)***	0.0256 (0.76)
const	0.0514 (0.72)	-0.0001 (-0.56)	-0.0002 (-0.01)	0.0003 (2.14)**	0.1946 (0.85)	-0.0010 (-2.05)**	0.0990 (0.60)	0.0000 (-0.05)
$\Delta Euribor_t$	-7.3211 (-2.11)**	0.0172 (2.15)**	-1.1653 (-0.81)	-0.0024 (-0.33)	-22.6257 (-2.98)***	0.0133 (0.83)	45.4544 (2.94)***	0.0096 (0.27)
$\Delta Vol_{P,t}$	-327.5970 (-3.77)***	1.0400 (5.20)***	-74.6520 (-1.21)	0.3903 (1.24)	-317.7549 (-1.64)	1.9413 (4.75)***	-265.3628 (-1.69)*	0.1780 (0.49)
$\Delta Steep_t$	0.5027 (0.71)	-0.0007 (-0.43)	-0.2953 (-0.90)	0.0029 (1.71)*	2.5078 (1.30)	-0.0011 (-0.28)	-0.2199 (-0.16)	-0.0061 (-1.97)*
$\Delta Spread_t$	0.1449 (1.04)	0.0002 (0.76)	1.3288 (3.21)***	0.0007 (0.31)	0.1467 (0.45)	-0.0008 (-1.16)	0.2229 (1.05)	0.0010 (2.10)**
$\Delta ALLLIQ_t$	0.0211 (0.11)	-0.0001 (-0.22)	-0.0179 (-0.36)	0.0000 (-0.04)	-4.8356 (-0.44)	0.0244 (1.06)	4.7632 (0.55)	-0.0128 (-0.64)
$R_{MSCI,t}$	-128.0997 (-15.25)***	0.6746 (34.85)***	-18.5060 (-2.80)***	0.5544 (16.39)***	-141.3565 (-7.93)***	0.6069 (16.16)***	-136.4626 (-7.82)***	0.7839 (19.42)***
$\Delta VStox_t$	0.5000 (10.26)***	-0.0030 (-26.29)***	0.2998 (6.82)***	-0.0043 (-19.23)***	0.3886 (3.88)***	-0.0030 (-14.131)***	0.8358 (8.12)***	-0.0028 (-11.56)***
$R_{Gold,t}$	-7.3422 (-1.35)	-0.0312 (-2.48)**	-3.0476 (-1.28)	-0.0063 (-0.52)	-14.1937 (-1.07)	-0.0648 (-2.32)**	-3.2729 (-0.26)	-0.0379 (-1.29)
Adj. R^2	0.42	0.79	0.24	0.73	0.42	0.81	0.54	0.80

Quinn information criterion (see Hannan and Quinn (1979)).

VARX-results for the benchmark index

The regression results for the benchmark index are given in Table 3.11. The first panel shows the results of for the full sample. The lead-lag relationship between the spread changes and the stock return is two-sided. While the second lag of spread changes is significant at the 1% level when regressing stock returns, the first, second and fourth lag of stock returns is significant when regressing spread changes. The regression coefficients for the second lag of iTraxx spread changes and the first lag of stock returns are positive. This is not in line with theory. In contrast, the coefficients for the second and fourth lag of stock returns are negative, which is in line with theoretical arguments. Hence, we conclude that there is a two-sided information flow between the two markets. This is a novel finding which is generally not in line with previous empirical findings and suggests that market participants actually use the iTraxx index as a source of additional information regarding systemic risk. However, information is flowing from stock markets to the iTraxx market quicker than vice versa.

In a next step we reestimate the VARX-model to examine the development of the lead-lag relationship throughout our sample period. The results for the different subsamples are given in panels one to four of Table 3.11. In the pre-crisis subsample, no lead-lag relationship between iTraxx spread changes and stock returns on the portfolio of iTraxx constituents can be observed. T-statistics for lagged spread changes are higher than for lagged stock returns, but do not reach common levels of significance.

During the crisis subsample stock returns lead spread changes. The first lag of stock returns is significant at the 1% level when regressing iTraxx spread changes, with a positive regression coefficient. The positive regression coefficient contradicts theoretical arguments. A possible explanation might be that shocks in the stock market tempt investors to invest in other asset classes, especially in crisis periods. Hence corporate bond spreads decline, leading to tighter iTraxx spread levels. In calm periods no such effect is observed. No other lags are significant at standard significance levels. New information is processed quickly, as only the first lag is significant.

In the post-crisis period, the results convey a different picture. We observe a two-sided relationship between the iTraxx spread changes and stock returns. The second lag of iTraxx spread changes is significant at the 1% level, while the second and fourth lagged stock returns are significant when regressing iTraxx spread changes at the 1% level. The regression coefficient of the second lag of iTraxx spread changes is not with theoretical predictions. A possible interpretation of this result might again be that shocks in credit markets tempt investors to invest in equity markets as a consequence of increasing hedging needs. In contrast to the opposite case, this seems to be the case only in calm periods and not during crises. The coefficients of lagged stock returns are in line with theory.

Concerning the exogenous variables, the VARX-results are generally in line with the OLS-regression results. Throughout the different subsamples different factors are needed to explain iTraxx spread changes, while the variation in iTraxx spread changes explained by the exogenous variables constantly rises throughout the sample.⁸

The results for the benchmark index lead us to the conclusion that credit and stock markets both play a role in processing new information, possibly concerning systemic risk. No market has an obvious lead over the other one. Furthermore, the relationship changes throughout our sample period. While lead-lag relationship can be observed in the pre-crisis subsample, stock returns lead spread changes during the recent financial crisis. In the aftermath of the crisis we observe a two-sided relationship. Hence, we conclude that the lead-lag relationship is subject

⁸Note that the explained variation measured in terms of the adjusted R-squared is generally lower than for the OLS-regression, although the same set of explanatory variables is used. This is due to the fact that contemporaneous stock returns are not included in the VARX-model, in contrast to the OLS-model.

Table 3.12: VARX-regression results for the HighVol index

This table provides the regression coefficients and t-values of the VARX-model for the iTraxx Europe HighVol index. T-values are given in parentheses. Coefficients which are statistically significantly different from zero are marked with asterisks. * refers to a 10%, ** refers to a 5% and *** refers to a 1% level of significance. The results for the full sample period are given in the first panel. The second panel contains the results for the pre-crisis subsample, the third panel contains the results for the crisis subsample and the fourth panel contains the results for the post-crisis period.

	Full sample		Pre-crisis		Crisis		Post-crisis	
	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$
$\Delta iTraxx_{t-1}$	0.1874 (7.01)***	0.0000 (-0.41)	0.2860 (7.68)***	0.0000 (0.47)	0.2091 (3.96)***	-0.0001 (-1.08)	0.0725 (1.35)	0.0001 (1.19)
$\Delta iTraxx_{t-2}$	-0.0273 (-1.00)	0.0000 (-0.11)	-0.0323 (-0.83)	0.0001 (0.59)	-0.0452 (-0.83)	0.0000 (-0.04)	-0.0463 (-0.85)	0.0000 (0.19)
$\Delta iTraxx_{t-3}$	-0.0838 (-3.03)***	0.0001 (2.19)**	-0.0181 (-0.46)	-0.0001 (-0.98)	-0.1504 (-2.66)***	0.0001 (1.34)	-0.0843 (-1.56)	0.0001 (1.08)
$\Delta iTraxx_{t-4}$	0.0288 (1.06)	0.0000 (0.88)	-0.0265 (-0.68)	0.0001 (1.45)	0.1215 (2.24)**	0.0001 (0.91)	-0.1327 (-2.44)**	0.0000 (0.26)
$R_{P,t-1}$	37.0876 (2.93)***	-0.0145 (-0.94)	1.5378 (0.18)	0.0015 (0.07)	67.0270 (2.59)**	-0.0389 (-1.25)	-25.5158 (-0.90)	0.0161 (0.51)
$R_{P,t-2}$	-26.7863 (-2.12)**	0.0244 (1.59)	7.8001 (0.91)	0.0129 (0.61)	-30.4209 (-1.17)	-0.0113 (-0.36)	-68.7980 (-2.46)**	0.0648 (2.06)**
$R_{P,t-3}$	-27.6353 (-2.14)**	0.0096 (0.62)	3.4805 (0.40)	0.0247 (1.17)	-27.2698 (-1.02)	0.0104 (0.32)	-56.4951 (-2.03)**	0.0031 (0.10)
$R_{P,t-4}$	8.0267 (0.62)	0.0417 (2.67)***	-3.2142 (-0.38)	-0.0028 (-0.13)	79.1761 (2.99)**	0.0527 (1.65)	-114.3776 (-4.03)***	0.0491 (1.54)
const	0.0469 (0.35)	-0.0001 (-0.54)	0.0077 (0.14)	0.0003 (2.08)**	0.5518 (1.35)	-0.0010 (-2.00)**	-0.1695 (-0.49)	0.0000 (0.07)
$\Delta Euribor_t$	-19.6870 (-2.98)***	0.0192 (2.40)**	-3.6218 (-1.21)	-0.0014 (-0.19)	-52.5534 (-3.91)**	0.0223 (1.38)	114.1309 (3.32)***	0.0080 (0.21)
$\Delta Vol_{P,t}$	-305.1222 (-1.98)**	0.6514 (3.49)***	-58.9561 (-0.50)	0.2284 (0.79)	-165.3728 (-0.52)	1.1409 (2.96)***	-588.1014 (-1.85)*	0.1503 (0.42)
$\Delta Steep_t$	1.8566 (1.36)	-0.0007 (-0.44)	-0.6279 (-0.92)	0.0027 (1.63)	4.7871 (1.37)	-0.0024 (-0.58)	1.5120 (0.54)	-0.0028 (-0.88)
$\Delta Spread_t$	-0.0074 (-0.06)	0.0003 (2.26)**	1.9257 (3.58)***	0.0000 (-0.03)	0.4247 (0.91)	-0.0004 (-0.78)	-0.0520 (-0.30)	0.0003 (1.81)*
$\Delta AILLIQ_t$	-0.5733 (-0.11)	0.0086 (1.32)	280.0000 (0.67)	2.1884 (2.12)**	-1.8050 (-0.23)	0.0082 (0.87)	86.2478 (0.14)	0.9699 (1.43)
$R_{MSCI,t}$	-247.0277 (-15.46)***	0.6771 (34.92)***	-33.4760 (-2.43)**	0.5538 (16.43)***	-277.2575 (-8.87)***	0.6071 (16.08)***	-243.7097 (-6.69)***	0.7835 (19.12)***
$\Delta Vstoxx_t$	0.6675 (7.27)***	-0.0029 (-26.10)***	0.5834 (6.40)***	-0.0044 (-19.49)***	0.4822 (2.76)***	-0.0029 (-13.85)***	1.2445 (5.88)***	-0.0027 (-11.53)***
$R_{Gold,t}$	-28.7768 (-2.77)***	-0.0277 (-2.20)**	-7.9675 (-1.60)	-0.0100 (-0.82)	-46.3355 (-1.96)*	-0.0651 (-2.28)**	-28.8391 (-1.09)	-0.0215 (-0.72)
Adj. R ²	0.38	0.79	0.24	0.74	0.43	0.80	0.43	0.80

to variation, as it is the case for the determinants of spread changes.

VARX-results for the subindices

The results for the different subindices are given in Tables 3.12 to 3.15. The empirical findings for the different subindices confirm the results for the benchmark index in most respects. In the full sample we observe a two-sided relationship between iTraxx and spread changes for three out of four indices. Stock returns lead spread changes only for the iTraxx Non-Financial index. However, lagged stock returns are better suited to explain spread changes than vice versa, as more coefficients differ significantly from zero when regressing spread changes against lagged stock returns compared to the results when regression stock returns against lagged spread changes. This suggests that stock markets are faster in processing relevant information than the iTraxx index universe due to their higher liquidity.

