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Thomas BUSCH
Born on 23 June 1981 in Mainz (Germany)

LIQUIDITY RISK IN CAPITAL MARKETS

Dissertation Defense Committee:
Dr. Thorsten Lehnert, dissertation supervisor
Professor, Université du Luxembourg, Luxembourg
Dr. Theoharry Grammatikos
Professor, Université du Luxembourg, Luxembourg
Dr. Jang Schiltz
Associate Professor, Université du Luxembourg, Luxembourg
Dr. Susanne Emmer
External Lecturer, ESSEC Business School, France
Dr. Andreas Nadler
Executive Director, UBS, Switzerland

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After finishing my business informatics studies at the University of Mannheim, I started the Graduate Trainee Program at UBS Switzerland in March 2009. There I was able to gain experience with various teams, including risk methodology and risk control. The motivation to study for a PhD was the desire to engage in further academic work and to close the gap between financial theory and practical usability.

I was inspired to write about the impact of liquidity risk in capital markets after spending a significant part of my Trainee Program in the area of collateralized lending. There I realized that beside several other risk factors, liquidity risk plays an important role. This could be seen especially during the crisis in 2008.

As mentioned in the thesis, there are many different liquidity measures, with substantial variation in quality. I was very pleased that, thanks to cooperation from Deutsche Börse, I could receive the XETRA Liquidity Measure (XLM). This advanced measure is not often used in academic papers and therefore opened various paths for analysis. I want to thank Deutsche Börse for this support.

As well, this thesis would not have been possible without direct and indirect support from many people.

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Zürich, October 2013 Thomas Busch

Abstract

This thesis focuses on liquidity risk in capital markets. The main aim is to help practitioners to better understand and manage liquidity risk by analyzing the following three topics: modeling correlations in a Liquidity Adjusted VaR ($L - VaR$) (Chapter Three), impact of regulatory interventions on stock liquidity (Chapter Four) and liquidity commonality and option prices (Chapter Five).

The first topic focuses on an appropriate way to measure expected stock losses by considering liquidity risk (see Chapter Three). The need for a new measure, which also includes stock liquidity, is based on the concern of investors only being able to sell stock at a huge discount or not at all. In reaction, various papers with new methodologies have been published, including the liquidity adjusted Value at Risk ($L - VaR$) models proposed by Bangia et al. (1998) and Ernst et al. (2012). Based on their approach, we analyze different ways to extend these models and to optimize performance. This is done using advanced conditional volatility models like $AR - GARCH$ and $AR - GJR$ models and by considering correlations between spread and return data. The new model is called correlation and liquidity adjusted VaR ($CL - VaR$) and shows (based on a five-year observation period) better performance compared to the models by Bangia et al. (1998) and Ernst et al. (2012). The models are calculated and back-tested using unique data called Xetra Liquidity Measure (XLM) provided by Deutsche Börse.

The collapse of Lehman Brothers in 2008 marked the beginning of a financial crisis affecting the entire world of finance. This period is characterized by increasing fear of further defaults by corporations (including banks) or even by countries. In reaction, investors began shifting their assets to more stable and secure investments and this resulted in stock market crashes. Various interventions were made by government institutions to restore stability.

The target of the second topic is to analyze the impact of these interventions on liquidity (measured by volume-weighted bid-ask spreads) and market reaction (measured by returns) at the announcement date (see Chapter Four). In the event, we study abnormal changes of stocks listed on the Dax. The interventions which we consider are published by the Federal Reserve Bank (FED) in the form of a crisis time-line. Here they are further combined to the following

categories: bank liability guarantees, liquidity and rescue interventions, unconventional monetary policy and other market intervention. The results show that, for example, the market reacts positively to liquidity and rescue interventions, whereas bank liability guarantees reduce liquidity. In addition, we show that international events have a significant impact on the domestic market in a "spillover effect". By analyzing the spreads of different traded volumes, an asymmetric increase can be detected at the announcement date.

The last topic focuses on the link between equity and option markets (see Chapter Five). There we analyze, on one hand, the link between stock market liquidity and option prices and, on the other hand, the impact of liquidity commonality in equity and option markets. We can show that systematic liquidity (rather than idiosyncratic liquidity) gives a better explanation of changes in “at-the-money” implied volatility. This effect was especially strong during the financial crisis in 2008. Another result is that liquidity risk of higher traded stock volumes is not properly reflected in the option price. This can result in higher hedging costs, as mentioned by Certin et al. (2006). To shed more light into liquidity commonality within the stock market we calculate the $LiqCom$ measure as mentioned by Chordia et al. (2000). The results show a continuously changing liquidity commonality which decreases with increasing traded volume. This is because the market maker focuses for bigger stock positions more on the idiosyncratic liquidity risks while for smaller stock positions the systematic liquidity risk is more important. We confirmed our findings with a robustness check.

Contents

Chapter One

General Introduction

Liquidity is an important factor in financial markets. There are two main types: funding liquidity and market liquidity (Dowd K. , 2005). Funding liquidity means that corporates or countries are able to fund their liabilities, while market liquidity focuses on asset liquidity. In this thesis we will only focus on asset liquidity.

An asset is assumed to be liquid if it fulfills the following criteria: small transaction costs, easy trading, timely settlement and that large trades have little impact on market prices (Loebnitz, 2006). Under such conditions financial markets are called "sufficient" or "perfect". The contrast to that is "illiquidity". This is the case when the investor is not able to sell assets. Between liquid and illiquid assets is a gap in which assets can only be sold partly or at a price discount. The pressure to liquidate such assets, within insufficient markets, can lead to companies collapsing. A frequently mentioned example is the default of LTCM in 1998. This hedge fund was managing an undiversified and highly leveraged portfolio, but after a financial market fall they were not able to sell concentrated asset positions to cover margin calls. As a result the Federal Reserve Bank of New York organized a bailout to avoid a wider collapse of the financial markets (Jorion P. , 2000). These kinds of events are rare but can lead to a disruption in the global financial economy. However, less liquid assets and the associated risk do only appear during crises. Trading strategies and investments with high yield profits are invested mostly in less liquid assets such as private equity, emerging markets or low capitalized stocks. To manage the risk, investors should always be able to identify the degree of liquidity of their assets.

Beside the different participants in financial markets, the regulator is also aware of liquidity risk. Regulation is established due to the fear that a shortfall by a financial institution or corporate can lead to system-wide disruption. For example, banks must ensure an appropriate handling of liquidity, including having liquidity measures (Basel Committee on Banking Supervision, 2008). In chapter two we give an introduction to the topic of market risk. There the different roles of the market participants, market maker and regulator are defined.

To determine the worst expected loss based on a given level of confidence, a Value at Risk (VaR) approach is commonly used (Dowd K. , 1999). This approach is also accepted under the new Basel III regulation (Basel Committee on Banking Supervision, 2011). In general, the VaR is calculated on return series and therefore does not capture liquidity risk. Due to this deficit, several research papers have been published recently on how to integrate liquidity risk into the VaR methodology. In chapter three we give both an overview of different liquidity adjusted VaR methodologies and we show ways to improve existing measures.

The financial crisis in 2008 was characterized by increasing fear of further defaults by corporations, such as banks, or even by countries. In reaction, there was a “flight to liquidity” as investors began to shift their assets to more stable and secure investments. As a consequence market prices dropped and liquidity dried up. In these instances, investors are less willing to invest in certain securities, even when the price is low. This leads to various interventions by government institutions to restore stability. In chapter four, we analyze the impact of these interventions on liquidity (measured by volume-weighted bid-ask spreads) and market reaction (measured by returns) at the announcement date, focusing on stocks listed in the Dax. The test scenarios of the event-study consider: bank liability guarantees, liquidity and rescue interventions, unconventional monetary policy and other market intervention.

Directly linked with equity markets are derivative markets. These markets are important because they enable investors to leverage or buy protection for their investments. Our study in chapter five focuses on the relationship between stock liquidity and option-implied volatility. Firstly, we study which impact stock market liquidity has on implied volatility. Based on these results we further analyze if stock market (systematic) liquidity or single stock (idiosyncratic) liquidity has the biggest impact on option prices. In the final question, we focus on the relationship between stock and option markets during the Lehman crisis in 2008.

The chapter structure of the thesis is as follows. In chapter two we give an introduction to market liquidity risk. In this context we explain how this risk can be measured and we present the advanced Xetra Liquidity Measure which is used in the thesis. The following chapters (three, four and five) deal with separate research topics which can be read separately from each other. Beside the fact that all chapters deal with the topic of stock market liquidity, the different perspectives result in separate conclusions for each chapter. A general conclusion of the thesis can be found in the last chapter.

Chapter Two

Market Liquidity Risk

2.1 Introduction

Liquidity is an important factor in financial markets. This thesis focuses on liquidity from a practical point of view. The intention is to increase the understanding of liquidity risk and therefore help to improve risk management systems.

The classical financial market theory is based on several assumptions which reduce the complexity of the financial system. Two common examples are that markets are “frictionless” and competitive. Frictionless markets are assumed to have no trading costs (e.g. taxes or fees) and no restraints on transactions (e.g. short-selling bans). A competitive market assumes that a trader can buy or sell an unlimited amount of securities at any time without this transaction altering the price. These assumptions are not valid in the financial markets and result in various risks (Çetin, Jarrow, & Protter, 2004). In this thesis we focus on liquidity risk.

In general, liquidity can be subdivided into funding liquidity and market liquidity (Dowd K. , 2005). Funding liquidity means that corporates or countries are able to settle obligations immediately when required. If this is not possible the debtor is said to be insolvent. The risk of not being able to settle future obligations is defined as funding liquidity risk (Drehmann & Nikolaou, 2013). In contrast to that, market liquidity deals with asset liquidity. Here the focus is on marketability and the ease of trading a security (Longstaff, 1995). Liquidity risk appears when the seller has problems unwinding market positions, often at a discount. In this thesis we will only focus on asset liquidity.

The chapter is organized as follows. In the next section (2.2) we introduce some fundamentals of financial markets. Then in section 2.3 we deal with different definitions of market liquidity including the one which we use in this thesis. In section 2.4 we demonstrate how liquidity can be measured and managed. A specific focus is on the advanced Xetra Liquidity Measure (XLM) presented in section 2.5.

2.2 The Role of Market Participants, Market Maker, and Regulator

A financial market sees exchanges between sellers who have excess capital and buyers who need capital. Securities (such as equities) are traded, with funds transferred between the buyer and seller. Generally, financial markets have the advantage of relatively easy trading conditions partly due to the high number of market participants facilitating fund flows (Madura, 2008). Another advantage is that prices are quoted regularly and transparently, which finds an appropriate market price for every asset.

Stock markets began with the first tradable stocks issued by joint-stock companies in the early seventeenth century, such as the Dutch East India Company founded in 1602. Trading companies were given charters by the state to support the colonization process. To fund their voyages and larger fleets they issued the first publicly quoted stocks. The shareholders received in return a dividend based on company revenue. At the same time, the Amsterdam stock exchange was founded to allow continual trading of these shares. The Amsterdam stock exchange is considered to be the oldest in the world. In 1795 the London Stock Exchange (LSE) emerged and became the leading financial market after French troops had invaded Amsterdam. The lead changed again in 1914 to the New York Stock Exchange (NYSE) which benefited from its large size (Wójcik , 2011). More exchanges were established in subsequent years.