In the pre-crisis sample no lead-lag relationship is observed for all subindices. In contrast, stock returns lead spread changes during the crisis period for all subindices except the Non-Financials index. Interestingly, only the first lag of stock returns has a regression coefficient statistically different from zero. All other lags cannot be distinguished from zero for

Table 3.13: VARX-regression results for the Senior Financials index

This table provides the regression coefficients and t-values of the VARX-model for the iTraxx Europe Senior Financials index. T-values are given in parentheses. Coefficients which are statistically significantly different from zero are marked with asterisks. * refers to a 10%, ** refers to a 5% and *** refers to a 1% level of significance. The results for the full sample period are given in the first panel. The second panel contains the results for the pre-crisis subsample, the third panel contains the results for the crisis subsample and the fourth panel contains the results for the post-crisis period.

	Full sample		Pre-crisis		Crisis		Post-crisis	
	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$
$\Delta iTraxx_{t-1}$	0.1588 (6.11)***	0.0000 (0.17)	0.2222 (6.05)***	0.0000 (0.13)	0.2132 (4.00)***	0.0001 (0.77)	0.0601 (1.16)	0.0000 (-0.58)
$\Delta iTraxx_{t-2}$	-0.0949 (-3.61)***	0.0000 (0.91)	0.0263 (0.70)	0.0002 (0.39)	-0.1063 (-1.94)*	0.0000 (0.23)	-0.1297 (-2.62)***	0.0001 (1.77)*
$\Delta iTraxx_{t-3}$	-0.0380 (-1.41)	0.0001 (2.07)**	0.0191 (0.50)	-0.0003 (-0.77)	-0.0415 (-0.73)	0.0000 (0.20)	-0.0900 (-1.75)*	0.0002 (2.30)**
$\Delta iTraxx_{t-4}$	-0.1325 (-4.92)***	0.0000 (-0.08)	0.0148 (0.39)	0.0001 (0.23)	-0.0998 (-1.76)*	0.0001 (1.04)	-0.1446 (-2.82)***	-0.0001 (-1.19)
$R_{P,t-1}$	32.7991 (4.12)***	-0.0085 (-0.59)	-4.0557 (-2.08)**	-0.0061 (-0.31)	55.3943 (3.51)***	-0.0067 (-0.25)	6.6538 (0.33)	-0.0249 (-0.77)
$R_{P,t-2}$	-25.9160 (-3.25)***	0.0390 (2.72)***	1.4735 (0.76)	0.0059 (0.30)	-14.1019 (-0.88)	0.0019 (0.07)	-71.9146 (-3.84)***	0.1069 (3.50)***
$R_{P,t-3}$	-4.1297 (-0.51)	0.0078 (0.54)	-3.7446 (-1.94)*	0.0311 (1.56)	6.8789 (0.42)	-0.0019 (-0.07)	-28.5238 (-1.50)	0.0187 (0.61)
$R_{P,t-4}$	-12.6434 (-1.55)	0.0321 (2.19)**	-1.1761 (-0.61)	-0.0165 (-0.83)	8.7054 (0.53)	0.0666 (2.35)**	-52.0262 (-2.70)***	0.0070 (0.22)
const	0.0702 (0.77)	-0.0001 (-0.56)	-0.0012 (-0.10)	0.0003 (2.07)**	0.2372 (0.87)	-0.0010 (-2.11)***	0.2301 (0.97)	0.0000 (-0.04)
$\Delta Euribor_t$	-4.7167 (-1.06)	0.0182 (2.27)**	-0.1676 (-0.23)	-0.0013 (-0.17)	-16.0948 (-1.76)*	0.0093 (0.59)	21.4288 (0.99)	0.0273 (0.78)
$\Delta Vol_{P,t}$	-231.5547 (-3.69)***	0.6120 (5.42)***	6.9056 (0.25)	0.1481 (0.53)	-311.8259 (-1.91)*	1.6576 (5.87)***	-179.9884 (-1.77)*	-0.0056 (-0.03)
$\Delta Steep_t$	1.1327 (1.25)	-0.0004 (-0.26)	0.0233 (0.14)	0.0030 (1.80)*	3.8177 (1.67)*	-0.0003 (-0.08)	0.5732 (0.30)	-0.0033 (-1.06)
$\Delta Spread_t$	0.1408 (0.65)	0.0011 (2.87)***	0.1935 (2.06)**	-0.0016 (-1.69)*	0.0713 (0.15)	0.0021 (2.55)**	0.3063 (0.82)	0.0003 (0.56)
$\Delta ALLIQ_t$	4.8699 (1.42)	-0.0109 (-1.77)*	36.1214 (0.59)	-0.4326 (-0.69)	2320.0000 (1.85)*	0.0803 (0.04)	4.5440 (1.05)	-0.0117 (-1.66)*
$R_{MSCI,t}$	-152.5539 (-14.25)***	0.6750 (35.09)***	0.7427 (0.23)	0.5581 (16.53)***	-131.3070 (-6.17)***	0.6051 (16.48)***	-207.0969 (-8.12)***	0.7817 (18.82)***
$\Delta Vstox_t$	0.3211 (5.13)***	-0.0030 (-26.43)***	0.1204 (5.56)***	-0.0042 (-19.06)***	0.2068 (1.72)*	-0.0031 (-15.07)***	0.8323 (5.37)***	-0.0028 (-11.00)***
$R_{Gold,t}$	1.3125 (0.19)	-0.0333 (-2.66)***	-2.0667 (-1.75)*	-0.0061 (-0.50)	0.2199 (0.01)	-0.0773 (-2.82)***	6.0247 (0.33)	-0.0291 (-0.99)
Adj. R^2	0.33	0.79	0.13	0.73	0.30	0.82	0.48	0.80

Table 3.14: VARX-regression results for the Subordinated Financials index

This table provides the regression coefficients and t-values of the VARX-model for the iTraxx Europe Subordinated Financials index. T-values are given in parentheses. Coefficients which are statistically significantly different from zero are marked with asterisks. * refers to a 10%, ** refers to a 5% and *** refers to a 1% level of significance. The results for the full sample period are given in the first panel. The second panel contains the results for the pre-crisis subsample, the third panel contains the results for the crisis subsample and the fourth panel contains the results for the post-crisis period.

	Full sample		Pre-crisis		Crisis		Post-crisis	
	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$
$\Delta iTraxx_{t-1}$	0.1648 (6.33)***	0.0000 (-0.01)	0.3423 (9.28)***	-0.0001 (-0.30)	0.2011 (3.83)***	0.0000 (0.37)	0.0805 (1.53)	0.0000 (-0.32)
$\Delta iTraxx_{t-2}$	0.0053 (0.20)	0.0000 (1.67)*	-0.1299 (-3.30)***	0.0002 (0.95)	0.0094 (0.18)	0.0000 (0.88)	-0.0252 (-0.49)	0.0001 (2.17)**
$\Delta iTraxx_{t-3}$	-0.0016 (-0.06)	0.0000 (0.02)	0.0392 (0.98)	-0.0002 (-0.84)	-0.0381 (-0.68)	0.0000 (-0.88)	-0.0102 (-0.19)	0.0000 (0.08)
$\Delta iTraxx_{t-4}$	-0.1013 (-3.78)***	0.0000 (0.95)	-0.0310 (-0.82)	0.0003 (1.19)	-0.0773 (-1.41)	0.0001 (0.96)	-0.1116 (-2.07)**	0.0000 (0.09)
$R_{P,t-1}$	58.1985 (4.00)***	-0.0093 (-0.65)	-5.3733 (-1.50)	-0.0080 (-0.39)	100.2335 (3.65)***	-0.0121 (-0.44)	12.1946 (0.32)	-0.0187 (-0.58)
$R_{P,t-2}$	-12.9224 (-0.89)	0.0415 (2.91)***	1.2138 (0.34)	0.0103 (0.52)	5.5821 (0.20)	0.0047 (0.17)	-55.1271 (-1.52)	0.1041 (3.36)***
$R_{P,t-3}$	14.3416 (0.96)	-0.0083 (-0.57)	-4.9964 (-1.40)	0.0323 (1.61)	46.6232 (1.65)	-0.0109 (-0.39)	-50.1585 (-1.38)	-0.0206 (-0.67)
$R_{P,t-4}$	-35.5997 (-2.40)**	0.0389 (2.69)***	-4.1212 (-1.16)	-0.0114 (-0.57)	-11.6791 (-0.41)	0.0606 (2.17)**	-110.4516 (-2.95)***	0.0300 (0.94)
const	0.0370 (0.22)	-0.0001 (-0.56)	-0.0037 (-0.16)	0.0003 (2.11)**	0.2287 (0.48)	-0.0010 (-2.12)**	0.4471 (0.97)	0.0000 (-0.03)
$\Delta Euribor_t$	-7.5904 (-0.93)	0.0172 (2.14)**	-0.6792 (-0.52)	-0.0014 (-0.19)	-29.2012 (-1.83)*	0.0077 (0.49)	61.7045 (1.47)	0.0242 (0.68)
$\Delta Vol_{P,t}$	-498.4757 (-4.32)***	0.6185 (5.47)***	32.2146 (0.65)	0.1431 (0.51)	-1005.2620 (-3.48)***	1.6760 (5.86)***	-224.7501 (-1.15)	0.0513 (0.31)
$\Delta Steept$	1.4730 (0.88)	-0.0005 (-0.29)	-0.1483 (-0.50)	0.0030 (1.79)*	5.4303 (1.35)	-0.0002 (-0.06)	1.9111 (0.53)	-0.0041 (-1.34)
$\Delta Spread_t$	1.0187 (4.33)***	-0.0001 (-0.29)	-0.1304 (-0.92)	-0.0010 (-1.25)	1.5173 (2.82)***	-0.0005 (-0.90)	0.5918 (1.50)	0.0001 (0.34)
$\Delta AILLIQ_t$	12.5600 (1.98)**	-0.0114 (-1.83)*	50.4124 (0.46)	-0.4422 (-0.71)	4300.0000 (1.96)*	-0.0894 (-0.04)	8.5070 (1.02)	-0.0102 (-1.44)
$R_{MSCI,t}$	-276.5923 (-14.08)***	0.6769 (35.19)***	-4.1316 (-0.69)	0.5519 (16.31)***	-221.8832 (-6.02)***	0.5882 (16.09)***	-426.4380 (-8.64)***	0.7957 (18.96)***
$\Delta Vstox_t$	0.6031 (5.29)***	-0.0029 (-26.26)***	0.2110 (5.35)***	-0.0043 (-19.19)***	0.4931 (2.36)**	-0.0032 (-15.32)***	1.1607 (3.95)***	-0.0026 (-10.54)***
$R_{Gold,t}$	26.3088 (2.05)**	-0.0318 (-2.53)**	-2.1285 (-0.98)	-0.0070 (-0.57)	71.9650 (2.57)**	-0.0703 (-2.54)**	3.4059 (0.10)	-0.0341 (-1.14)
Adj. R ²	0.32	0.79	0.19	0.74	0.35	0.82	0.44	0.80

Table 3.15: VARX-regression results for the Non-Financials index

This table provides the regression coefficients and t-values of the VARX-model for the iTraxx Europe Non-Financials index. T-values are given in parentheses. Coefficients which are statistically significantly different from zero are marked with asterisks. * refers to a 10%, ** refers to a 5% and *** refers to a 1% level of significance. The results for the full sample period are given in the first panel. The second panel contains the results for the pre-crisis subsample, the third panel contains the results for the crisis subsample and the fourth panel contains the results for the post-crisis period.

	Full sample		Pre-crisis		Crisis		Post-crisis	
	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$	$\Delta iTraxx_t$	$R_{P,t}$
$\Delta iTraxx_{t-1}$	-0.0030 (-0.12)	-0.0001 (-1.62)	0.2229 (6.54)***	0.0000 (-0.02)	0.2011 (3.83)***	0.0000 (0.37)	0.0805 (1.53)	0.0000 (-0.32)
$\Delta iTraxx_{t-2}$	-0.0657 (-2.54)**	0.0000 (0.98)	0.0136 (0.39)	0.0001 (0.65)	0.0094 (0.18)	0.0000 (0.88)	-0.0252 (-0.49)	0.0001 (2.17)**
$\Delta iTraxx_{t-3}$	-0.0471 (-1.79)*	-0.0001 (-1.12)	0.0060 (0.17)	0.0000 (-0.14)	-0.0381 (-0.68)	0.0000 (-0.88)	-0.0102 (-0.19)	0.0000 (0.08)
$\Delta iTraxx_{t-4}$	-0.0766 (-2.98)***	0.0000 (0.23)	0.0498 (1.46)	0.0002 (0.93)	-0.0773 (-1.41)	0.0001 (0.96)	-0.1116 (-2.07)**	0.0000 (0.09)
$R_{P,t-1}$	-8.3902 (-1.30)	-0.0128 (-1.03)	-5.9762 (-1.46)	-0.0017 (-0.08)	100.2335 (3.65)***	-0.0121 (-0.44)	12.1946 (0.32)	-0.0187 (-0.58)
$R_{P,t-2}$	-12.0634 (-1.87)*	0.0293 (2.34)**	2.1438 (0.53)	0.0120 (0.59)	5.5821 (0.20)	0.0047 (0.17)	-55.1271 (-1.52)	0.1041 (3.36)***
$R_{P,t-3}$	-25.1629 (-3.84)***	-0.0162 (-1.28)	-1.4866 (-0.37)	0.0344 (1.70)*	46.6232 (1.65)	-0.0109 (-0.39)	-50.1585 (-1.38)	-0.0206 (-0.67)
$R_{P,t-4}$	-14.3395 (-2.19)**	0.0274 (2.16)**	4.5720 (1.14)	-0.0082 (-0.41)	-11.6791 (-0.41)	0.0606 (2.17)**	-110.4516 (-2.95)***	0.0300 (0.94)
const	0.0411 (0.48)	-0.0001 (-0.46)	-0.0038 (-0.14)	0.0003 (2.04)	0.2287 (0.48)	-0.0010 (-2.12)**	0.4471 (0.97)	0.0000 (-0.03)
$\Delta Euribor_t$	-9.1635 (-2.21)**	0.0192 (2.39)**	-2.0861 (-1.40)	-0.0012 (-0.17)	-29.2012 (-1.83)*	0.0077 (0.49)	61.7045 (1.47)	0.0242 (0.68)
$\Delta Vol_{P,t}$	226.3420 (1.95)*	0.9222 (4.10)***	-34.6043 (-0.55)	0.4903 (1.56)	-1005.2620 (-3.48)***	1.6760 (5.86)***	-224.7501 (-1.15)	0.0513 (0.31)
$\Delta Steep_t$	0.4305 (0.51)	-0.0007 (-0.45)	-0.1152 (-0.34)	0.0030 (1.76)*	5.4303 (1.35)	-0.0002 (-0.06)	1.9111 (0.53)	-0.0041 (-1.34)
$\Delta Spread_t$	-0.0223 (-0.66)	0.0001 (0.84)	0.5624 (11.96)***	0.0000 (-0.17)	1.5173 (2.82)***	-0.0005 (-0.90)	0.5918 (1.50)	0.0001 (0.34)
$\Delta ALLIQ_t$	-0.0033 (-0.02)	-0.0001 (-0.18)	-0.0082 (-0.20)	0.0000 (-0.06)	4300.0000 (1.96)*	-0.0894 (-0.04)	8.5070 (1.02)	-0.0102 (-1.44)
$R_{MSCI,t}$	-62.7936 (-6.28)***	0.6815 (35.16)***	-5.6313 (-0.83)	0.5540 (16.37)***	-221.8832 (-6.02)***	0.5882 (16.09)***	-426.4380 (-8.64)***	0.7957 (18.96)***
$\Delta Vstox_t$	0.2534 (4.36)***	-0.0029 (-25.79)***	0.2797 (6.26)***	-0.0043 (-19.30)***	0.4931 (2.36)**	-0.0032 (-15.32)***	1.1607 (3.95)***	-0.0026 (-10.54)***
$R_{Gold,t}$	0.2902 (0.04)	-0.0279 (-2.21)**	-1.4285 (-0.58)	-0.0079 (-0.65)	71.9650 (2.57)**	-0.0703 (-2.54)**	3.4059 (0.10)	-0.0341 (-1.14)
Adj. R^2	0.13	0.79	0.27	0.73	0.35	0.82	0.44	0.80

all subindices. This can be interpreted as a sign that investors are especially sensitive to new information in times of crises and therefore incorporate new information promptly.

In the post-crisis period we observe a two-sided relationship for all subindices except for the HighVol index, where stock returns lead spread changes. For the Senior Financials and the Subordinated Financials index, the predictive power of lagged spread changes when regressed against stock returns is equal to the predictive power when regressing spread changes against lagged stock returns or even slightly higher. The lead-lag relationship has shifted in favor of lagged spread changes in the aftermath of the crisis. This is true for all but one index, and most pronounced for the two financial indices. As the financial sector is widely believed to contribute significantly to systemic risk, this actually leads us to the conclusion that the iTraxx index contains useful information regarding systemic risk that is actually incorporated by market participants.

Again, there is empirical evidence that there is variation in the lead-lag relationship between the market for credit risk and stock markets. While stock returns lead spread changes in the crisis period, no apparent lead-lag relationship between the two can be observed in the pre-crisis period. In the post crisis period we observe a two-sided relationship between the two markets. In general, the results suggest that the role of credit markets in processing firm specific information has strengthened through time. Thus, systemic risk measured in credit markets is priced in equity markets and it is necessary to rely on information from both markets when one engages in trading or hedging.

3.7 Conclusion

This paper empirically investigates the behavior of iTraxx Europe spread changes around the 2007-2009 financial crisis. The iTraxx index universe is of special interest, as iTraxx spreads can be interpreted as a measure of systemic risk. We examine the determinants of iTraxx spread changes, as well as changes in these determinants due to the recent financial crisis. We find empirical evidence that iTraxx spread change determinants are subject to variation in the course of the financial crisis. While stock returns and implied stock market volatility explain most of the variation in the post crisis period, global variables have a statistically significant influence in the pre-crisis and crisis period. In general the explanatory power of our set of independent variables is increasing throughout the sample.

In order to check for the robustness of the regression results we perform a quantile regression. This approach allows us to assess the explanatory power of our set of independent variable for spread changes in the upper and lower tail of the empirical distribution. We find empirical

evidence that a significant systematic fraction of spread changes in the tails of the empirical distribution is not explained by the independent variables, suggesting that additional factors have to be incorporated when explaining large spread widenings or large spread tightenings that are not implied by structural models.

We additionally investigate changes in the lead-lag relationship between iTraxx spread changes and stock returns during the recent financial crisis in order to assess whether market participants rely on the iTraxx index universe as a source of information regarding systemic risk. We find empirical evidence that the lead-lag relationship is subject to variation as well. While stock returns lead spread changes in the crisis period, a two-sided relationship is observed in the post crisis period.

Our results provide further insights in the mechanics of credit markets. Future research might focus on the modeling of iTraxx spread changes in the upper and lower tail of the empirical distributions, since standard models fail to explain large spread changes. Another interesting approach is whether changes in factor sensitivities of spreads can be observed before a market turmoil evolves, i.e. whether factor sensitivities can be used as a warning signal in financial markets.

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4 The Method of Maximum Implied Default Correlation and its Potential Applications

The Method of Maximum Implied Default Correlation and its Potential Applications

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Abstract

Default dependence is of paramount importance when portfolio products or credit derivatives subject to counterparty risk have to be evaluated. Unfortunately, the modeling of default dependence is non-trivial and very sensitive to the underlying assumptions. In this light, a method that makes it possible to estimate the potential influence of default dependence on a certain financial instrument is desirable. I introduce the method of maximum implied default correlation as a potential solution to this problem. It is based on market-implied pairwise bounds for the default correlation of the entities under consideration. I apply the method to default swaps subject to counterparty risk and basket credit derivatives to illustrate the potential influence of default correlation on the respective spreads. I show that the potential influence of assumptions concerning default correlation is especially large for homogeneous portfolios with investment grade issuers. In general, the bounds for spreads implied by the method of maximum implied default correlation are wide, in particular for portfolio products, limiting its practical relevance as a pricing tool. However, although the method seems to have limited practical relevance as a pricing tool, it is well suited to assess the potential influence of assumptions concerning default correlation on financial securities sensitive to default dependence and as a tool for stress testing.

Keywords: default correlation, counterparty risk, credit derivatives, credit risk

4.1 Introduction

The pricing of securities subject to credit risk has gained major attention within financial market research in recent years. Usually, this task involves deriving the distribution of default times of the entities under consideration. In case that securities subject to counterparty risk or portfolio products have to be priced, joint distributions of default times have to be estimated. If default times are dependent, i.e. if defaults are correlated, this becomes a complex task. Furthermore, the results obtained are highly sensitive to assumptions concerning the dependence structure of the entities' default times.

During the recent financial crisis many of the assumptions behind standard pricing models for portfolio products proved to be myopic. Approaches such as the Gaussian copula, which is applied in latent variable models, do not account for extreme default dependence, i.e. the clustering of defaults. However, this clustering is a common feature of distressed financial markets and was also observed during the recent financial crisis. Therefore, the market's perception concerning the inherent risks of portfolio products were not adequate, as common models of dependent defaults are highly sensitive with respect to assumptions regarding the dependence structure (Frey and McNeil (2003)). Models allowing for extreme (possibly asymmetric) dependence of default times are available. However, they are complex and difficult to implement. In this light there is a pronounced need for concepts allowing to stress test prices of portfolio products, possibly leading to bounds within the prices (spreads) of such products have to lie in between in the absence of arbitrage opportunities and that hold regardless of the actual dependence structures within the portfolio members. Such concepts allow for a decent understanding of the inherent risk of portfolio products as they provide insights concerning the impact of default correlation on the pricing of these products. Hence, market participants can assess in which range changes in the assumptions concerning the dependence structure of entities within the portfolio do affect the fair prices of these securities.

This paper addresses the problem outlined above by introducing the method of maximum implied default correlation. It contributes to the existing literature by deriving upper and lower bounds for the default correlation for pairs of entities using market data. These bounds hold as long as no arbitrage opportunities exist. These bounds in turn can be used to derive upper and lower bounds for the prices of securities that are subject to credit risk and sensitive to default correlation. Examples of such securities are credit default swaps (CDS) subject to counterparty risk and n th-to-default baskets.

I apply the method of maximum implied default correlation to derive bounds for the prices of these two securities using an intuitive and easy to implement Monte Carlo simulation algorithm, which is based on a simple intensity model of default. The algorithm involves several steps.

First, implied upper bounds for the default correlation of certain entities are calculated based on observed market data. Next, the implied upper default correlations are converted into a variance-covariance matrix of the respective default processes. In a succeeding step I model the default processes relying on the overlapping sums (OS) method. This involves expressing the default process of each entity under consideration as a sum of independent idiosyncratic as well as common default processes. For each entity its respective sum of default processes is calibrated to match the respective implied variance-covariance matrix of its default process. This is achieved by applying the algorithm of Park and Shin (1998).¹ Consequently, the default times of each entity under consideration are simulated, allowing to derive the upper bound for securities with sensitivity to the default of the entity under consideration. The respective lower bound can be simulated by assuming that defaults are independent, i.e. that no default correlation is present. In addition to calculating upper and lower bounds for n th-to-default baskets and CDS subject to counterparty risk, I analyze the sensitivity of the respective spreads concerning changes in the correlation structure of the underlying entities to provide a better understanding of the potential impact of default correlation.