The Deutsche Börse is located in Frankfurt and was founded in 1992. Initially, trading was only possible on the trading floor but this changed in 1997 with the launch of the fully automatic trading platform Xetra. This system collects buy and sell orders from market participants in a limit order book (LOB). While in the past, a market maker was responsible for matching different trades, this is now performed automatically by the system. Beside the mentioned matching system there are still market markers in the Xetra system called

Designated Sponsors. Their task is to quote prices regularly and to ensure continual trading, mainly in less liquid stocks. The Deutsche Börse controls specific requirements such as the minimum quote size and maximum bid-ask spread (Deutsche Börse AG, 2012). By using the electronic trading platform, the investor is able to trade around 900,000 German and international securities. On peak days around 107 million trades are processed. Access to Xetra is given to banks, financial services institutions and financial enterprises from EU countries, other European signatory states and the United Arab Emirates. Overall, 4,500 traders from 18 countries are connected (Deutsche Börse AG, 2012).

The people involved in financial markets can be split roughly into two groups: market participants and market maker.

The *market participant* can be a buyer or a seller of a security, for reasons such as speculation or hedging. When an investor is on the buy side he requests liquidity, while the seller supplies liquidity to the market. Participants who supply the market are called investors or speculators and provide the market with capital and therefore with liquidity. On the other side is the request (demand) for liquidity to convert securities into cash.

In general, it is not possible for market participants to access the market directly. Therefore a *market maker* is needed; either a broker or a dealer. A broker only executes trades on behalf of others for a fee. A dealer buys and sells securities out of their own account, generating revenues through the development of inventory (e.g. buy low and sell high). It is also common for individuals or firms to act both as broker and dealer (Harris, 2002).

When a security is bought or sold this is usually done at different prices. The bid price is paid when a market participant wants to buy and the ask price is paid when a market participant wants to sell. Between both prices is a gap called the "bid-ask spread" (or simply the "spread"). The spread represents, on one side, possible revenues for the market maker. On the other side, it is a compensation for the interim risk of buying and subsequently selling the stock to another investor. The risk depends, for example, on current market conditions (crisis/no crisis) or the trading volume. Based on different characteristics, the market maker will raise or lower the bid-ask spread to be compensated for the risk and to manage his inventory (Chordia, Roll, & Subrahmanyamb, 2002).

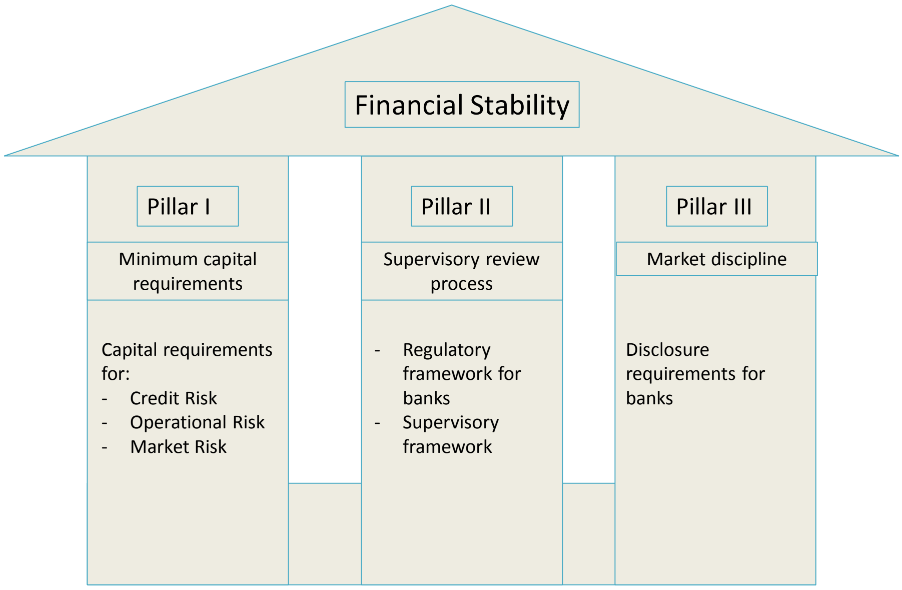
Financial institutions (like banks) play an important role in the national and international financial system. While in the past the main function of banks was to receive savings and grant loans, today they have many more product possibilities. The result is a fast growing financial industry interconnected via the interbank market (Bank For International Settlemts, 1983). The risk inherent in this system was demonstrated during the global financial crisis of 2007/2008. There, several large financial institutions collapsed, banks were bailed out by governments and stock markets around the word fell. To avoid worldwide financial system collapse, states (thus tax payers) acted as the lender of last resort[1] and took over the costs. Subsequently, new institutions and rules were created to ensure better regulation. The intention is to limit the risk for banks and others to ensure that market shocks can be absorbed during market downturns.

A regulatory framework was set up by the Basel Committee of Banking Supervision (Basel). The first Basel accord (Basel I) was published in 1988 and defined the minimum capital requirements for banks. In 2004 the next Basel accord (Basel II) established a three pillar concept with minimum capital requirements, supervisory review and market discipline (figure 2.1).

[1] The lender of last resort is defined by Freixas et al. (2000) in the following way: "the discretionary provision of liquidity to a financial institution (or the market as a whole) by the central bank in reaction to an adverse shock which causes an abnormal increase in demand for liquidity which cannot be met from an alternative source"

Figure 2.1: Three pillar concept of Basel II

The figure shows the three pillars of the Basel II approach. Financial stability is based on minimum capital requirements, the supervisory review process and market discipline.



In the first pillar, minimum capital requirements are regulated with the focus on credit risk, operational risk and market risk. C*redit risk* concerns the risk of default by counterparties (e.g. borrowers). There are three ways to calculate the required capital: the Standard Approach, Foundation Internal Ratings-Based (IRB) approach and the Advanced IRB approach. Which is the most appropriate depends on the size of the bank and the specific services they offer. O*perational risk* is defined as "the risk of a direct or indirect loss resulting from inadequate or failed internal processes, people and systems or from external events" (Basel Committee on Banking Supervision, 2001). The operational risk component can be calculated in three different ways: the Basic Indicator Approach, Standard Approach and Internal Measurement Approach. Finally, there is *market risk* when a bank faces problems based on changes of market prices. The Value at Risk (VaR) approach is widely recommended here.

The second pillar is called Supervisory Review Process. In this, the bank must have an appropriate process to assess capital adequacy in relation to the risk profile called ICAAP (Internal Capital Adequacy Assessment Process). The regulator aims to intervene early if the bank is not fulfilling its requirements.

In the last pillar the roles for market discipline are defined. The institution is obligated to disclose information to market participants such as the capital structure, Tier I and Tier II capital and the methodologies used to ensure capital adequacy[2].

Based on different financial crises in the 20th century, the Basel committee improved the regulations and published a new accord in 2010 (Basel III). The focus is on higher capital requirements, a new leverage ratio and liquidity ratio. Compared to Basel II the regulator requires higher capital to better absorb shocks in the financial system.

2.3 Definition of Market Liquidity

Market liquidity risk is mentioned and discussed in several papers. With the increasing number of papers, the number of definitions has also increased.

In general there are explicit and implicit costs which have to be paid when financial products are traded. Explicit costs are already known before the trade, while implicit costs can only be determined after the trade is executed. Examples for explicit costs are trading fees, commission and taxes. In this thesis we neglect the explicit costs and define that liquidity risk only consists of implicit costs. This is done because the implicit costs represent around 80% of overall transaction costs (Krogmann, 2011).

A more general definition is mentioned by Amihud and Mendelson (1986) where they state that liquidity is equal to the "costs of immediate execution". In their opinion, an investor has to make a tradeoff between waiting to get a favorable price or buying or selling the security directly. The price for immediacy is represented by the bid-ask spread. These costs are split between the buy and sell side. Therefore Amihud and Mendelson suggest that the spread is an optimal measure for liquidity. In the same way, Jorion (2006) argues that liquidity costs can be neglected given a sufficiently long liquidation time horizon.

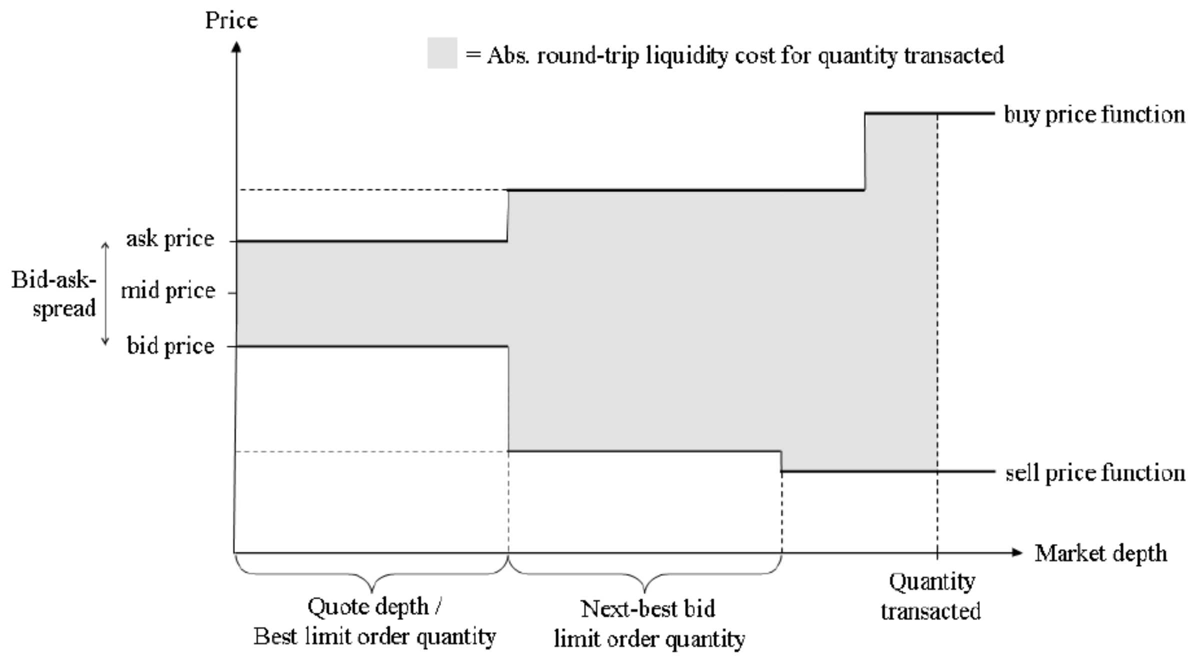
[2] Tier 1 and Tier 2 capital are indicator for the banks' financial strength. The difference between both indicators is the way of calculation. For more information see (Basel Committee on Banking Supervision, 2011).

The most common definition determines liquidity by using the following attributes: *tightness*, *depth*, *resilience* and *immediacy* (Hasbrouck & Schwartz, 1988) (Roll, 1984). All four attributes have influence on the costs which appear when a stock is sold.

To understand the meaning of tightness and depth in a market see figure 2.2. The *tightness* is defined as the gap between the bid price and ask price. In other words these are the costs which are born when a stock is bought and subsequently sold again (roundtrip) (y-axis). In contrast, *depth* focuses on the trading volume (x-axis). It can be seen in the figure that the bid-ask spread grows with increasing trading volume. When a higher position of shares is sold both tightness and depth must be considered. An example is given in the figure marked by the gray area. Here different spreads are available for limited ranges of trading volume. If the amount which has to be sold exceeds this range, the next spread with the corresponding volume has to be taken. The overall liquidity cost in this example is equal to the gray area.

Figure 2.2 Structure of a limit order book

The following figure shows an example of a limit order book. In this different bid and ask prices are listed for which investors are willing to buy or sell shares. The difference between both values is the bid-ask spread. Beside the bid and the ask price the dimension of the trading volume can also be seen. With increasing volume the spreads increase. (Source (Kaserer & Stange, 2008))



Trading in the market is a dynamic process. Therefore it is possible for a market to get out of equilibrium if more people want to sell than to buy, and vice versa. The attribute *resilience* focuses on this and measures how long it takes to return to a normal situation after a market shock. This attribute considers the time dimension in the trading process.

As for *immediacy*, the time between submission and execution of the order is considered. Slow trade execution might have a negative impact on the other three dimensions.

One definition along these lines is mentioned by Ernst et al. (2009). The difference is in the assignment of a cost function which is equal to the sum of different attributes. The advantage for an investor is that by transferring the risk dimensions into a cost framework it becomes more intuitive. The function is:

$$\mathrm{L}_t(\mathrm{q}) = \mathrm{T}_t(\mathrm{q}) + \mathrm{PI}_t(\mathrm{q}) + \mathrm{D}_t(\mathrm{q}) \tag{2.1}$$

Where $\mathrm{T}_t(\mathrm{q})$ is the explicit cost of trading (fees, commissions, taxes, etc.). The parameter $\mathrm{PI}_t(\mathrm{q})$ is the price impact and $\mathrm{D}_t(\mathrm{q})$ captures delay costs for an order quantity q. The difference to the before mentioned definition is that $\mathrm{PI}_t(\mathrm{q})$ combines tightness and depth of the market. Resilience is equal to the delay costs.

In this thesis we focus on the liquidity costs which appear when a stock position is sold directly in the market. Therefore we neglect the explicit liquidity costs $\mathrm{T}_t(\mathrm{q})$, which are already known before the trade, and delay costs $\mathrm{D}_t(\mathrm{q})$, which are subject of another topic called optimal execution models. Based on that, the question is now in which way $\mathrm{PI}_t(\mathrm{q})$ can be measured. The following section deals with this topic.

2.4 Measure and Manage Market Liquidity

The ability to measure liquidity is the key to preventing losses. In general, financial institutions or private investors should aim to have a diversified portfolio. But even here, the diversification effect can be neutralized by illiquidity (e.g. during a crisis). Therefore continuous liquidity risk management is necessary. On several occasions in the past, companies have failed due to market liquidity problems, including the hedge funds LTCM or Amaranth Advisors.

The LTCM hedge fund used complex mathematical models in the fixed income market to make arbitrage trades. Because of the small income received from each trade they had to use a high degree of leverage to maximize returns. The fund collapsed after being hit by the Russian financial crisis of 1998. Because of an undiversified and highly leveraged portfolio, the hedge fund was not able to sell concentrated asset positions to cover margin calls (Jorion P. , 2000).

A similar pattern can be found by looking at the collapse of the multi-strategy hedge fund Amaranth Advisors in 2006. At its peak, the hedge fund had around USD 9.2 billion assets under management, but they were highly concentrated in natural gas futures. Within one week the net asset value decreased by around 65% (Till, 2008) resulting in the biggest loss ever made by a hedge fund. Ultimately, the fund was forced into liquidation. Based on a detailed analysis by Chincarini (2007) one can see that the fund faced extreme liquidity and market risk.

Beside hedge funds, banks also offer services which are exposed to liquidity risk. An example is collateralized lending where a client is granted a loan backed by securities. When a client is not able to repay the loan, the securities are sold. If the liquidation value is lower than the exposure the result is a loss for the bank. A reason for that can be illiquidity in the specific market. With a diversified loan book this is generally not a fundamental problem. However, it can become critical during times of crisis where many actors have difficulty repaying loans. This can result in losses which have to be absorbed by the bank.

In general, financial institutions are motivated to manage market liquidity. To ensure this is done in an appropriate way, the Basel Committee of Banking Supervision (Basel) created regulations which oblige banks to identify, measure, monitor and control liquidity risk (Basel Committee on Banking Supervision, 2008). These are minimum standards which are applied by each individual bank.

One common measure for risk is the Value at Risk (VaR) approach (Dubil, 2003). The VaR determines the maximum expected loss based on a probability level and a time horizon. This methodology is also accepted by the regulator in the advanced approach to calculate capital requirements (Basel Committee on Banking Supervision, 2005). Without any doubt, simplicity is the main advantage of this methodology. On the other side, the main criticism is that the VaR is not a coherent measure[3] and expectation for the future is based on data from the past. Furthermore the basic VaR methodology assumes that the underlying data are distributed normally (Wolke, 2008).

While in the next chapter liquidity adjusted VaR methodologies are presented, in this section we want to continue to analyze which kind of pure liquidity measures are available.

In various papers different liquidity measures are proposed. To determine which one should be favoured and what are the differences, we focus on the different measures' characteristics. According to Houweling et al. (2003) they can be separated into direct and indirect measures. The direct liquidity measures focus on bid-ask spread data or on the limit order book. As mentioned by Amihud and Mendelson (1986) the bid-ask spread is the best measure for liquidity. Different papers are published for example by Bangia et al. (1999) and Ernst et al. (2012) where they confirm the quality of the measure. This is because the bid-ask spread reflects the costs for immediate execution of a transaction in the market. In contrast to this, the limit order book contains future information of non-executed trades. Compared to the bid-ask spread of the last executed trade[4] the limit order book also contains spreads for higher traded volumes. Papers which use weighted spread data are published by Francois-Heude and Van Wyendaele (2001), Giot and Grammig (2006) and Ernst et al. (2009)[5].

Indirect liquidity measures are proxies for the direct liquidity measures. These can be, for example, number of transactions or traded volumes, as mentioned by Berkowitz (2000) and Cosandey (2001). The issues surrounding indirect measures are discussed by Krogmann (2011). One problem is that they only focus on the past. Another is that they do not differentiate between liquidity and, for example, market activity. So, the transaction volume may be misleading if a few very large transactions give the impression of a liquid market.

[3] A coherent risk measure is defined to fulfill the following criteria: Monotonicity, sub-additivity, homogeneity and translation invariance. For more information see (Artzner, Delbaen, Eber, & Heath, 1999).
[4] In the paper by Amihud and Mendelson (1986) they focus on bid-ask spreads of executed trades. These are normally trades for marginal amount of shares and therefore neglect the risk of higher traded volumes.
[5] In section 2.5 we will give an introduction into this advanced liquidity measure.

Based on the above-mentioned advantages we have decided to ignore indirect liquidity measures and focus on the direct. Special focus is on the Xetra Liquidity Measure (XLM) which is calculated based on the limit order book. This measure contains volume-weighted bid-ask spreads. An introduction and definition can be found in the following section.

2.5 Xetra Liquidity Measure (XLM)

The Xetra Liquidity Measure (XLM) is a direct liquidity measure which is calculated using the electronic limit order book (LOB). This measure contains volume-weighted bid-ask spreads for different traded volumes and is provided daily by the Deutsche Börse. The XLM is denoted in basis points (bps) and is a measure for the cost of buying and subsequently selling a stock (round trip). An advantage of the XLM is that the costs of a round trip are calculated based on different quantities q. These amounts can be different for the Dax, MDax and SDax. Overall the XLM is provided for 10 traded volumes which can be found in table 2.1 for Dax, MDax and SDax.

The XLM is calculated for a trading volume q at time t in the following way:

$$\mathrm{XLM}(\mathrm{q},\mathrm{t}) = \left[\frac{\frac{1}{v}\left(\sum_{\mathrm{i}} \mathrm{b}_{\mathrm{i},\mathrm{t}}\mathrm{v}_{\mathrm{i},\mathrm{t}} - \sum_{\mathrm{j}} \mathrm{a}_{\mathrm{j},\mathrm{t}}\mathrm{v}_{\mathrm{j},\mathrm{t}}\right)}{P_{mid,t}}\right] * 10{,}000 \tag{2.2}$$

In this formula b_i and a_j are bid and ask prices for limit order volumes v_i and v_j. The formula can be simplified in the following way:

$$XLM(q) = \frac{P(q)_{bid} - P(q)_{ask}}{P_{mid}} \tag{2.3}$$

Where $P(q)_{bid}$ contains the volume-weighted bid prices and $P(q)_{ask}$ contains the volume-weighted ask prices. When the XLM measure is, for example, 10 bps by considering a traded volume of EUR 25,000 of a company the costs of a round trip is equal to EUR 25.

The costs of liquidation are, by assuming a symmetric limit order book, equal to half of the bid-ask spread.

$$cost\ for\ liquidation(q) = \frac{XLM(q)}{2} \tag{2.4}$$

In this paper we use XLM data for an observation period of 5 years and different indices (namely Dax, MDax, SDax). The problem of liquidity measures, which do not consider trading volume, is that the volume effect is a significant part of the overall transaction cost (Kaserer & Stange, 2008). This can be seen in figures 2.3, 2.4 and 2.5 where the average Dax, MDax and SDax XLM spreads for different traded volumes are presented.

Figure 2.3: Average XLM spreads for stocks listed in the Dax

The figure shows average XLM spreads for the Dax index by considering different traded volumes. The spreads are in bps and have to be paid when a stock is bought and subsequently sold again (roundtrip). The traded volumes are in 1,000 EUR.

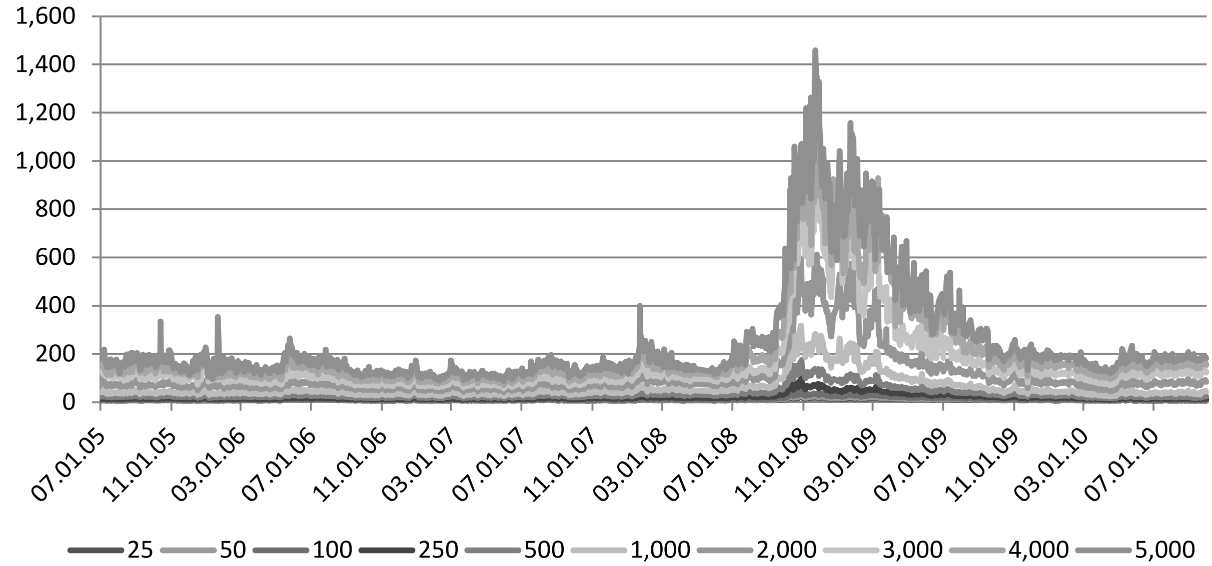


Figure 2.3 shows the average XLM spreads of the Dax by considering different traded volumes. An extreme volatile period starts around the Lehman crisis in October 2008 until the end of 2009. During that time an asymmetric increase can be seen by comparing the reaction of lower and higher traded volumes. Keeping in mind that we are talking here about Germany's blue chips, spreads increase dramatically. This is the risk which, for example, a hedge fund has when it is concentrated in stocks with liquidity problems. A margin call combined with the need to liquidate assets can result in huge losses. Table 2.1 shows a statistical analysis of the spreads over the total observation period. The results for the Dax show extreme increases not only for the average spreads but also for the standard deviations

with increasing trading volume. To get a better understanding how the data are distributed, the average skewness and average excess kurtosis are also presented. For a normal distribution, both parameters are equal to 0. In contrast to that, the skewness and excess kurtosis of the spreads with respectively 2 and 6 show an extreme behavior. These values are rising with increasing trading volume and decreasing slightly after EUR 2m are traded. At maximum, skewness is close to 3 and the excess kurtosis around 8.