The proposed approach allows for the comparison of market spreads for credit derivatives with model-implied maximum and minimum spreads, without extensive modeling of default correlations. In the absence of arbitrage opportunities, market quotes have to lie in between the implied bounds, regardless of the underlying default correlation structure between the entities contributing to the risk of the security under consideration. Hence, this paper provides further insights on the impact of default correlation on spreads of credit derivatives sensitive to default correlation and the efficiency of the credit derivatives market as a whole.

The remainder of this paper is organized as follows. In Section 4.2 I provide an overview of models for pricing credit derivatives such as CDS and introduce the intensity model on which the Monte Carlo simulations are based. In Section 4.3 I discuss the concept of default correlation and show how upper and lower bounds for the default correlation between two issuers can be implied from market data. The issue of simulating an intensity model incorporating default correlation is addressed in Section 4.4. Section 4.5 presents the results of the simulations. In Section 4.6 I present an alternative application for the method of maximum implied default correlation. Section 4.7 concludes the paper.

¹An example how the algorithm works is provided in the appendix.

4.2 Related Literature

There are two major classes of models for dependent defaults. The first class comprises extensions of the Merton (1974) structural model. In this class of models, default occurs if a latent variable, usually interpreted as the asset value of the obligor, hits a certain threshold. Dependence between the defaults of multiple issuers is introduced via dependent latent variables, e.g. correlated asset value processes. Examples for this class of models are the Moody's KMV Model or RiskMetrics. The second class of models consists of so called mixture models. In this class of models the default probability of an obligor is expressed as a function of certain, possibly economic, factors. Default dependence is introduced if certain obligors are exposed to similar factors. Conditioning on the factors, defaults of the single obligors are independent. The CreditRisk⁺ model is an example of this class of models. According to Frey and McNeil (2003) both approaches share the feature that they are highly sensitive to the assumptions regarding the dependence structure between different obligors. Mixture models can be combined with the class of intensity models in the spirit of Jarrow and Turnbull (1995). This approach has e.g. been applied by Duffie and Gârleanu (2001). In intensity models, default is an unpredictable event governed by the first jump of a Poisson process. The default probability depends on the respective hazard rate. In this class of models default dependence can be introduced by correlating the hazard rate processes of different entities. However, as stated by Jarrow and Yu (2001), the default correlation attainable in this class of models is low unless one allows for large jumps in the default intensities of the surviving entities in case of an observed default.

For the pricing of securities subject to credit risk, default dependence plays a role in two distinct ways. On the one hand, default correlation has to be incorporated when portfolio products, such as collateralized debt obligations (CDO) and n th-to-default swaps, have to be priced. In both cases the cash flows of the security depend on the solvency of a portfolio of entities. In case of pronounced default dependence within the portfolio, a clustering of defaults is possible, i.e. multiple portfolio constituents default almost simultaneously before the security matures. Several papers address the pricing of portfolio products. Duffie and Gârleanu (2001), Longstaff and Rajan (2008) and Giesecke and Kim (2011) rely on an intensity framework to evaluate CDO tranches. Hull and White (2004) and Laurent and Gregory (2005) price CDO and n th-to-default swaps relying on a mixture model with different copula assumptions. Li (2000) relies on a latent variable model with applications to single name CDSs and first-to-default swaps. Jabbour et al. (2009) evaluates n th-to-default swaps with default dependence governed by Gaussian and Student-t copulas.

On the other hand, default correlation is an issue when credit derivatives subject to counter-

party risk, such as over-the-counter (OTC) CDS, have to be evaluated. As credit derivatives are often OTC products, introducing the concept of counterparty risk is a natural expansion to the problem of pricing such derivatives. The presence of counterparty risk in CDS markets is confirmed by Jorion and Zhang (2008), who find significant empirical evidence that counterparty risk is an important driver of CDS spreads. The issue of pricing credit derivatives subject to counterparty risk has been addressed in numerous papers. Hull and White (2001) rely on a structural framework, while Jarrow and Yu (2001) and Leung and Kwok (2005) employ an intensity model to price credit risky securities subject to counterparty risk such as CDSs. Mashal and Naldi (2005) introduce the concept of bounds for credit derivatives. They derive upper and lower bounds for swap spreads subject to counterparty risk. Furthermore, Turnbull (2005) adds to the aforementioned approach and derives upper and lower bounds for profits and losses due to such default swaps. However, as opposed to the approach proposed in this paper, these bounds do not hold regardless of the assumptions made concerning the default correlation between the different entities involved.

4.3 Correlated Defaults and Implied Bounds for Default Correlation

Correlated defaults contribute significantly to credit risk. Default correlation refers to the case when the default process of an entity is related to the default process of another or several other entities. There are several potential sources of default correlation, with some examples discussed below:

- Several entities are exposed to common systematic factors,
- entities have direct exposures with other entities,
- unhedged protection selling and default of the reference entity,
- regulatory capital requirements due to positions in the CDS market which are hedged via offsetting positions written by a distressed entity.

An exposure to common systematic factors is an obvious reason for default correlation. This is the case when entities are engaged in the same region, or in the same industry. If the industry faces a demand shock, all entities will be negatively affected, although to different degrees. Some of the entities in the industry might not survive the shock and hence, their defaults are correlated due to the common exposure to the demand shock. A direct involvement between

different entities is another source of default correlation. To give an example, suppose a bank has a large credit exposure with a single obligor. If the obligor defaults, this may create losses for the bank, which in turn will cause it to default. Unhedged protection selling as a potential source of default correlation is typically found, although not exclusive to, in the financial services industry. Financial institutions, which sell protection on a certain reference entity in the CDS market without hedging their positions are exposed to large cash drains in case the reference entity defaults. If the unhedged position is large, this may have severe consequences for the financial stability of the protection seller. The last source of default dependence may not seem obvious in the first place, although it is clearly of high importance. Financial institutions typically hedge their positions in the credit derivatives market via offsetting transactions. These hedges in turn reduce regulatory capital requirements related to the respective exposures. If the counterparty of the offsetting transaction defaults, the hedging institution ends up with an unhedged position. If it fails to replace the offsetting transaction by an equivalent transaction with another counterparty, it has to hold regulatory capital according to the risk of the unhedged position. Depending on the size of the position in the credit derivatives market, the regulatory capital requirements may lead to liquidity problems for the institution.

A technical treatment of the concept of default correlation can be found in Lucas (1995). I build on the work of Lucas (1995) and introduce the concept of market implied bounds for default correlation. To clarify this concept suppose the following. The T -year yield spreads of two bonds issued by different reference entities a and b are known to be s_a and s_b , respectively. Furthermore, I assume the yield spread is a pure default risk premium, implying that it does not depend on market imperfections such as liquidity premia or taxation effects. Then a maximum implied default correlation between the two issuers can be derived as follows (see also Lucas (1995)). The default event of entities a and b are denoted by A and B , respectively. The risk-neutral T -year default probabilities, given the relevant information at time t , \mathcal{F}_t , for a and b are denoted by $P(D_{a,T} = 1|\mathcal{F}_t)$ and $P(D_{b,T} = 1|\mathcal{F}_t)$, which can be written as $P(\tau_A \leq T|\mathcal{F}_t)$ and $P(\tau_B \leq T|\mathcal{F}_t)$. For notational simplicity I denote the default event of entities a and b by A and B , hence $P(A) = P(D_{a,T} = 1|\mathcal{F}_t)$ and $P(B) = P(D_{b,T} = 1|\mathcal{F}_t)$. Given that the entities under consideration have traded debt, the risk neutral default probabilities can be derived from the yield spreads of the respective bonds. Assuming zero recovery at default, the T -year default probability is approximately equal to the T -year yield spread of the respective bond. Hence,

$$P(A) \approx s_a, \text{ and } P(B) \approx s_b. \quad (4.1)$$

The T -year joint default probability of the two entities, $P(D_{a,T} = 1 \wedge D_{b,T} = 1|\mathcal{F}_t) = P(\tau_A \leq T \wedge \tau_B \leq T|\mathcal{F}_t) = P(A, B)$, can be expressed in terms of their individual default probabilities

and their T -year default correlation $\rho_{A,B}$, i.e.

$$P(A, B) = P(A)P(B) + \rho_{A,B}\sqrt{P(A)(1 - P(A))}\sqrt{P(B)(1 - P(B))}, \quad (4.2)$$

where

$$\rho_{A,B} = \frac{\sigma_{A,B}}{\sigma_A\sigma_B},$$

$$\sigma_A = \sqrt{P(A)(1 - P(A))}, \quad \sigma_B = \sqrt{P(B)(1 - P(B))},$$

and

$$\sigma_{A,B} = E(AB) - E(A)E(B).$$

As the joint default probability is unobservable, the default correlation between entity a and b cannot be derived from equation (4.2). Nevertheless, market yield spreads of the two entities can be used to imply upper and lower bounds for the joint default probability, which in turn can be used to derive upper and lower bounds for the default correlation between the two entities. This is because the maximum joint default probability of the two entities cannot exceed the lower of the two individual default probabilities, whereas the minimum joint default probability is zero, implying that defaults of the reference entities are mutually exclusive events. Hence, for the joint default probability $P(A, B)$,

$$0 \leq P(A, B) \leq \min[P(A), P(B)] \quad (4.3)$$

must hold.

Substituting equation (4.3) into equation (4.2) and rearranging terms leaves us with upper and lower bounds for the default correlation between default events A and B , i.e.

$$\rho_{A,B} \geq \frac{-P(A)P(B)}{\sqrt{P(A)(1 - P(A))}\sqrt{P(B)(1 - P(B))}}, \quad (4.4)$$

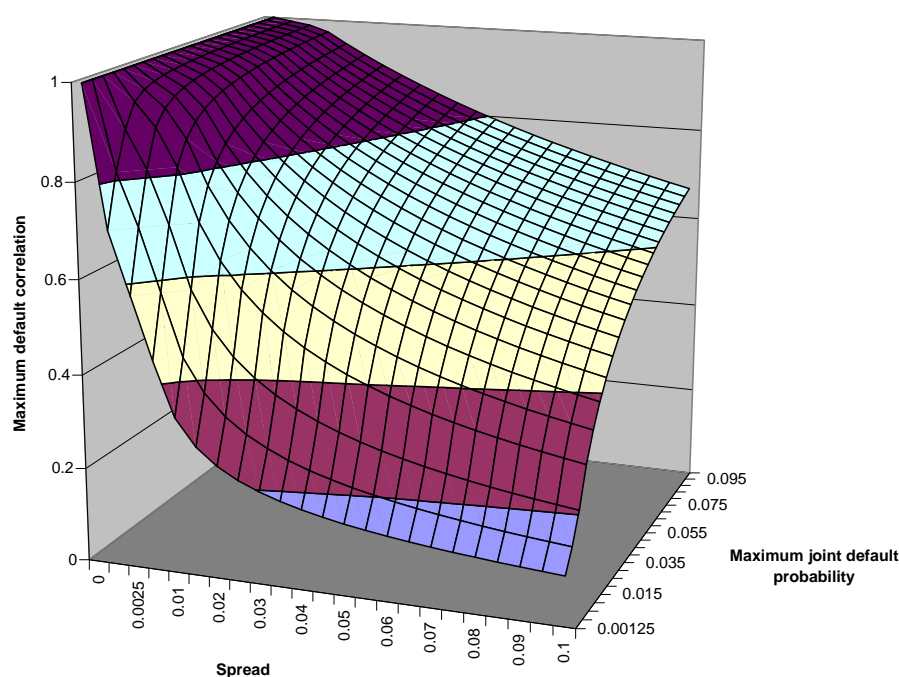
and

$$\rho_{A,B} \leq \frac{\min[P(A), P(B)] - P(A)P(B)}{\sqrt{P(A)(1 - P(A))}\sqrt{P(B)(1 - P(B))}}. \quad (4.5)$$

From inequalities (4.4) and (4.5) we see that the maximum, as well as the minimum implied default correlation between two issuers is a function of the individual default probabilities as well as the maximum attainable joint default probability of the two reference entities. Figure 4.1 illustrates the maximum attainable default correlation as a function of the spread between the individual default probabilities and the maximum joint default probability. We see that the maximum attainable default correlation is positively related to the maximum joint default

probability and negatively related to the spread between the individual default probabilities of the two entity under consideration.