Table 2.1: Statistical analysis of the XLM for stocks listed in the Dax, MDax and SDax

The following table shows a statistical analysis of the average XLM data (in bps) for Dax, MDax and SDax over the total observation period. The table is based on the data presented in figure 2.3, 2.4 and 2.5.

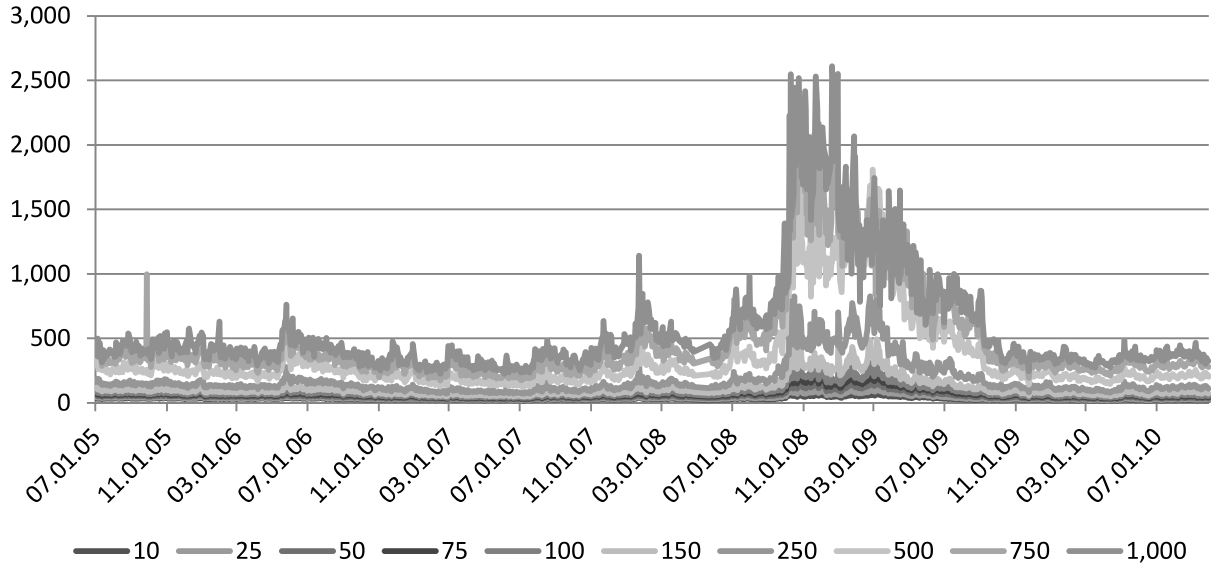
Traded Volume*		25	50	100	250	500	1,000	2,000	3,000	4,000	5,000
Dax	mean	8.54	9.95	12.77	21.01	34.31	59.43	108.49	159.79	207.03	249.00
	SD	2.94	4.08	6.33	12.99	24.44	47.54	99.50	155.18	192.56	221.60
	Skew	2.22	2.33	2.40	2.55	2.63	2.75	2.94	2.85	2.62	2.57
	Kurt	5.71	6.02	6.29	7.01	7.02	7.32	8.34	7.73	6.50	6.28
Traded Volume*		10	25	50	75	100	150	250	500	750	1.000
MDax	mean	30.23	39.13	54.34	69.15	83.90	114.04	179.15	357.42	474.12	560.45
	SD	10.86	17.41	28.18	38.44	49.06	73.14	132.73	321.76	374.72	406.65
	Skew	1.59	1.96	2.15	2.23	2.31	2.45	2.53	2.42	2.35	2.53
	Kurt	2.88	3.70	4.20	4.57	5.05	5.95	6.16	4.98	5.10	6.54
Traded Volume*		10	25	50	75	100	150	250			
SDax	mean	86.56	120.76	177.86	259.23	327.72	489.71	651.54			
	SD	30.73	55.77	116.78	201.56	282.52	413.76	486.01			
	Skew	1.98	2.64	2.85	2.60	2.45	2.24	2.16			
	Kurt	5.67	10.04	10.91	7.32	5.94	4.64	4.48			

* Traded volume in 1,000 EUR

In the following figure (2.4) we focus on average spread data of the MDax. When comparing the Dax and MDax figures they seem similar. Both have relatively flat pre-crisis and post-crisis periods while during the crisis there are very high spreads. Also the asymmetric increase of the spreads with increasing trading volume can be seen. Beside the common characteristics, the difference is based on the gap between the spreads (y-axis). This can be seen in table 2.1. The mean spreads of the MDax for a lower trading volume (25,000 EUR) is around 4.6 times higher compared to the Dax spreads (25,000 EUR). For higher traded volumes, the values get slightly closer to a factor of around 2. Beside the increase of the average spreads the standard deviation also increases much more with increased trading volume. By comparing the results listed in table 2.1 it must be considered that the traded volumes for both indices are different.

Figure 2.4: Average XLM spreads for stocks listed in the MDax

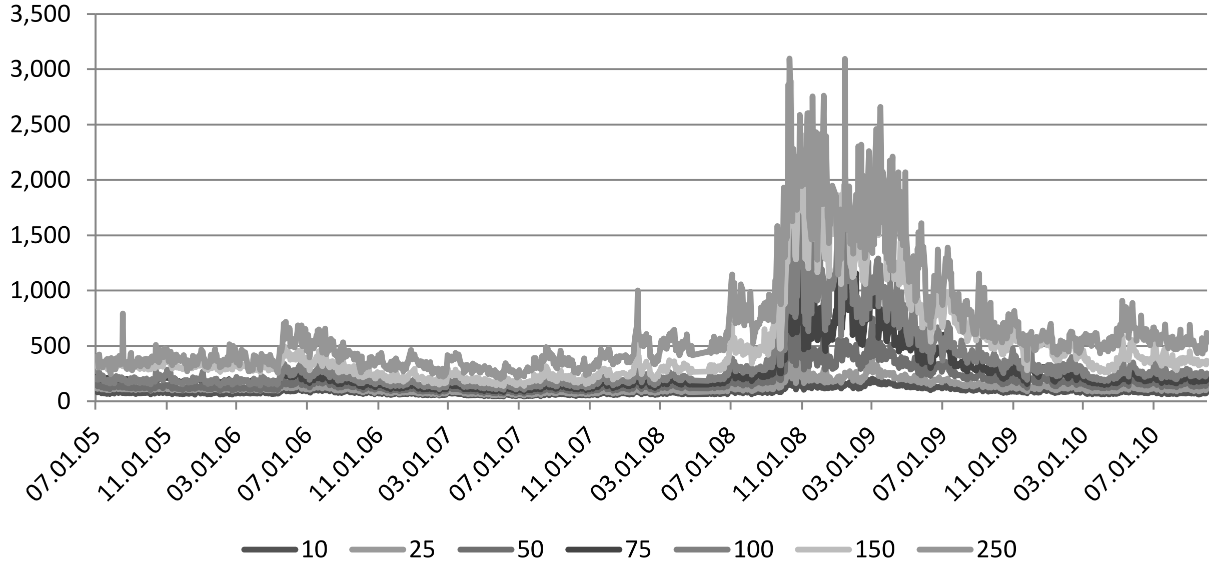
The figure shows average XLM spreads for the MDax index by considering different traded volumes. The spreads are in bps and have to be paid when a stock is bought and subsequently sold again (roundtrip). The traded volumes are in 1,000 EUR.



In figure 2.5, we present the average SDax spreads. To exclude excessively extreme values we focus on 7 out of 10 trading volumes. The same pattern can be seen when comparing the shape of the SDax with that of the Dax and MDax. The difference is clear when looking at table 2.1. For a trading volume of 25,000 EUR, the average spread (standard deviation) of the SDax is around 3.9 (5.1) times higher and for a trading volume of 250,000 EUR it is 3.63 (3.66) times higher compared to the MDax. By comparing the maximums in figures 2.3, 2.4 and 2.5 we can see that for the Dax the value is around 1,400 bps, for the MDax around 2,500 bps and the SDax shows more than 3,000 bps.

Figure 2.5: Average XLM spreads for stocks listed in the SDax

The figure shows average XLM spreads for the SDax index by considering different traded volumes. The spreads are in bps and have to be paid when a stock is bought and subsequently sold again (roundtrip). Based on the highly volatile data only 7 out of 10 trading volumes are presented. The traded volumes are in 1,000 EUR.



Chapter Three

Modeling Correlations in a Liquidity Adjusted VaR[6]

3.1 Motivation

A common way to control and measure risk is to use the Value at Risk (VaR) approach. By specifying a confidence level, the risk manager is able to determine a loss threshold which is probably not exceeded. In the past, this measure was used mainly to capture market risk. As a result of the last crisis where liquidity risk played an important role, several researchers came up with models to capture both risks. One possible way is to use a Liquidity adjusted Value at Risk ($L-VaR$) model. Beside market risk, liquidity risk is also captured by summing the individual VaRs. A weakness is that the correlation between both risk measures is neglected (Ernst C., 2009). In this chapter a new and more sophisticated Correlation and Liquidity Adjusted VaR ($CL-VaR$) model is presented. Beside the Pearson correlation coefficient, several correlation models like the Constant Correlation (CC) model, EWMA model and the Dynamic Conditional Correlation (DCC) model are focused on. The CC and DCC models are calculated using the symmetric $AR-GARCH$ and asymmetric $AR-GJR$ models with normal and Student-T distributed residuals. To evaluate the performance, we look at the Xetra Liquidity Measure (XLM) which contains volume-weighted bid-ask spreads. Based on back-testing we analyze which model works best.

The reminder of this chapter is organized as follows. First is the literature review in section 3.2 and then in section 3.3 the econometric framework is set out. Section 3.4 deals with the back-testing framework and in chapter 3.5 the empirical data are presented. The results are discussed in section 3.6 and we conclude with section 3.7.

[6] This chapter is based on the working paper (Busch & Lehnert, 2011).

3.2 Literature Review

Liquidity risk in stock markets is discussed extensively and from different perspectives in various papers. In general it can be said that two main research areas exist.

The first considers optimal execution models where the focus is on liquidating a stock or a portfolio within a given time. The intention is to minimize liquidity costs while maximizing the return. This topic is not discussed further in this chapter but for the interested reader we refer to Subramanian et al. (2001), Dubil (2003) or Engle (1982).

The second area focuses on measures for liquidity risk. Here the research papers deal with the question of expected costs (or losses) for the investor when a stock or portfolio is liquidated immediately. To answer this question different attributes (which are assumed to describe liquidity) are focused. The common attributes are bid-ask spread data used by Bangia et al. (1999) and Ernst et al. (2012), number of transactions and traded volumes used by Berkowitz et al. (2000), Cosandey (2001) and weighted spread data used by Francois-Heude et al. (2001), Giot et al. (2006) and Ernst et al. (2009). In the paper by Ernst et al. (2009) they demonstrate the outperformance of the $L - VaR$ models based on XLM data. But they accept that their model does not consider correlations between bid-ask spreads and returns. In the paper by Francois-Heude et al. (2001) a kind of correlation (overestimation of the spreads) is considered in the form of a correction term. The idea is to reduce the current bid-ask spread by the means of spreads measured over the observation period. The back-testing results presented by Ernst et al. (2009) indicate an underperformance of the model. A paper which discusses how to calculate a portfolio VaR by using liquidity adjusted stock prices was published by Botha (2008). There he adds the corresponding bid-ask spreads to stock prices which result in liquidity adjusted stock prices. These data are used to calculate a portfolio VaR proposed by Markowitz (1952). But they neglect the correlation between spreads and returns.

In several research papers which focus on L-VaR models, unconditional volatility is used. In the paper by Stange et al. (2010) the authors detect volatility clustering in the spread and return data and therefore use the Exponentially Weighted Moving Average ($EWMA$) methodology. We found no articles where the usability of advanced volatility models (e.g.

GARCH model) or correlation models (e.g. DCC model) are analyzed in combination with a $L - VaR$ framework.

3.3 Econometric Framework

3.3.1 Basic L-VaR Model

The basic $L - VAR$ approach which is used in this chapter is proposed by Bangia et al. (1998) and extended by Ernst et al. (2009). An advantage of this approach is simplicity. From a practical point-of-view, the methodology is easy to implement and to process. The aim is to capture liquidity risk and market risk in one measure: the *L-VaR*. This consists out of two separate VaRs. The first (VaR_R) captures market risk by focusing on the uncertainty of stock price changes with the second (VaR_S) considering liquidity risk. The result is an expected loss threshold which is not exceeded with a given probability over a specified time (Dowd K. , 1999).

$$L - VaR = VaR_r + VaR_s \tag{3.1}$$

Summing both risk measures is obviously a special case, because the underlying assumption is that the correlation is equal to one[7]. However, the authors argue that in "adverse market environments extreme events in returns and extreme events in spreads happen concurrently" (Bangia A. D., 1998).

The loss based on *asset returns* is defined as:

$$Loss\left(\Delta(t)\right) = P_{mid,t-1} * (1 - exp^{r_t}) \tag{3.2}$$

In this formula $P_{mid,t}$ is the mid-price between the bid price and ask price at time t. The continuously compounded log return is defined as $r_t = ln\left(\frac{P_{mid,t}}{P_{mid,t-1}}\right)$. To consider a stressed

[7] According to Markowitz the portfolio variance of two assets A and B is defined as $var_P{}^2 = var_A{}^2 + var_B{}^2 + 2 * \rho_{A,B} * var_A * var_B$. By assuming a correlation of one we can write $var_P{}^2 = var_A{}^2 + var_B{}^2 + 2 * var_A * var_B = (var_A + var_B)^2$. The standard deviation is equal to the square root and results in $var_P = var_A + var_B$

market, the formula is modified by substituting r_t with the Value at Risk formula $\mu_r + z_{\alpha,r}\sigma_r$. The parameter μ_r is the expected value of the returns and σ_r is the standard deviation. The expected value of the returns is assumed to be zero. This is a common assumption for log returns[8]. In the paper by Ernst et al. (2009) two extensions are made to improve the basic model by Bangia et al. (1998). Firstly, the standard deviation of the returns is calculated by using the Exponentially Weighted Moving Average (EWMA) (J.P.Morgan/Reuters, 1996). This is done to account for volatility clustering in spread and return data[9]. The second difference is that in the paper by Ernst et al. (2009) the parameter z_α is calculated using Cornish Fisher approximation[10].

The Cornish Fisher approximation is a semi-parametric approach for calculating quantiles of non-normal distributions. The methodology is a function of the standard normal quantile in combination with the skewness and kurtosis (Alexander, 2009). The fourth order Cornish Fisher approximation is defined as

$$\hat{z}_\alpha = z_\alpha + \frac{1}{6}(z_\alpha^2 - 1) * \gamma + \frac{1}{24}(z_\alpha^3 - 3z_\alpha) * K - \frac{1}{36}(2z_\alpha^3 - 5z_\alpha) * \gamma^3 \tag{3.3}$$

Where $z_\alpha = \Phi^{-1}(\alpha)$ is the α quantile of the normal distribution. Furthermore the skewness is defined as $\gamma = \frac{1}{n}\sum_{t=1}^{n}\frac{(y_t - \bar{y})^3}{\sigma^3}$ and the excess kurtosis is equal to $K = \frac{1}{n}\sum_{t=1}^{n}\frac{(y_t - \bar{y})^4}{\sigma^4} - 3$

Finally the loss based on stressed markets is

$$VaR_r = 1 - exp^{(z_{\alpha,r}\sigma_r)} \tag{3.4}$$

Liquidity risk is by definition related to the bid-ask spread which is calculated as the difference between the bid price and ask price (Amihud & Mendelson, 1986).

$$Spread\ (t) = ask\ price_t - \ bid\ price_t \tag{3.5}$$

---

[8] In the statistical analysis of the underlying log spread and log return data in table 3.1 it can be seen that this assumption is valid.

[9] A more detailed description of the EWMA model can be found in chapter 3.3.2.

[10] Instead of using the empirical quantile method which is mentioned by (Ernst C., 2012). There they calculate $z_{\alpha,s} = \left(\frac{S_\alpha - \bar{\mu}}{\sigma}\right)$ where S_α is the percentile spread of the last 20 days.

If a trader has to sell a stock, in general he will receive half the bid-ask spread below mid-market price[11]. The costs for selling are then equal to

$$Cost\ of\ liquidation\ =\ 0{,}5 * S_t P_{mid}\ \ = 0{,}5 * \left(\mu_s + z_{\alpha,s}\sigma_s\ \right) P_{mid} \qquad (3.6)$$

In this formula $S_t = \frac{P_{ask,t} - P_{bid,t}}{P_{mid,t}}$ and $P_{mid,t}$ is in the middle between the bid price and ask price at time t. To account for stressed liquidity in the markets S_t is replaced by the $VaR_s = \mu_s + z_{\alpha,s}\sigma_s$. The parameter μ_s stands for the expected spread and σ_s stands for the standard deviation of the spread. The variable $z_{\alpha,s}$ specifies the confidence level (e.g. 99%). As for the returns, so also for the spreads, Ernst et al. (2009) use the EWMA to calculate σ_s and the Cornish Fisher approximation to calculate $z_{\alpha,s}$. They demonstrate that the spreads show volatility clustering and a non-normal distribution. Another adjustment of the basic model is proposed by Loebnitz (2006). The author mentions that the VaR_s should be used in combination with the stressed mid-price and not with the current mid-price. The adjustment is to replace P_{mid} with the VaR_s which is equal to $\exp(\tilde{\alpha} * \sigma_r)$.

The stress loss based on liquidity is defined as

$$VaR_s = 0{,}5 * \left(\mu_s + z_{\alpha,s}\sigma_s\ \right) * \exp(\tilde{\alpha} * \sigma_r) \qquad (3.7)$$

By substituting the VaR_r and VaR_s in the $L - VaR$ formula the result is the following formula:

$$L - VaR = 1 - exp(\mu_r + z_\alpha * \sigma_r) + 0{,}5 * (\mu_s + z_\alpha * \sigma_s) * \exp(\tilde{\alpha} * \sigma_r) \qquad (3.8)$$

3.3.2 Accounting for Heteroscedasticity

One important parameter in financial time series models is volatility. The volatility of return and spread series shows characteristics like volatility clustering (Mandelbrot, 1963) and the asymmetric response of volatility to changes in the underlying value. There are different methods to account for that. Within this section, the *Exponential Weighted Moving Average*

[11] Buying an asset is normally done $\frac{1}{2}$S above and selling $\frac{1}{2}$S below the mid-market price.

(EWMA) model is used as in Bangia et al. (1998) and Ernst et al. (2012). Additionally, we focus on more sophisticated models, namely *Generalized Autoregressive Conditional Heteroscedasticity (GARCH(1,1))* and the model developed by *Glosten, Jagannathan and Runkle GJR(1,1).* The methodologies are extended to model the conditional mean of log spreads by using $AR - GARCH$ and $AR - GJR$ models.

The first volatility model we want to introduce is the EWMA model. A characteristic of the methodology is that exponential weights are used for the observations. These weights are highest for the most recent observation and decrease for older observations. This is done using the following formula:

$$\sigma_t^2 = (1 - \lambda) \sum_{i=1}^{\infty} \lambda^{i-1} r_{t-i}^2 \tag{3.9}$$

Where λ is called the smoothing constant in the range $0 < \lambda < 1$. The parameter r^2 is the squared return. The above-mentioned formula can be rewritten into a recursion which is more practical for calculation.

$$\sigma_t^2 = (1 - \lambda) r_{t-1}^2 + \lambda \sigma_{t-1}^2 \tag{3.10}$$

In this formula we have two terms. The first $(1 - \lambda) r_{t-1}^2$ determines the reaction of a market shock on volatility. With decreasing λ the reaction on market information in the past is increasing. The second term $\lambda \sigma_{t-1}^2$ measures the persistence of volatility. The higher the λ, the longer volatility stays high.

In comparison to the EWMA model, we now want to introduce the GARCH and GJR volatility model. The dynamic conditional behavior of a symmetric normal $AR(R) - GARCH(P, Q)$ process is given by the following formula:

$$\boldsymbol{y_t} = \boldsymbol{C} + \sum_{i=1}^{\boldsymbol{R}} \boldsymbol{AR}_i \, \boldsymbol{y}_{t-1} + \boldsymbol{\varepsilon}_{\mathbf{t}} \tag{3.11}$$

The conditional mean for an $AR(R)$ is calculated as the r-th order autoregressive process.

$$\mathbb{E}(y_t | I_{t-1}) = C + \sum_{i=1}^{R} AR_i \, y_{t-1} \tag{3.12}$$

$$\varepsilon_t | I_{t-1} \sim N(0, \sigma_t^2)$$

The volatility of the $GARCH(P, Q)$ can be calculated by using the following formula:

$$\sigma_t^2 = \omega + \sum_{i=1}^{P} \beta_i \sigma_{t-1}^2 + \sum_{j=1}^{Q} \alpha_j \varepsilon_{t-1}^2 \qquad (3.13)$$

Where ε_t denotes the unexpected return (market shock) which follows a process with a zero mean and a time varying conditional variance. In the simple form AR(0), the conditional mean error process ε_t is calculated as the mean deviation $y_t - C = y_t - \bar{y}$ of the expected returns within the information set I_{t-1}. The information set contains return data for a specified time period. Within this paper the GARCH(1,1) is used: $\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha\varepsilon_{t-1}^2$. The combination of $\alpha + \beta$ indicates how quickly conditional volatility decreases to unconditional volatility (long run volatility). This is a required constraint for stable results of $GARCH$ models. Long run volatility is defined as $\bar{\sigma}^2 = \frac{\omega}{1-(\alpha+\beta)}$. The formula of the GARCH(1,1) volatility has the following constraints: $w > 0$, $\alpha, \beta \geq 0$ and $\alpha + \beta < 1$. The calculation of the parameter α and β is made using the following log likelihood function:

$$lnL(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\left(ln(\sigma_t^2) + \left(\frac{\varepsilon_t}{\sigma_t}\right)^2\right) \qquad (3.14)$$

where θ denotes the parameters of the conditional variance formula.

In contrast to the above-mentioned symmetric GARCH model, asymmetric models also exist. In symmetric GARCH models no differentiation between the impact of positive or negative returns or spread changes are made. This is not the case especially in equity markets. It can be seen that market volatility increases more after a negative return than a positive return, as mentioned by Black (1976) and Cristie (1982). To account for that, different authors have proposed extensions of the GARCH model to capture this asymmetric behavior. Within this chapter the GJR model by Gloster (1993) is chosen. This model uses a "leverage" parameter λ which increases the conditional volatility when the last return ε_{t-1} was negative. The model is calculated based on the following formula:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \lambda 1_{\{\varepsilon_{t-1}<0\}}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad (3.15)$$

The different parameters are calculated using the same Maximum Likelihood Estimator (MLE) which is also used for the symmetric normal GARCH model (see formula 3.14).