Figure 4.1: Maximum attainable implied default correlation as a function of the spread between individual default probabilities and maximum attainable joint default probability



4.4 Incorporating Default Correlation into an Intensity-Based Pricing Framework for Credit Derivatives

When it comes to the pricing of securities subject to credit risk, default correlation is of particular importance if the payments the security promises are contingent to the solvency of more than one entity. This is for example the case with credit derivatives subject to counterparty risk or securities with payoffs contingent on the solvency of a portfolio of entities. In this case we have to explicitly incorporate the dependence structure between the default times of the single entities.

Intensity models are commonly used to price securities subject to credit risk. One possible way to incorporate default correlation between different entities into an intensity-based model

is by allowing for correlated intensity processes. Nevertheless, as discussed in Hull and White (2001), the magnitude of default correlation attainable by means of correlated default intensities is low, even if the processes are perfectly correlated. One way to overcome this problem, is to allow for large jumps in the default intensity of one entity, if a related entity defaults, as proposed by Jarrow and Yu (2001).

In this paper I rely on an alternative way to incorporate default correlation in an intensity-based pricing framework, the overlapping sums (OS) method. The OS method is discussed in Holgate (1964), among others. The method has been applied by Madsen and Dalthorp (2007) to simulate correlated count data. The idea behind the OS method is to split the default processes of the entities under consideration into idiosyncratic and common components. To illustrate this concept, suppose we are interested in generating correlated Poisson variables A and B with intensity λ_A , λ_B and covariance $\sigma_{A,B}$, i.e. the default processes of entities a and b . Suppose that the Poisson variables are constructed as a sum of independent Poisson variables X , Y , and Z , such that

$$A = X + Y$$

and

$$B = X + Z.$$

Although X, Y and Z are independent, the processes A and B are correlated via the common component X . The covariance between the two sums is governed by the overlapping component, i.e.

$$\sigma_{A,B} = \lambda_X,$$

where λ_X denotes the intensity of the process X . This method can be easily adapted to the method of maximum implied default correlation described in Section 4.3 by modeling the default process of each entity under consideration as a sum of overlapping default processes that yields the desired dependence structure. An example is provided in the appendix.

Using the OS method to model the default process has some intuitive implications. The default process for each entity is split into an idiosyncratic component, the non-overlapping Poisson process and a common, or correlation component, the overlapping Poisson process. Hence, there are two possible reasons for a specific entity to default. Default can be triggered by the idiosyncratic component, representing a default due to firm specific reasons. Additionally, an entity can default due to contagion effects. These contagion effects may represent inter-firm relations between two entities, or a systemic component, where the default of a major player within a certain industry has negative effect for the financial stability of other members of the industry.

Due to the nature of the OS method, firms defaulting as a consequence of contagion default simultaneously. In this case there is no lag between their respective default times, as it would be likely in the real world. In order to model lagged dependent defaults, a model like the one of Jarrow and Yu (2001) needs to be applied, where the default of an entity may cause jumps in the default intensities of its counterparties. Nevertheless, for the evaluation of a CDS, a lagged dependent default has no influence on expected payoffs due to the default of the reference entity, as long as we assume immediate settlement of the contract as soon as a credit event occurs. In case portfolio products are under consideration, the simultaneous defaults become an issue. For my purpose this feature of the OS method is actually desirable, as I am interested in deriving bounds for the spreads of these securities, and simultaneous defaults are helpful for describing the worst case scenario.

The OS method is used in the remainder of this paper to generate dependent default times and examine the effect of default correlation on the prices of securities sensitive to default dependence via Monte Carlo simulation.² One drawback of the OS method is that negative default correlations cannot be attained. However, this is not critical for deriving upper and lower bounds for CDS prices, as long as we assume that the CDS contract is immediately closed after one of the three involved parties defaults. In other words, for protection payment counterparty risk is only an issue, if defaults happen simultaneously. In this case, two special cases are of interest. In the first one, the protection seller and the reference entity default simultaneously, in which case the protection buyer is not compensated for his losses. In the second one, the protection buyer and the reference entity default simultaneously, and accordingly the protection seller does not have to compensate the protection buyer. What happens after the first credit event, be it a correlated or a single entity default, is of no relevance for the pricing of the CDS at hand, and therefore negative default correlations do not have to be accounted for.

When credit derivatives with payoffs depending on the default processes of a portfolio of entities are considered, negative default correlation matters. However, the (downside) risk of the portfolio is clearly determined by positive default correlation. Additionally, there are few cases where pronounced negative default correlation is observed in reality. Therefore, I do not consider negative default correlation when simulating the implied bounds for these securities.

²Alternative approaches to simulate dependent default times are discussed in Duffie and Singleton (1999), Joshi and Kainth (2004), Chen and Glasserman (2008) and Giesecke et al. (2011) among others.

4.5 Possible Applications for the Method of Maximum Implied Default Correlation

4.5.1 General Methodology

For the simulation analysis I rely on the reduced form pricing framework. Therefore, I suppose that the uncertainty within the economy during the time horizon T can be described by the filtered probability space $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t=0}^T, P)$, where $\mathcal{F} = \mathcal{F}_T$, and P is the equivalent martingale measure under which discounted security prices are martingales. I assume the uniqueness and existence of P , hence security markets are priced by arbitrage as shown by Harrison and Kreps (1979) in a discrete time setting and Harrison and Pliska (1981) in continuous time. The default time of entity i is defined as

$$\tau_i = \inf \left\{ t : \int_0^t \lambda_{i,s} ds \geq \xi_i \right\}, \quad (4.6)$$

where $\{\xi_i, i = 1, \dots, N\}$ is a set of independent unit mean exponential random variables. The intensity $\lambda_{i,t}$ is predictable under \mathcal{F}_t and has right-continuous sample paths. Therefore, the default time of entity i conditional on the information set \mathcal{F}_t is given by the distribution function

$$P(\tau_i > t | \mathcal{F}_t) = \exp \left(- \int_0^t \lambda_{i,s} ds \right), \quad t \in [0, T],$$

and the default process of entity i is defined as

$$D_{i,t} = \mathbf{1}_{\{\tau_i \leq t\}}.$$

The process governing the default intensity $\lambda_{i,t}$ can be modeled in various ways. Lando (1998), for instance, models the default intensity as a double stochastic Poisson process (Cox process), driven by set of economic state variables. These state variables are governed by an R^d -valued state process X_t , where d is the number of the state variables governing the intensity process. In case default correlation is present $\lambda_{i,t}$ also depends on the default processes of other entities. Hence, the filtration \mathcal{F}_t is generated jointly by the state variables and the default processes, i.e.

$$\mathcal{F}_t = \mathcal{F}_{X,t} \vee \mathcal{F}_{1,t} \vee \dots \vee \mathcal{F}_{N,t},$$

where

$$\mathcal{F}_{X,t} = \sigma\{X_s, 0 \leq s \leq t\} \text{ and } \mathcal{F}_{i,t} = \sigma\{D_{i,s}, 0 \leq s \leq t\}$$

represent the filtrations generated by the the processes X_t and $D_{i,t}$, respectively.

4.5.2 Deriving Bounds for a CDS Subject to Counterparty Risk

In a CDS transaction three parties are involved, the protection buyer a , the protection seller b and the reference entity c . In brief, a CDS insures the protection buyer against losses due to a credit event related to a third party, the reference entity. The insurance is provided by the swap counterparty, the protection seller. CDS contracts are credit derivatives traded in OTC markets. As such, CDSs are subject to counterparty risk. In general, counterparty risk in credit derivatives contracts has two dimensions, mark-to-market-risk and failure to perform (see also Turnbull (2005)). To illustrate these two aspects, suppose a setting with a default free protection buyer. If the protection seller defaults the swap contract terminates and the protection seller is no longer insured against potential losses due to the default of the reference entity. Hence he needs to find a new swap counterparty. If the credit quality of the reference entity has worsened since initiation of the original swap, he incurs replacement costs as the original swap has positive value. This represents the mark-to-market risk component. If the reference entity is subject to a credit event and the protection seller defaults prior to the settlement of the swap contract, the protection buyer bears all losses due to the reference entity's default. This represents the failure to perform component.

Hence, the value of a specific contract is particularly driven by the creditworthiness of the swap counterparty. In case the default risk of the swap counterparty depends on the default risk of the reference entity, i.e. in the presence of (positive) default correlation between the two, counterparty risk in CDS contracts is even more pronounced. The pricing of a CDS in an arbitrage-free setting is described below.

Due to the existence and uniqueness of P we can price contingent claims such as CDS using arbitrage arguments. In an arbitrage-free setting the expected present value of the premium leg has to equal the expected present value of the default leg. Without loss of generality, I assume that there is zero recovery at default and that the risk-free rate follows the process r_t . The information relevant to determine r_t is adapted to $\mathcal{F}_{X,t}$. Then, the present value of the premium leg, given that all three parties are subject to credit risk, can be expressed as

$$\begin{aligned} & \mathbb{E} \left[\int_0^T \exp \left(- \int_0^s r_u du \right) p_{CDS} \mathbf{1}_{\{\tau^a > s\}} \mathbf{1}_{\{\tau^b > s\}} \mathbf{1}_{\{\tau^c > s\}} ds \right] = \\ & p_{CDS} \int_0^T \mathbb{E} \left[\exp \left(- \int_0^s r_u du \right) \mathbf{1}_{\{\tau^a > s\}} \mathbf{1}_{\{\tau^b > s\}} \mathbf{1}_{\{\tau^c > s\}} \right] ds, \end{aligned} \quad (4.7)$$

where \mathbb{E} denotes the risk neutral expectation. From (4.7) we can see that the protection buyer

makes payments to the protection seller at the rate p_{CDS} , or swap spread, as long as none of the relevant entities has defaulted yet. As soon as one of these entities defaults the payments cease immediately.

In case the reference entity defaults, the protection buyer compensates the protection seller for her losses due to the default. The present value of this compensation, the default leg, is given by

$$\mathbb{E} \left[\mathbf{1}_{\{\tau^a \leq T\}} \exp \left(- \int_0^T r_u du \right) \mathbf{1}_{\{\tau^b > \tau^a\}} \mathbf{1}_{\{\tau^c > \tau^a\}} \right]. \quad (4.8)$$

From (4.8) we see that the compensation payment is only made if the reference entity is the first of the three entities to default within the maturity of the CDS. If either the protection seller or the protection buyer defaults prior to the reference entity, the contract expires.³

Since a fairly priced CDS has zero value at initiation, the premium leg has to equal the default leg and we may solve for the fair swap spread p_{CDS} at initiation of the CDS, which can be calculated as

$$p_{CDS} = \frac{\mathbb{E} \left[\mathbf{1}_{\{\tau^a \leq T\}} \exp \left(- \int_0^T r_u du \right) \mathbf{1}_{\{\tau^b > \tau^a\}} \mathbf{1}_{\{\tau^c > \tau^a\}} \right]}{\int_0^T \mathbb{E} \left[\exp \left(- \int_0^s r_u du \right) \mathbf{1}_{\{\tau^a > s\}} \mathbf{1}_{\{\tau^b > s\}} \mathbf{1}_{\{\tau^c > s\}} \right] ds}. \quad (4.9)$$

There might not necessarily be a solution for equation (4.9) in closed form. This is especially true if the default processes of the three relevant entities are not independent. Jarrow and Yu (2001) and Brigo and Chourdakis (2008) impose several assumptions allowing them to solve equation (4.9) in closed form. In this paper I rely on the approach of Hull and White (2001) and derive an analytical solution for the fair swap spread p via Monte Carlo simulation.