Until now, the symmetric normal GARCH and asymmetric GJR model have been presented. One weakness of both models is that they assume that the underlying return data are distributed normally. In reality, and especially at the time of stressed markets, the return and also the spread data have a skewness and excess kurtosis which is different from zero. This is because the underlying distributions have heavy tails (leptokurtic). It is mentioned in several papers that in reality these data show (especially during times of crisis), more the shape of a Student-T distribution (Engle & Bollerslev, 1986) (Lambert & Laurent, 2001). Therefore the GARCH(1,1) and the GJR(1,1) models are also calculated by assuming a Student-T distribution. The model is changed by using a different MLE.

$$lnL(\theta) = -\sum_{t=1}^{T}\left(ln(\sigma_t) + \left(\frac{\upsilon+1}{2}\right) ln\left(1 + (\nu-2)^{-1}\left(\frac{\varepsilon_t}{\sigma_t}\right)^2\right)\right) + Tln\left[\left((\nu-2)\pi\right)^{-\frac{1}{2}}\Gamma\left(\frac{\nu}{2}\right)^{-1}\Gamma\left(\frac{\nu+1}{2}\right)\right] \quad (3.16)$$

One common criterion, which the EWMA and the GARCH model must fulfill, is that the underlying data are stationary. One way to change the data to fulfill this requirement is by using log changes instead of absolute values. While the bid-ask spread calculations of Ernst et al. (2012) are based on absolute values, formula 3.7 must be changed in the following way to allow the usability of the GARCH models:

$$VaR_S = 0{,}5 * \exp(\tilde{\alpha} * \sigma_{LogR}) * \left(\mu_L * exp\left(\mu_{LogL} + \widetilde{\alpha_{LogL}} * \sigma_{LogL}\right)\right) \quad (3.17)$$

The mean of the absolute spreads (μ_L) is multiplied by the VaR of the most negative change based on the log spreads. By using the Dickey Fuller[12] test during the simulations the log returns and log spreads displayed stationary behavior overall.

[12] Dickey Fuller test assesses the null hypothesis of a unit root using the model $y_t = c + \delta t + \phi y_{t-1} + \beta_1 \Delta y_{t-1} + \cdots + \beta_p \Delta y_{t-p} + \varepsilon_t$ where $\Delta y_t = y_t - y_{t-1}$, p number of lagged differences and ε_t is the zero mean innovation process. H_0 is that $\phi = 1$ and the alternative $\phi < 1$ which indicates stationarity.

3.3.3 Correlation Adjusted L − VaR Models (CL − VaR)

There are different methods to measure correlations between two variables. In this section we consider the Pearson correlation coefficient and the $GARCH$, GJR and $EWMA$ models.

The basic formula presented by Bangia et al. (1999) or Ernst et al. (2012) does not allow a calculation of the $CL - VaR$. Therefore the $L - VaR$ formula 3.8 has to be adjusted. Instead of considering the expected loss of returns (formula 3.4) the formula is changed to capture the most negative expected change.

$$VaR_r = z_{\alpha,r}\sigma_r \tag{3.18}$$

In our opinion this can be done because the liquidation value (formula 3.34) is also calculated accordingly.

The change of the VaR_s formula has already been described in formula 3.17 and is as follows:

$$VaR_s = 0{,}5 \ * \exp(\tilde{\alpha} * \sigma_{LogR}) * \ \left(\mu_L * exp(\mu_{LogL} + \widetilde{\alpha_{LogL}} * \sigma_{LogL})\right) = z_{\alpha,L}\sigma_L \tag{3.19}$$

To extend formula 3.1, that correlation can also be considered, the basic and well-known portfolio VaR formula presented by Markowitz (1952) can be used.

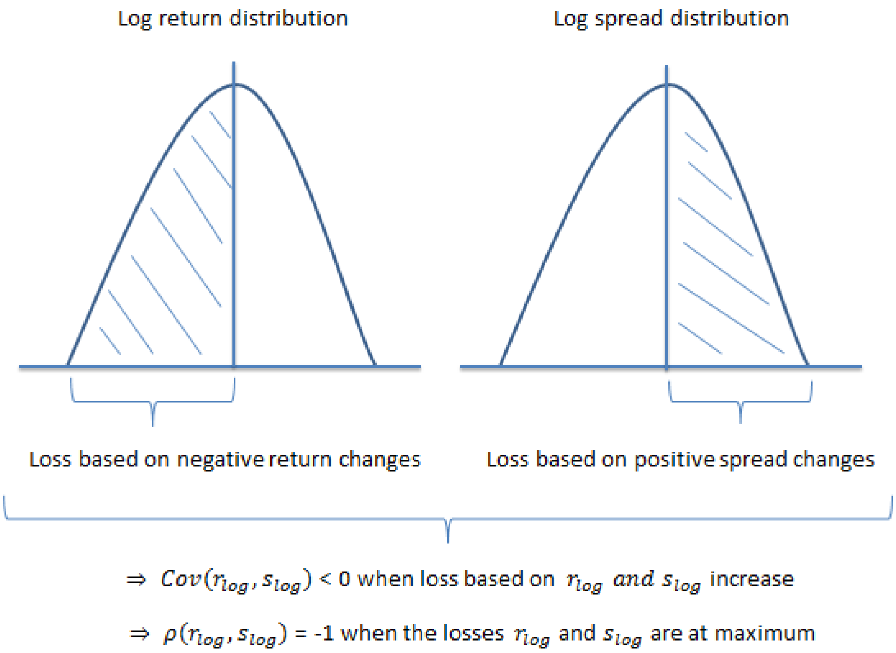
$$CL - VaR = \sqrt{{VaR_r}^2 + {VaR_s}^2 + 2 * \rho_{s,r} * VaR_r * VaR_s} \tag{3.20}$$

Another change we make is based on the distribution of log returns and log spreads. Figure 3.1 shows an example of both distributions. It is important to understand that the risks for the log spread distribution and log return distribution are contrary. While negative log changes have to be considered for the VaR_r (left part of the distribution) the positive spread changes have to be covered by the VaR_s (right part of the distribution). In Figure 3.1 it can be seen that when both risks increase the $Cov(r_{log}, s_{log})$ goes negative. The impact of negative correlations on formula 3.2 is that the $CL - VaR$ is decreasing. This is contrary to the intention that when both risks are increasing, the correlation term should also increase.

Therefore the prefix of the correlation term has to be changed. The target is that when both $VaRs$ are moving in the same direction the calculated value should be $\rho_{s,r} = 1$ and not $\rho_{s,r} = -1$.

Figure 3.1: Impact of the log return and log spread distributions on covariance and correlation

The following figure shows that risk is contrarily distributed for spread and return data. While for returns, negative changes are critical, for spreads positive changes should be considered. Therefore the correlation between spreads and returns is also different. A correlation of -1 indicates that risk is moving concurrently while a correlation of 1 indicates no common movement.



The Pearson correlation coefficient is defined as:

$$\rho_{s,r} = corr(r_t, s_t) = \frac{cov(r_t, s_t)}{\sigma_s \sigma_r} \tag{3.21}$$

Through the standardization of the covariance the correlation is in the range $-1 \leq \rho_{s,r} \leq 1$. By changing the formula the covariance is defined as:

$$cov(r_t, s_t) = \sigma_s * \sigma_r * \rho_{s,r} \tag{3.22}$$

Changing the formula to matrix notation the result is:

$$V_t = D_t C D_t \tag{3.23}$$

Where D_t is a positive definite diagonal matrix of time varying GARCH or GJR volatility models. The rest of the matrix is assumed to be zero. The correlation matrix C is not time varying and is therefore called the Constant Correlation (CC) model. The matrix C can contain any correlations with the condition that the covariance matrix V_t is positive definite. Based on the above-mentioned model, Engle (2000) propose a Dynamic Conditional Correlation (DCC) where C is time varying. The covariance matrix for log spreads and log returns is:

$$V_t = \begin{bmatrix} \sigma_s & 0 \\ 0 & \sigma_s \end{bmatrix} \begin{bmatrix} 1 & \rho_{s,r} \\ \rho_{s,r} & 1 \end{bmatrix} \begin{bmatrix} \sigma_r & 0 \\ 0 & \sigma_r \end{bmatrix} \tag{3.24}$$

The volatility σ_s^2 and σ_r^2 can be estimated by using the GARCH, GJR or the EWMA model as described previously in section 3.3.2. The next step is that each return and spread has to be standardized by their dynamic standard deviation.

$$\text{Returns: } z_{r,t} = \frac{r_{t-1}}{\sigma_{r,t-1}} \qquad \text{Spreads: } z_{s,t} = \frac{s_{t-1}}{\sigma_{s,t-1}} \tag{3.25}$$

The time-varying correlation based on the EWMA methodology can then be calculated as follows:

$$\rho_{s,r}^{EWMA} = \frac{\sigma_{sr,t}}{\sqrt{\sigma_{s,t} * \sigma_{r,t}}} \tag{3.26}$$

Where the covariance is equal to:

$$\sigma_{sr,t} = (1-\lambda) r_{r,t-1} r_{s,t-1} + \lambda \sigma_{sr,t-1}^2 \tag{3.27}$$

Within this paper the parameter λ is assumed to be 94%[13]. The matrix notation is:

[13] The value is used by Risk Metrics for the daily update of the volatility within the Risk Metrics database. For for information see: J.P. Morgan Risk Metrics Monitor, Fourth Quarter 1995.

$$Q_t = (1-\lambda)\left(z_{r,t-1}z_{r,t-1}^{`}\right) + \lambda Q_{t-1} \tag{3.28}$$

By using the GARCH(1,1) model the correlation is defined as:

$$\rho_{sr,t} = \overline{\rho_{sr}} + \alpha\left(z_{r,t-1}z_{s,t-1} - \overline{\rho_{sr}}\right) + \beta\left(\rho_{sr,t-1} - \overline{\rho_{sr}}\right) \tag{3.29}$$

where $\overline{\rho_{sr}} = E\left(z_{r,t-1}z_{r,t-1}^{`}\right)$ is the unconditional long run correlation. This value can be calculated as $\overline{\rho_{sr}} = \frac{1}{T}\sum_{t=1}^{T}\left(z_{r,t-1}z_{s,t-1}\right)$. The matrix notation is:

$$Q_t = E\left(z_{r,t-1}z_{r,t-1}^{`}\right)(1-\alpha-\beta) + \alpha\left(z_{r,t-1}z_{r,t-1}^{`}\right) + \beta Q_{t-1} \tag{3.30}$$

As in the chapter before, a MLE function is used to find the best solution. For a two-asset case, the formula can be expressed as:

$$L_c = -\frac{1}{2}\sum_{t=1}^{T} ln\left(1-\rho_{r,s}^2\right) + \frac{\left(r_t^2+s_t^2-2\rho_{12,t}r_ts_t\right)}{\left(1-\rho_{r,s}^2\right)} \tag{3.31}$$

There are different extensions possible for that model. For example Tsay (2006) extended the model by assuming that the standardized innovations follow a Student-T distribution. Also he introduced asymmetric treatment of the standardized innovations to capture leverage effects within the volatility.

3.4 Back-testing Framework

To determine the quality of the different $L-VaR$ models the numbers of exceedances are focused upon. If the model has excellent performance, the exceedances of the model should be equal to the number of exceedances determined by the confidence level. If this is not the case, the reason can be an underestimation (too many exceedances) or an overestimation (too few exceedances) of risk. A test that considers this differentiation is the unconditional coverage test presented by Kupiec (1995).