4.5.3 Simulation Results

To illustrate the effect of default correlation on the spread of a CDS subject to counterparty risk I assume the following. The time horizon is one year and premium payments are made on a yearly basis. The protection payment is made immediately after the default of the reference entity. If either the protection seller or the protection buyer defaults prior to the reference entity and the final maturity, the contract is closed without any further payments. I suppose

³This might not hold in every circumstance. As an example suppose that the protection seller defaults prior to maturity of the CDS and the reference entity has not defaulted yet. In case the contract has positive value for the protection seller, it is likely to be part of her bankruptcy assets. Hence the CDS will rather be sold to a third party, instead of expiring.

Table 4.1: Results for scenario 1

	Lower bound	Upper bound
Spread	0.00294	0.00506
Standard deviation	0.00002	0.00002

Table 4.2: Results for scenario 2

	Lower bound	Upper bound
Spread	0.02863	0.04996
Standard deviation	0.00005	0.00007

a recovery rate of zero at default and a constant risk-free rate of 300 basis points (bps). I perform 10^7 simulation steps for each scenario under investigation.

The simulation comprises three scenarios. First I simulate upper and lower bounds for the CDS spread on a reference entity with a one year default probability of 50 bps. The protection seller has a default probability of 10 bps and the protection buyer has a default probability of 20 bps. I repeat the simulation for a reference entity with default probability of 500bps, a default probability for the protection seller of 100 bps and a protection buyer with default probability of 200 bps to illustrate the effect of creditworthiness on the implied bounds. Additionally, I illustrate the effect of the homogeneity of the underlying entities by assuming a reference entity with a default probability of 100 bps a protection seller with 5 bps and a protection buyer with 25 bps

Table 4.1 provides the results for the first scenario. The lower bound for the spread of the CDS at hand is given by the spread simulated under the assumption of maximum implied default correlation, which is 29.4 bps. The upper bound, which is attained under the assumption of zero default correlation, is 50.6 bps. In this scenario, an investor who is willing to buy protection the reference entity potentially overestimates the fair spread by 21.2 bps or 172%, if he assumes zero default correlation between him, the protection buyer and the reference entity.

The results for the second scenario are provided in Table 4.2. The upper bound for the fair spread is 499.6 bps, while the lower bound has a simulated value of 286.3 bps. Again, an investor who assumes zero default correlation potentially overestimates the fair spread by 213.2 bps or 174.5%, which confirms the result of the first scenario.

Table 4.3 contains the results for the simulation of the third scenario. The simulated lower bound for the CDS spread amounts to 469.5 basis points. The upper bound, as implied by the spread simulated under the assumption of independent defaults of the entities involved,

Table 4.3: Results for scenario 3

	Lower bound	Upper bound
Spread	0.04695	0.05039
Standard deviation	0.00007	0.00007

is 503.9 bps. In this case we see that the bounds, within the fair spread has to lie, are much tighter than in the previous scenarios, which is due to the increased inhomogeneity concerning the creditworthiness of the entities under consideration. This inhomogeneity largely determines the maximum implied default correlation and consequently the simulated spreads.

The results for the simulation analysis can be summarized as follows. When we assume homogeneous, investment grade entities, the gap between the maximum and the minimum spread becomes large. If we look at inhomogeneous entities this gap becomes significantly smaller. In this case, assuming the maximum implied spread correlation results in spread estimates which are close to the potential true value. Hence, extensive modeling of default dependence seems unnecessary in this particular case.

4.5.4 Pricing *N*th-to-Default Baskets

A *n*th-to-default basket or *n*th-to default swap is a credit derivative that is in many respects similar to a CDS. The protection buyer pays a periodic fee in exchange for a contingent payment made by the protection seller prior to maturity. Rather than a single reference entity, baskets have a specified pool of reference entities, the reference portfolio. The typical size of the pool ranges from two to ten entities. The contingent payment is triggered by the default of a specified number *n* of reference entities that are included in the basket. In contrast to a CDS, it is irrelevant which of the reference entities has defaulted. The protection payment can be determined as a function of one single default or a function of several defaults of basket constituents. In the remainder I suppose that the contingent payment is a fraction of the loss due to the default of the *n*th entity. Similar to CDS, *n*th-to-default swaps are OTC products and subject to counterparty risk.

To price the *n*th-to-default basket one needs to specify the time of the *n*th default in the reference portfolio. Suppose that the reference portfolio comprises *J* entities. I define

$$K_t = \sum_{j=1}^J D_{j,t} \quad (4.10)$$

as the number of reference entities that have defaulted up to time t . The point in time of the n th default is denoted by

$$\tau^n = \inf \{t : K_t \geq n\}. \quad (4.11)$$

I suppose that there is zero recovery at default. Furthermore, to come up with general results, I assume that both the protection buyer and the protection seller may default. Every member of the reference pool has a notional principle of 1. The protection seller continues to make periodic payments at the rate p_{Basket} unless $K_t \leq n$ or until maturity T , given that the protection seller has not yet defaulted. Hence the premium leg can be expressed as

$$\begin{aligned} & \mathbb{E} \left[\int_0^T \exp \left(- \int_0^s r_u du \right) p_{Basket} \mathbf{1}_{\{\tau^n > s\}} \mathbf{1}_{\{\tau^b > s\}} \mathbf{1}_{\{\tau^c > s\}} ds \right] = \\ & p_{Basket} \int_0^T \mathbb{E} \left[\exp \left(- \int_0^s r_u du \right) \mathbf{1}_{\{\tau^n > s\}} \mathbf{1}_{\{\tau^b > s\}} \mathbf{1}_{\{\tau^c > s\}} \right] ds, \end{aligned} \quad (4.12)$$

where \mathbb{E} denotes the risk neutral expectation with respect to \mathcal{F}_t .

In case the reference entity defaults, the protection buyer compensates the protection seller for her losses due to the default of entity n , given that both the protection seller and the protection buyer have survived up to time τ_n . The present value of this compensation, the default leg, is given by

$$\mathbb{E} \left[\mathbf{1}_{\{\tau^n \leq T\}} \exp \left(- \int_0^{\tau^n} r_u du \right) \mathbf{1}_{\{\tau^b > \tau^n\}} \mathbf{1}_{\{\tau^c > \tau^n\}} \right]. \quad (4.13)$$

For the n th-to-default basket to be fairly priced, the present value of the premium leg has to equal the present value of the default leg. Solving for the fair premium p_{Basket} I obtain

$$p_{Basket} = \frac{\mathbb{E} \left[\mathbf{1}_{\{\tau^n \leq T\}} \exp \left(- \int_0^{\tau^n} r_u du \right) \mathbf{1}_{\{\tau^b > \tau^n\}} \mathbf{1}_{\{\tau^c > \tau^n\}} \right]}{\int_0^T \mathbb{E} \left[\exp \left(- \int_0^s r_u du \right) \mathbf{1}_{\{\tau^n > s\}} \mathbf{1}_{\{\tau^b > s\}} \mathbf{1}_{\{\tau^c > s\}} \right] ds}. \quad (4.14)$$

Equation (4.14) represents the most general case as the protection seller as well as the protection buyer is subject to default risk. Although there might not be a closed form solution to it, it can easily be solved numerically via Monte Carlo simulation. This is done in the next section.

4.5.5 Simulation Results

In order to illustrate the effects of the maximum implied default correlation concept on the pricing of n th-to-default basket, I perform several tasks. For computational ease, I examine a basket with three reference entities and perform simulations for the 1st-, 2nd- and 3rd-to-default swap of this illustrative basket. For simplicity, I assume that there is no counterparty risk involved. Throughout the simulations I rely on the assumption that the default probabilities of the reference entities as well as the risk-free rate are constant through time. I choose a time horizon of one year and yearly premium payments. The default premium is paid immediately after the n -th reference entity defaults. The recovery is set to be zero. I choose a risk free rate of 300 bps and perform 10^7 simulation steps for each scenario under investigation. Although these are restrictive assumptions they allow me to illustrate the effects of default correlation while keeping computation time in reasonable levels. The simulations focus on two main aspects. First, I derive the upper and lower bounds for the defaults swaps on the basket to illustrate the effect of default correlation. Second, I illustrate the effect homogeneity of entities within the basket has on the pricing of the tranches. For this purpose I vary the relative spread differences of the entities included in the basket.

Derivation of Bounds

I simulate fair spreads for the independence case and the maximum implied default correlation case. I start with a basket of investment grade issuers ($P(A)=0.00065$, $P(B) = 0.004$, $P(B)=0.007$) and repeat the simulation for a basket consisting of non-investment grade issuers ($P(A)=380$ bps, $P(B)=800$ bps, $P(C)=1290$ bps). In order to provide a better understanding of the effect of default correlation I also include spread estimates for a given default correlation of 10% between all basket constituents. This gives a hint of how conservative the bounds are.

Table 4.4: Simulation results for the investment grade scenario

This table provides simulated spread levels for the investment grade scenario as well as the standard deviations of the estimates. For each m th-to-default swaps the first column contains the results when no default correlation is present, the second column contains the simulated spreads when maximum implied default correlations is applied and the third column contains the simulation results when a constant default correlation of 10% between basket constituents is assumed.

Correlation	1st-to-default			2nd-to-default			3rd-to-default		
	None	Max	Fixed	None	Max	Fixed	None	Max	Fixed
Spread	0.01146	0.00690	0.01073	0.00003	0.00392	0.00058	0.00000	0.00064	0.00016
Deviation	0.00003	0.00003	0.00003	0.00000	0.00002	0.00001	0.00000	0.00003	0.00000

Table 4.4 contains the bounds for 3rd-, 2nd- and 1st-to default swaps on the basket of investment grade reference entities. The results for the 3rd-to-default basket, which is most sensitive to default dependence, show that the upper bound of the spread level is much higher (6.4 bps) than the spread in the independence case, which is close to zero due to diversification effects. Obviously the maximum implied default correlation method allows for only very moderate diversification effects. In fact the fair spread is close to the spread we would expect on a CDS on the best issuer in the basket. In the independence case the spread is indistinguishable from zero, i.e. the probability of all three counterparties defaulting within a one year horizon is close to zero. Hence, the possible impact of default correlation on our 3rd-to-default swap written on the basket at hand is as large as approximately 6.4 bps, which is not much in absolute terms but enormous on a relative basis. As expected, the spread for an assumed default correlation of 10% lies within the bounds manifested by the zero dependence and the maximum implied correlation case. The simulated spread for a 3rd-to-default basket amounts to 1.6 bps or 26% of the maximum implied spread. Accordingly an investor assuming a default correlation of 10% potentially underestimates the true spread by a factor of approximately four.

The results for the 2nd-to-default swap are similar. Again, the upper spread bound (39bps) is far from the independence spread (0.3 bps). The simulated spread for the moderate default correlation (5.8 bps) is also significantly lower. The potential effect of assumptions concerning default correlation on the 2nd-to-default swap amount to 38.7 bps. Again, the method of maximum implied default correlation yields only very limited diversification effects and can be regarded as a very conservative estimate.

In line with expectations, the results for the 1st-to-default swap are different from the previous ones. In case the effect of maximum implied default correlation works in the opposite direction, i.e. the probability of observing one or more defaults is lower than in the independence case. The maximum implied default correlation spread, which is a lower bound of the 1st-to-default swap spread, amounts to 69.0 bps, while the independence spread is at 114.6 bps, which is 66% higher on a relative basis. The spread for the moderate default correlation of 10% is in between the bounds and amounts to 107 bps. This confirms that the holders of tranches absorbing the first losses actually benefit from higher default correlations, while holding individual default probabilities fixed.

Table 4.5: Simulation Results for the Non-Investment Grade Scenario

This table provides simulated spread levels for the non-investment grade scenario as well as the standard deviations of the estimates. For each m th-to-default swaps the first column contains the results when no default correlation is present, the second column contains the simulated spreads when maximum implied default correlations is applied and the third column contains the simulation results when a constant default correlation of 10% between basket constituents is assumed.