The Kupiec test assumes that the number of exceedances x follow a binomial distribution with the probability p. Based on the assumption that a model works perfectly, the value $1 - p$ is equal to the confidence level α. In the simulations α is assumed to be 95%. The parameter n_1 is the number of exceptions, n is the number of days that are considered in the VaR calculation and $n_0 = n - n_1$ are the days when the VaRs are calculated correctly. Based on the parameter the following Likelihood Ratio (LR) test static can be used:

$$LR = -2 * \left(n_1 ln(\alpha) + n_0 ln(1-\alpha) - n_1 ln\left(\frac{n_1}{n}\right) - n_0 ln\left(1 - \frac{n_1}{n}\right)\right) \qquad (3.32)$$

In the formula, the LR follows a Chi-square distribution with one degree of freedom. By assuming a confidence level of 95% the test will be rejected if $LR < 3.84$. The confidence level for the test can be chosen independently from the confidence level of the VaR.

In the simulations, the value n is equal to the total observation period. The number of exceedances n_1 is the sum of Boolean values and is defined as:

$$n = \begin{cases} 1 \; if \; VaR \leq Liq_t \\ 0 \; if \; VaR > Liq_t \end{cases} \qquad (3.33)$$

Where $t = 1 \ldots 20$ are the number of days in the observation window and

$$Liq_t = ln\left(\frac{P_t^{mid}}{P_{t-1}^{mid}}\right) + ln\left(1 - \frac{1}{2} * spread(t)\right) \qquad (3.34)$$

The price Liq_t of a stock which has to be sold at time t is equal to the log return plus the loss from liquidity costs (Ernst, Stange, & Kaserer, 2009).

3.5 Empirical Data Analysis

The empirical data in this chapter are from stocks listed either in the Dax, MDax or SDax. A time period of 5 years is considered. Due to new listings, de-listing and data quality problems not all stocks could be taken for simulation. In the end, 23 stocks of the Dax, 45 stocks of the MDax and 23 of the SDax qualified. From these data the stock mid-prices are taken. The weighted bid-ask spreads for different traded volumes are provided by Deutsche Börse. They calculate and offer these values daily under the name Xetra Liquidity Measure (XLM). The XLM is denoted in bps and is a measure of the costs which appear by buying and then selling directly a stock ("round trip"). An advantage of the XLM is that the costs of a round trip are calculated for different quantities q. These quantities can be different for the Dax, MDax and SDax. With increasing traded volumes, the XLM data have missing values. In our opinion, this is because few or no trades are made daily with this order size.

The XLM is calculated in the following way (Kaserer & Stange, 2008):

$$\mathrm{XLM(q)} = \left[\frac{\sum_i b_i v_i}{v} - \frac{\sum_j a_j v_j}{v}\right] * \frac{10{,}000}{P_{mid}} \tag{3.35}$$

In this formula b_i and a_j are different bid and ask prices for limit order volumes v_i and v_j. The formula can be simplified in the following way:

$$XLM(q) = \frac{P(q)_{buy} - P(q)_{sell}}{P_{mid}} \tag{3.36}$$

When the XLM measure is, for example, 10 bps by considering a traded volume of EUR 25,000, the costs of a round trip is equal to EUR 25.

The intention of the $L - VaR$ and $CL - VaR$ is to consider the costs which appear when a quantity of stocks is sold immediately. Therefore the costs of liquidation are, by assuming a symmetric limit order book, equal to the half of the bid-ask spread:

$$cost\ for\ liquidation(q) = \frac{XLM(q)}{2} \tag{3.37}$$

A statistical analysis of the underlying return and spread data can be found in table 3.1.
The return data show a mean of zero and a pretty low standard deviation over all indices. Non-normality can be seen by looking at the skewness and excess kurtosis. While both values are zero for the normal distribution, the excess kurtosis is particularly different with a mean of 11. The results of the MDax and SDax are a bit lower but they still show heavy tails. This

result is also achieved by using the Jarque-Bera[14] (JB) test. This test measures, by using the skewness and kurtosis, the difference to the normal distribution. In the zero hypotheses it is assumed that the tested values are normally distributed. In all indices the test was rejected in 100% of cases (confidence level 95%).

Within the statistical evaluation, not all traded volumes of the log spreads are considered. For the Dax, the volume of 50 and 100 thousand and 3 million, for MDax, 50, 100 and 500 thousand and for the SDax, 25, 50 and 150 thousand are in focus. The log spreads shown in table 3.1 also have a mean of zero but with a high standard deviation. The standard deviation increases from Dax to MDax and SDax. That the log spreads are also non-normally distributed can be seen from the skewness and excess kurtosis. While the skewness is around zero, which would imply normality, the excess kurtosis is far from normal. The kurtosis is highest for the MDax followed by the SDax and the Dax. Also for the log spreads, the JB test confirms the assumption of non-normality.

In the following discussion the impact of different traded volumes on the $L-VaRs$ and $CL-VaRs$ are discussed.

Table 3.1: Synthesis of statistical data of log spreads and log returns

The table shows a statistical analysis of the underlying log spread and log return data. The indices Dax, MDax and SDax are considered over an observation period of 5 years. Additionally to the standard attributes also the Jarque-Bera[14] test is performed which indicates if the underlying data come from a normal distribution.

	Dax (23 stocks)					MDax (45 stocks)					SDax (23 stocks)				
	Mean	Median	SD	Max	Min	Mean	Median	SD	Max	Min	Mean	Median	SD	Max	Min
Return statistics															
Mean	0	0	0	0,001	-0,001	0	0	0,001	0,001	-0,002	0	0	0,001	0,001	-0,001
SD	0,025	0,023	0,005	0,037	0,016	0,028	0,03	0,007	0,038	0,013	0,028	0,026	0,007	0,044	0,015
Skewness	-0,027	0,129	0,456	0,613	-0,902	-0,113	-0,116	0,333	0,451	-1,147	-0,213	-0,203	0,482	0,703	-1,156
Excess Kurtosis	11,92	10,829	5,085	26,137	6,4	8,41	7,9	3,075	17,646	4,58	10,118	8,858	4,839	23,264	5,815
JB-test (95%)	100%					100%					100%				
Max.	0,159	0,16	0,034	0,228	0,086	0,16	0,155	0,06	0,287	0,056	0,157	0,151	0,057	0,316	0,072
Min.	-0,156	-0,151	0,046	-0,069	-0,27	-0,166	-0,16	0,062	-0,069	-0,277	-0,173	-0,151	0,074	-0,097	-0,423
Spread statistics															
Mean	0	0	0	0,001	-0,001	0	0	0,001	0,002	-0,001	0	0	0,001	0,002	-0,001
SD	0,187	0,183	0,037	0,285	0,086	0,275	0,276	0,051	0,435	0,143	0,36	0,36	0,058	0,608	0,239
Skewness	-0,047	-0,062	0,131	0,306	-0,446	-0,01	0,004	0,175	0,757	-0,539	0,12	0,131	0,189	0,52	-0,501
Excess Kurtosis	4,504	4,097	1,377	10,59	3,152	14,192	4,184	31,114	152,718	3,308	7,372	5,241	7,373	52,649	3,272
JB-test (95%)	94%					97%					97%				
Max.	0,775	0,728	0,242	1,695	0,446	1,445	1,124	0,898	4,924	0,627	1,934	1,793	0,689	3,88	0,868
Min.	-0,827	-0,778	0,27	-0,485	-1,988	-1,431	-1,146	0,897	-0,682	-4,568	-1,791	-1,541	0,771	-0,922	-4,632

[14] The Jarque-Bera (JB) test is used to test if data are based on a normal distribution. Therefore the skewness S and kutosis K of the underlying data are focused on. The test is calculated with the following formula $JB = \frac{n-k}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right)$. For large samples, the JB result is Chi-square distributed with two degrees of freedom.

3.6 Empirical Performance and Discussion

In the following section the back-testing results of the $L - VaR$ and new proposed $CL - VaR$ are discussed. The methodologies used are defined in section 3.3. The performances of the different models are evaluated by using the Kupiec test (see section 3.4) with a confidence level of 95%. The discussion focuses on the following two main topics which have been neglected in other research papers. Firstly, the impact of different correlation models compared to the generally made assumption of perfect correlation like in Bangia et al. (1998) and Ernst et al. (2012). Secondly, the usability of advanced conditional volatility models like AR-GARCH and AR-GJR models compared to the basic EWMA model.

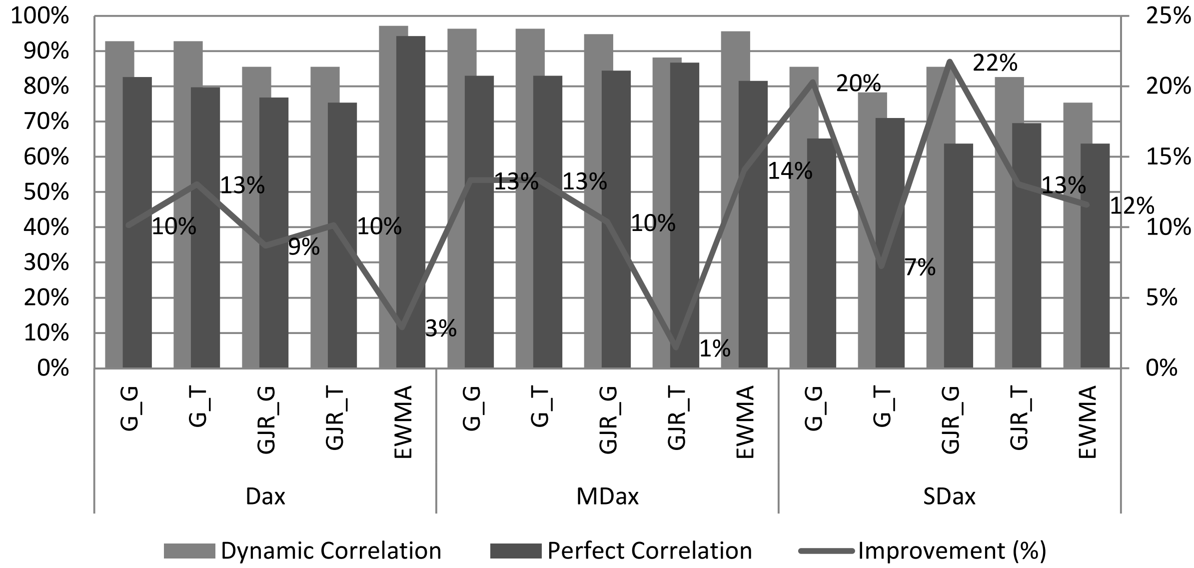
The simulations are calculated using rolling, non-overlapping, time-windows with a length of 20 days. To get stable results for the GARCH and GJR methodologies a fitting period of 1,000 days is taken. We applied a cap and a floor to the log returns at $+2.5 * Standard\ Deviation$ and $-2.5 * Standard\ Deviation$ before using the GARCH models. Based on the limited number of XLM data (approx. 1,320 days) 16 $L - VaRs$ and $CL - VaRs$ are calculated for each stock and index. Based on the low back-testing performance by using the Cornish Fisher approximation, the following results are calculated by assuming a normal distribution (confidence level 99%). At the end of this section the reason for the low performance of the CF methodology is discussed.

In figure 3.2 the overall back-testing results are demonstrated focusing in the Dax, MDax and SDax indices for a five year time period. The intention of this figure is to demonstrate the increase on the back-testing performance when the correlation is measured and not assumed to be perfect, as per Bangia et al. (1998) and Ernst et al. (2012). The performance increase is equal to the difference between the “Perfect Correlation” and the corresponding “Dynamic Correlation” bars. The “Improvement” line is the difference between the two bars in percentage terms. Each bar shows the average back-testing results by considering three different traded volumes for each index[15].