Correlation	1st-to-default			2nd-to-default			3rd-to-default		
	None	Max	Fixed	None	Max	Fixed	None	Max	Fixed
Spread	0.24899	0.11560	0.20762	0.01715	0.07195	0.02304	0.00039	0.03401	0.00561
Deviation	0.00004	0.00010	0.00013	0.00004	0.00008	0.00005	0.00001	0.00006	0.00002

The results for the non-investment grade issuers are given in table 4.5. In general they resemble the results of the previous analysis. The simulated upper bound for the 3rd-to-default basket is 340.1 bps. In case we assume independence of defaults, the simulated spread amounts to 3.9 bps, which is significantly lower. In our case the possible range of influence concerning assumptions on the default dependence is as large as 337 bps. Put differently, an investor assuming zero default correlation between the three entities contained in the basket potentially underestimates the spread by a factor of almost 100. This result emphasizes the large influence default dependence on portfolio products. The simulated spread for an assumed default correlation lies in between the two bounds, as expected and amounts to 56.1 bps. Assuming a default correlation of 10% increases the spread by a factor of 14.4 compared to the assumption of independent defaults.

For the 2nd-to-default basket the simulated upper bound of the spread is 719.4 bps, while under the assumption of independence it amounts to 171.5 bps. This shows that in relative terms the gap between the two spreads is reduced for the non-investment grade issuers compared to the investment grade case.

For the 1st-to default swap, the spread obtained under the assumption of maximum implied default correlation represents the lower bound for the spread level. It amounts to 1156 bps. The simulated spread for an assumed default correlation of 10% is 207.6 bps almost twice the lower spread bound.

In general the results point to the fact that the method of maximum implied default correlation provides very conservative spread estimates. As a consequence the upper and lower bounds of the spreads simulated for the independence and the maximum implied correlation case are far apart on a relative basis especially for n th-to default spreads with large n . However, this comes as no surprise since under the assumption of independence a clustering of defaults is unlikely. Under moderate dependence assumptions, the simulated spreads are closer to the implied upper bounds, but still significantly lower. One might argue that for this reason the method of maximum implied default correlation is of limited use. However, the recent financial crisis has shown that default correlations appear to be much higher than previously estimated. This is especially true if a common factor driving defaults, possibly unobservable, is not included in the pricing model. Since the method of maximum implied correlation provides conservative estimates, the danger of underestimating the dependence is significantly reduced. Therefore, it can be regarded as a tool for stress testing financial instruments that are sensitive to the assumptions concerning default correlation.

Effects of the homogeneity of the reference pool

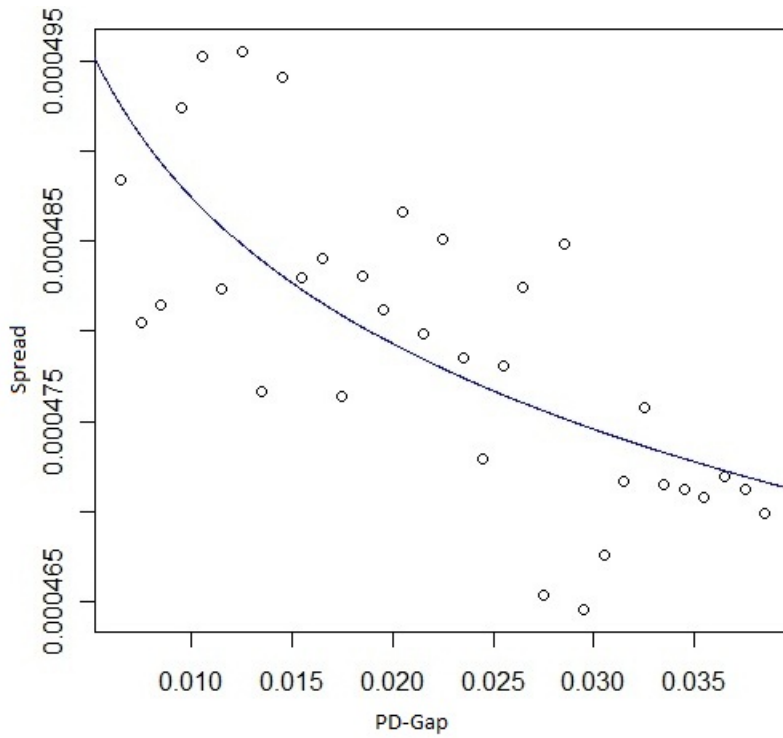
To examine the effects of homogeneity within the reference assets of the 3rd-to-default basket, I repeat the simulation by fixing the default probability of the best reference entity in the basket and allowing the default probability of the second best and worst entity to increase with every simulation step. The difference between the default probability of the second and third entity is either kept constant or is increased as well. The initial parameters are the same as in the investment grade scenario.

Figure 4.2 illustrates the effect of varying the homogeneity of the reference entities underlying the 3rd-to-default basket by fixing the default probability of the best entity and fixing the difference between the second best and the worst entity. The black dots represent the simulated spread levels and the blue line is the fitted spread as a function of the PD-gap between the best and the second best reference entity. We see that, although the maximum implied spread correlation between the first and the second best entity in the basket constantly declines, the maximum implied spread of the 3rd-to-default basket decreases only slowly. Overall it lies only slightly below 5 bps, i.e. the diversification effects within the basket are only moderate. In case we have no correlation between the assets, the spread would decline much more rapidly. We would expect a similar effect when the default correlation within the basket declines. However, we do not observe a significant decline.

The explanation of this result is the following. Although the default correlation between the best and the second best entity of the basket constantly declines, the diversification effect is limited. To understand why, think of a simple example. On the one hand we have an investment grade issuer, which is supposed to default in only very few cases. On the other hand we have an entity of limited credit quality that will default in a lot of cases. If there is measurable default correlation between the two, this means that in case the investment grade issuer defaults, the weaker entity is quite sure to default simultaneously. Otherwise, we would not be able to measure a significant default correlation between the two. In our case the best entity has a default probability of 5 bps, which is approximately the default probability of an A-rated entity according to historical default rates. The other two entities have default probabilities up to 400 bps. Hence, in order to have a measurable default correlation between the entities, a default of the best entity is accompanied almost surely by the default of the other two entities. This is why diversification effects are not pronounced when calculating spreads based on the method of maximum implied default correlation. This observation seems to be restrictive and limits the use of the maximum implied default correlation method. On the other hand there might be good reasons to accept this restriction. To put it in an economic context, the method suggests that the default of an entity with very good credit quality will

Figure 4.2: Effect of the basket's homogeneity on the spread level

This figure illustrates the influence of asset homogeneity on the spread level. The black dots are the simulated spreads. The blue line represents the fitted spread levels as a function of the PD-gap between the best and the second best issuer. The PD-gap between the second best and the worst reference entity is fixed.



be accompanied by the default of speculative grade entities. If we suppose that investment grade AAA obligors only default in case of a systemic crisis, it is not unrealistic to assume that this crisis will force many speculative grade issuers into default as well.

In a next step I further examine the effect of homogeneity between the reference assets by fixing the default probability of the best asset and letting the default probabilities of the other two increase. For each simulation step the default probability of the worst entity increases twice as much as the one of the second best entity. Therefore, the degree of homogeneity within the pool is lowered for every simulation step.

Figure 4.3 illustrates the effect of homogeneity on the maximum implied spread of the 3rd-to-default swap on the asset pool. The dots represent the simulated spreads and the blue line represents the spread level as a function of the PD-gap between the best and the second best reference entity, when the PD-gap between the second best and worst reference entity is increased. The red line represents the fitted spread level when the PD-gap between the second best and the worst reference entity is fixed, as in the previous example. Again, the method of maximum implied default correlation hampers diversification effects. However, the additional heterogeneity introduced by allowing the gap between the default probability of the second and third best entity to vary, decreases spread levels. Hence, the more heterogeneous the asset pool is composed, the lower is the maximum implied spread of the n th-to default basket, for n greater than one. This is because the more heterogeneous the assets are, the lower are their potential maximum implied default correlations and consequently the probability of simultaneous defaults.

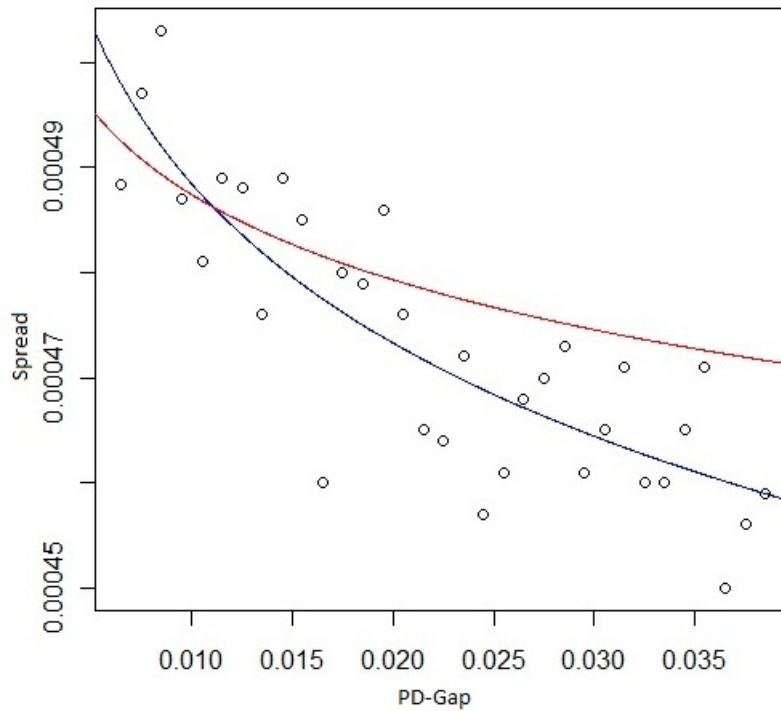
From the above examples, we see that the method of maximum implied default correlation accounts for diversification effects. However, the effect is much less pronounced than for other approaches, e.g. an independence assumption or the Gaussian copula. Therefore the method yield very conservative estimates concerning the spreads of portfolio products. Nevertheless, this might be desirable, e.g. to stress test the dependence structures of certain products to come up with estimates of how large the impact of misspecified default correlations might be.

4.6 An Alternative Use: Comparing Different Dependence Assumptions

Due to the very conservative nature of my approach, the practical relevance besides stress testing applications seems limited. However, the approach can be used to compare different assumptions concerning the dependence structure of defaults. This is achieved by comparing the spreads generated by the maximum implied default correlation method with spreads

Figure 4.3: Comparison of different degrees of homogeneity

This figure illustrates the influence of asset homogeneity on the spread level. The black dots represent the simulated spreads. The blue line represents the fitted spread levels as a function of the PD-gap between the best and the second best issuer, with varying gap between the second best and the worst reference. The red line represents the fitted spread levels with fixed PD-gap between the second best and the worst reference entity.



obtained by relying on different dependence assumptions, e.g the Gaussian copula or the Student-t copula model.

To illustrate the argument I refer to the 3rd-to-default basket of Section 4.5.4. Since the method of maximum implied default correlation provides an upper bound for the spread of a 3rd-to-default swap on the basket, we can compare the spreads obtained by alternative dependence assumptions and compare them to the maximum obtainable spread. Therefore I introduce the dependence measure dm , which is the ratio between the maximum implied spread, p_{Basket}^{max} , and the spread of the alternative model, p_{Basket}^{alt} , i.e.

$$dm = \frac{p_{Basket}^{alt}}{p_{Basket}^{max}}. \quad (4.15)$$

To give an example, I simulate the spread obtained for the same basket under the assumption that default dependence is governed by a Gaussian copula. To obtain n dependent default times governed by the Gaussian copula model I start with simulating a vector (X_1, \dots, X_n) of n correlated $N(0, 1)$ random variables (see Glasserman (2004) for a detailed description). These are transformed into a vector uniforms by the inverse transformation method

$$U_i = \Phi^{-1}(X_i), \quad i = 1, \dots, n, \quad (4.16)$$

where Φ^{-1} represents the inverse normal function. These uniforms are consequently transformed into dependent exponential random variables by setting

$$\xi_i = -\log(1 - U_i), \quad i = 1, \dots, n. \quad (4.17)$$

The vector of exponentials can then be used to generate a vector of dependent default times (τ_1, \dots, τ_i) via equation (4.6). I assume a correlation parameter of $\rho = 0.24$ for the correlated normals. The simulated spread for the Gaussian copula model is 5.6 bps. Hence, the copula model has a dependence measure of 0.016. This confirms the well known fact that the Gaussian copula provides only very limited default dependence. The same analysis can be repeated for a wide class of different dependence assumptions.

4.7 Conclusion

The method of maximum implied default correlation is not supposed to be able to render any assumptions concerning default dependence obsolete. The results show that generally the method is only of limited use for pure pricing purposes, as the bounds obtained are usually

far apart. Nevertheless, the method seems to be well suited to assess the impact default correlation can potentially have on a given security. By deriving the upper and lower bounds for spreads on such products, market participants are able to get an understanding of the actual risk behind a certain security, without having to rely on a cumbersome modeling approach, which in turn is likely to be very sensitive concerning its underlying assumptions. The method of maximum implied default correlation can therefore be understood as a possible way to stress portfolio products with regards to default correlations within their underlying reference pool. Furthermore, the method provides a benchmark to assess the degree of default dependence that is produced by specific assumptions, such as the Gaussian copula, by relating the result obtained with a certain assumption to the result of the method of maximum implied default correlation.

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4.A The Algorithm of Park and Shin (1998)

As discussed in section 4.4 the overlapping sums method is used to simulate the correlated default processes of the respective entities involved in a CDS contract. At the core of this task is the variance-covariance matrix of the respective default processes as implied by the maximum attainable default correlation, which can be calculated from equation (4.4). In a next step, this dependence structure has to be reproduced by an overlapping sum of independent Poisson processes. This is achieved by employing the algorithm of Park and Shin (1998). This algorithm expresses the random default vector \mathbf{D} as a product $\mathbf{W}\mathbf{x}$, where the matrix \mathbf{W} represents a weighing matrix consisting of zeros and ones and the vector \mathbf{x} , which is a vector of independent random variables with variances \mathbf{v} . To see how the algorithm works, suppose the following setting. A protection buyer b with a one year probability of default (PD) of 13 basis points (bps) wants to buy protection on a reference entity c with a PD of 50 bps. The protection seller a has a PD of 30 bps. Employing equation (4.4) the resulting variance-covariance matrix of maximum implied default dependence is

$$\Sigma_0 = \begin{pmatrix} 0.0012983 & 0.0012961 & 0.0012935 \\ 0.0012961 & 0.0029910 & 0.0029850 \\ 0.0012935 & 0.0029850 & 0.0049750 \end{pmatrix},$$

where the subscript 0 indicates that this is the initial variance-covariance matrix. This dependence structure has to be replicated by a set of independent default processes.

The algorithm works as follows. In a first step, the minimum upper triangular element of the variance-covariance matrix is chosen, which in the given example is 0.0012935. This is the variance of the common component shared by the default processes of the protection seller a and the reference entity c , i.e. $\sigma_{A,C} = 0.0012935$. Furthermore, as $\sigma_{A,B} = 0.0012983 > 0.0012935$ and $\sigma_{B,C} = 0.0029850 > 0.0012935$, also the protection buyer b shares this common default component with both a and c . This interrelation is expressed through the first entry in both, the matrix \mathbf{W} and the vector \mathbf{v} , i.e.

$$\mathbf{W} = \begin{pmatrix} 1 & & \\ 1 & \dots & \\ 1 & & \end{pmatrix}, \mathbf{v} = \begin{pmatrix} 0.0012935 \\ \vdots \end{pmatrix}$$

The interpretation is that all three default processes share a common component with variance 0.0012935. The initial variance-covariance matrix has to be adjusted for this common component. The residual matrix Σ_1 is given as

$$\begin{aligned}\Sigma_1 &= \Sigma_0 - \begin{pmatrix} 0.0012935 & 0.0012935 & 0.0012935 \\ 0.0012935 & 0.0012935 & 0.0012935 \\ 0.0012935 & 0.0012935 & 0.0012935 \end{pmatrix} \\ &= \begin{pmatrix} 0.0000048 & 0.0000026 & 0 \\ 0.0000026 & 0.0016975 & 0.0016915 \\ 0 & 0.0016915 & 0.0036815 \end{pmatrix}.\end{aligned}$$

After the adjustment of the variance-covariance matrix, the first iteration of the algorithm is complete. In the next iteration step, again the minimum non-zero upper triangular element of the matrix Σ_1 , is chosen. In the the above example this is 0.0000026, which is the variance of the default component shared by a and b . As the residual covariance $\sigma_{A,C} = 0 < 0.0000026$, a and c do not share this component. The matrix \mathbf{W} and the vector \mathbf{v} are adjusted accordingly, i.e.

$$\mathbf{W} = \begin{pmatrix} 1 & 1 & & & \\ 1 & 1 & \cdots & & \\ & 1 & 0 & & \\ & & & & \\ & & & & \end{pmatrix}, \mathbf{v} = \begin{pmatrix} 0.0012935 \\ 0.0000026 \\ \vdots \end{pmatrix}.$$

The residual matrix Σ_2 is calculated as

$$\Sigma_2 = \Sigma_1 - \begin{pmatrix} 0.0000026 & 0.0000026 & 0 \\ 0.0000026 & 0.0000026 & 0 \\ 0 & 0 & 0 \end{pmatrix} = \begin{pmatrix} 0.0000022 & 0 & 0 \\ 0 & 0.0016949 & 0.0016915 \\ 0 & 0.0016915 & 0.0036815 \end{pmatrix}.$$

The algorithm continues until there are no more non-zero upper triangular elements in the residual variance-covariance matrix. The remaining elements on the main diagonal, are the idiosyncratic default components of the single counterparties. These are not shared by any other entity. In the above example the algorithm has the final outcome

$$\mathbf{W} = \begin{pmatrix} 1 & 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 \end{pmatrix}, \mathbf{v} = \begin{pmatrix} 0.0012935 \\ 0.0000026 \\ 0.0016915 \\ 0.0000022 \\ 0.0000034 \\ 0.0019900 \end{pmatrix}.$$

The interpretation of the above results is straightforward. To simulate the default processes of the three entities a , b and c with the given maximum implied dependence structure Σ_0 , one has to simulate six independent default processes with variances given by the vector \mathbf{v} , of which the first three are contagious, leading to the simultaneous default of two or more entities and the last three are completely idiosyncratic. For example, if the default process with variance given by the first entry of the vector \mathbf{v} is the first to default, this triggers a simultaneous default of all three entities. In contrast if the default component with variance given by the fourth entry of the vector \mathbf{v} is the first to default, this would result in a default of entity a only.

In order to derive the default times of the entities under consideration according to equation (4.6), the variances of the default processes are converted into the respective default probabilities.⁴ These, in turn, are converted into one year default intensities via

$$\lambda_I = -\ln(1 - P(I)).$$

⁴Since the variance of entity i 's default process is calculated as $\sigma_N = P(I)(1 - P(I))$, this involves solving a quadratic equation. Hence, there are two possible solutions for the probability of default, which sum to one by construction. Of the two solutions the one which suits s_i is chosen. For reasonable choices of s_i this will always be the smaller one.

5 Epilog

As outlined in section 1, this dissertation is dedicated to several research questions that were addressed in the preceding three essays. At the core of all three essays is the relationship between the recent subprime financial crisis and the market for credit risk. The first essay is dedicated to the investigation, which causes are behind the subprime financial crisis, the role credit markets and credit derivatives played in the course of the crisis and how the crisis can be resolved from a government perspective. Several circumstances contributed to the subprime financial crisis and credit derivatives clearly played a significant role as an accelerant for the transmission of the crisis throughout the financial services industry.

In the first essay we discuss several possibilities how the crisis might be resolved by means of government intervention. Among these are direct recapitalization, state guarantees and purchase programs for troubled assets. We formally show that only the latter provide the possibility to establish a mechanism allowing to separate illiquid but solvent and insolvent banks and therefore to resolve the uncertainty within financial markets concerning the solvency of individual banks. If the price offered for the troubled assets is chosen correctly, solvent and insolvent banks will behave differently and reveal the state they are actually in to outsiders. In the end, all banks are better off revealing their true state than trying to mimic a solvent bank.

Given the tremendous impact of the subprime financial crisis, it is straight forward to raise the question, how a similar crisis can be prevented in the future. A stricter regulation of credit markets can not be the sole conclusion drawn out of the crisis. In general the innovations in the market for credit risk are beneficial for the economy. However, it must be assured that market participants are aware of the risks they are exposed to and act in a reasonable not solely profit driven way.

The second essay is dedicated to the question what impact the recent subprime financial crisis had on market participants' perceptions of credit risk. For this purpose we conduct an empirical analysis of the determinants of iTraxx spread changes, which can be regarded as a measure of aggregate credit risk. We find empirical evidence that the determinants of iTraxx spread changes have evolved in the course of the subprime financial crisis. This finding suggests that market participants have altered their perceptions concerning credit risk as a consequence of the crisis. In general, during the subprime financial crisis, determinants as implied by structural models of credit risk show a weakened explanatory power for iTraxx spread changes. This is especially true if we examine the determinants of large spread changes. A quantile regression reveals that factors, as implied by structural models of credit risk, are not sufficient to explain extreme spread changes, indicating that structural models of credit risk need further improvement. A VARX-model reveals that the role of credit markets in processing relevant information has changed during the subprime financial crisis. While stock returns

tended to lead iTraxx spread changes before the crisis, there is a tendency of iTraxx spread changes leading stock returns after the crisis. Hence, we conclude that market participants rely on iTraxx spreads as a source of information concerning systemic risk in financial markets.

Consequently, the third essay deals with the question, how complex credit derivatives can be modeled in a way that allows for an understanding of their inherent risk, while reducing the complexity of the modeling approach to a necessary minimum. For this purpose I introduce the method of maximum implied default correlation. The method is based on bounds for the default correlation of pairs of entities that can be inferred from market prices. The approach allows for a derivation of bounds for the prices of credit derivatives that hold in the absence of arbitrage, regardless of the true default correlation between the entities under consideration. I propose an easy to implement Monte Carlo algorithm that allows to derive a numerical solution for the bounds of credit derivatives that are sensitive towards default correlation. I apply the model to two types of credit derivatives that are sensitive towards default correlation, CDSs subject to counterparty risk and n th-to-default baskets.

While the method of maximum implied default correlation is of limited use when it comes to the exact pricing of credit derivatives that are sensitive towards default correlation, it proves to be a useful tool to assess the extent such products are actually exposed to default correlation. I show that given for some products, the simulated bounds for the prices of some credit derivatives are far apart from what one might expect given state of the art model of default correlation, such as the Gaussian copula model. Therefore, the method of maximum implied default correlation can be used as a benchmark for the conservativeness of different assumptions concerning default correlation.

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Eidesstattliche Versicherung

Hiermit versichere ich an Eides statt, dass ich die vorliegende Dissertation mit dem Titel Three Essays on Credit Risk with a Special Focus on the Subprime Financial Crisis selbständig, ohne unzulässige Hilfe Dritter und ohne Benutzung anderer als der angegebenen Quellen und Hilfsmittel verfasst habe und dass alle Ausführungen, die wörtlich oder sinngemäß übernommen wurden, als solche gekennzeichnet sind.

Die Arbeit wurde bisher keiner anderen Prüfungsbehörde vorgelegt.

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