[15] Traded volume buckets are described in section 2.5

Figure 3.2: Back-testing results by using different volatility and correlation models

The figure shows the back-testing results by using Dax, MDax and SDax data. On the y-axis (left) the ratio is visible demonstrating in which cases the Kupiec test was not rejected. On the y-axis (right) the improvement between considering dynamic versus perfect correlation is visible. The abbreviations in the figure are as follows: G_G: GARCH with Gaussian residuals, G_T: GARCH with Student-T residuals, GJR_G: GJR model with Gaussian residuals, GJR_T: GJR model with Student-T residuals.



In general, it can be seen in figure 3.2 that all models show better performance when the correlation is not assumed to be perfect ($Correlation < 1$). The relative improvement over all indices is around 1% to 22%. By focusing on each index individually the results show the following ranges of improvement: Dax 3% to 13%, MDax 1% to 14% and SDax 7% to 22%. In the paper by Bangia et al. (1998) they argue that at least during crisis, a correlation of one is realistic. Given that within our simulation windows a huge crisis took place (e.g. the default of Lehman Brothers end 2008, see figures 2.3, 2.4 and 2.5) the results show this assumption is not valid. A better performance can be achieved by considering dynamic correlation models like the DCC and EWMA approach. In a later stage of this discussion a more detailed analysis of the correlation results and models will take place.

The back-testing results based in the Dax data indicate that the best performance is achieved by using the correlation adjusted EWMA (CEWMA) model. The performance increase compared to the EWMA model is around 3%. More negative than the CEWMA and equal to the EWMA are the results achieved by the correlation adjusted GARCH model (CGARCH) with Student-T- or Gaussian distributed residuals. The GJR and correlation adjusted GJR

(CGJR) models show the worst performance. By focusing on the results based on the relative improvements, the CGARCH model with Student-T distributed residuals shows the best performance with an increase of around 13%.

A way to get more detailed information about the back-testing results is to focus on the rejected Kupiec tests and to analyze whether risk is over or underestimated. The analysis can be found in table 1.1 of the appendix. There it can be seen how for the Dax data the risk is never underestimated due to breaches of the L-VaRs. The reason is that the observation period contains a huge market shock and therefore the model expects an excessive shock in the future. It can be seen that the rejection rate of the test decreases when a correlation model is considered. This is based on the fact that the L-VaRs are reduced by considering correlations and therefore produce more exceedances. Because of that, the risk is not overestimated and the Kupiec test is accepted. By focusing on higher traded volumes, the performances of the correlation models increase. The back-testing results show no significant improvements within the GARCH and GJR models by using the Gaussian or Student-T distribution. The degrees of freedom which are calculated by maximizing the MLE (formula 3.16) can be found in table 3.2.

Table 3.2: Degrees of freedom by using the GARCH and GJR model with Student-T distributed residuals

The table shows the average degree of freedom which is the result of using the GARCH and GJR models with Student-T distributed residuals. For the calculation we use the MLE presented in formula 3.13.

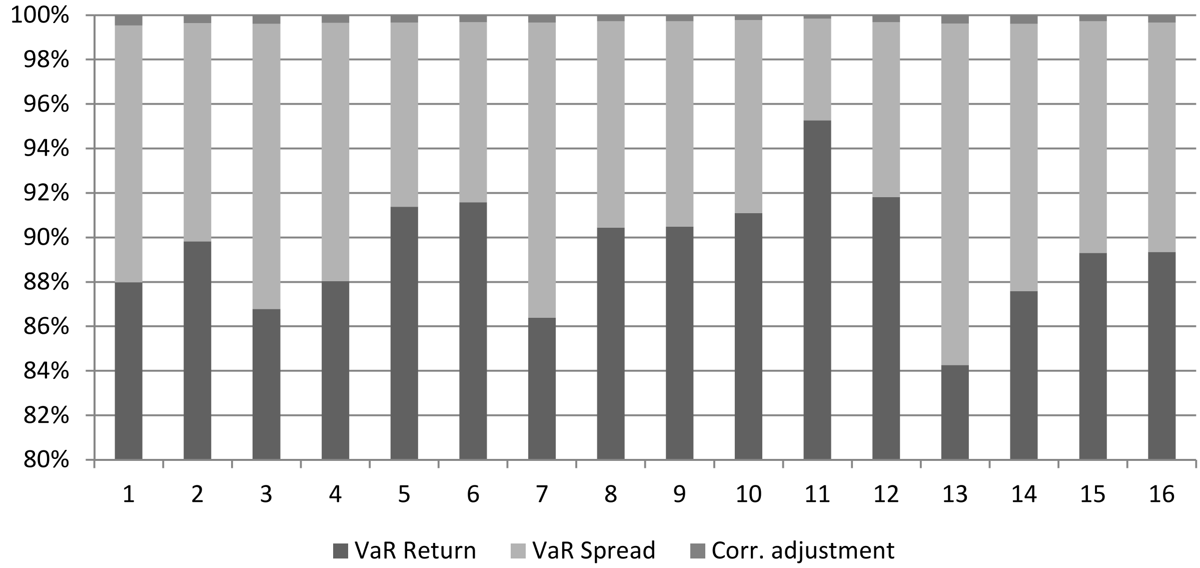
			Mean	SD	Max.	Min.
Dax	GARCH T	Spread	16	20	139	4
		Return	17	24	127	6
	GJR T	Spread	19	28	191	4
		Return	18	26	131	6
MDax	GARCH T	Spread	13	14	149	3
		Return	11	8	55	5
	GJR T	Spread	14	15	147	3
		Return	12	9	55	5
SDax	GARCH T	Spread	12	20	157	3
		Return	5	1	7	3
	GJR T	Spread	13	20	160	3
		Return	5	1	7	3

By comparing the simulation results of the Dax with the one of the MDax it can be seen that the GARCH and GJR models show a better performance compared to the EWMA model by assuming a perfect correlation. The highest result is achieved by the GJR-T model. In contrast to that have the CGARCH-G, CGARCH-T and the CEWMA model the best results by considering a dynamic correlation. While the EWMA model has the most negative performance, this is changed by using the CEWMA model which is among the best. The detailed analysis of the back-testing result (Appendix: Table 1.2) is close to that of the Dax. It can be seen that (especially for higher traded volumes) risk is switching from overestimation to underestimation when correlation is considered. To get an impression of the impact of the different VaR components figure 3.3 has been created. The different components are combined in formula 3.20 to get the $L - VaR$[16]. The example is based on the Deutsche Bank stock listed in the Dax. Here it can be seen that the VaR of the log returns has the biggest impact, followed by the VaR of the log spreads. The correction factor based on the correlation is pretty small at around 1%. Anyway, the increasing back-testing results indicate the positive impact. By comparing the results of the different traded volumes it is visible that the performance for the first two is more or less stable, while for the highest volume a decrease can be seen. This is based on the increased impact of the bid-ask spreads (see figure 2.3, 2.4 and 2.5). By analyzing the degree of freedom for the GARCH-T and GJR-T model, the results in table 3.2 indicate that the values for the returns are decreasing compared to the results of the Dax while the spread values stay constant. The result is an increase of the back-testing performance as demonstrated in figure 3.2.

[16] Compared to formula 3.20 the chart just focuses on the following three components while neglecting to calculate the root of the sum. VaR Return: ${VaR_r}^2$, VaR Spread : ${VaR_s}^2$, Corr. adjustment: $2 * \rho_{s,r} * VaR_r * VaR_s$

Figure 3.3: Portion of the VaR return, VaR spread and the correlation term by subdividing the L-VaR

In the figure the portions are demonstrated which each single component of formula 3.20[17] has of the total L-VaR. The components are $\boldsymbol{VaR_R}$, $\boldsymbol{VaR_S}$ and the common term $\mathbf{2 * \rho_{s,r} * VaR_r * VaR_s}$. The figure is calculated by focusing on the Dt. Bank stock and a traded volume of 3m EUR. The calculation is done for each of the 16 observation windows.



The back-testing based on the SDax are in general lower compared to the Dax and MDax. The best performance is reached through the GARCH-G and GJR-G model considering correlations. The improvements based on the correlations are 20% and 22%. These are the highest results recorded within the whole back-testing. In contrast to that, the best performance is achieved with the GARCH-T and GJR-T model, by assuming a perfect correlation. While the EWMA and CEWMA show constant good performance in the DAX and MDax back-testing, the results for the SDax are among the worst. The reason can be seen in the detailed analysis (Appendix: Table 1.3). Here the EWMA model overestimates the risk, while by considering correlations it turns into an underestimation. That indicates how the impact of the correlation adjustment is too high. By comparing the results based on traded volumes it can be seen that overall performance decreases with increasing traded volumes. It can be seen that by comparing these results with the ones of Dax and MDax, the models' performance decreases with declining index market capitalization. The bid-ask spreads show a much higher impact on small rather than big indices, as can be seen in figures 2.3, 2.4 and 2.5. The results of the calculated degree of freedom (table 3.2) show the same development as

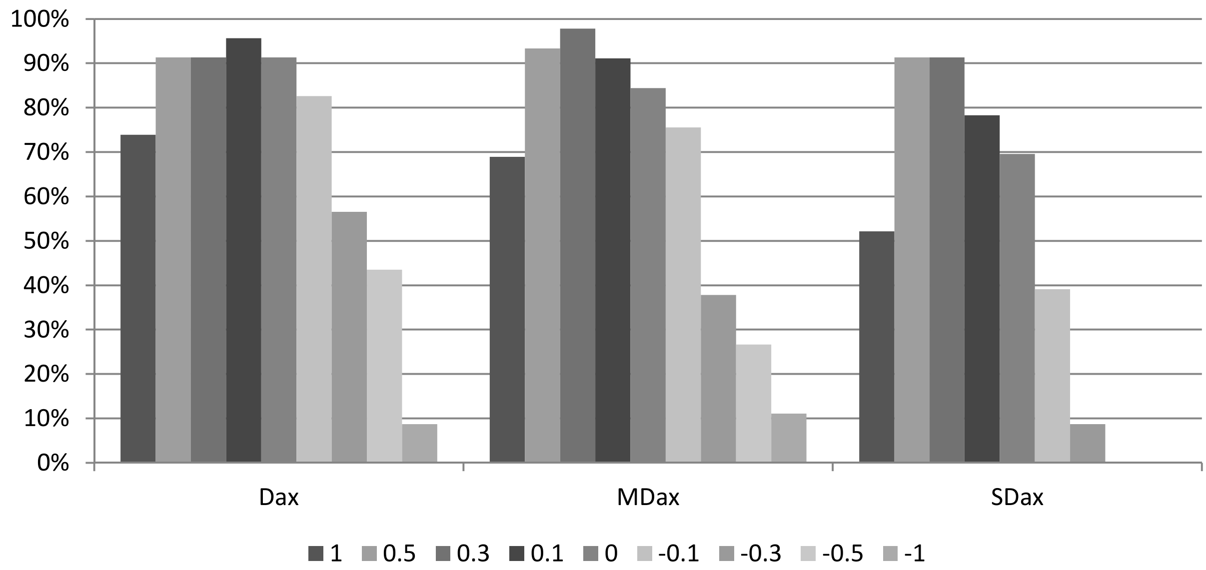
[17] The square root is not considered in this figure.

already mentioned for the Dax and MDax. While the value for the returns is decreasing again, the results for the spreads are more or less stable. The detailed analysis shows that the back-testing results based on the Student-T distribution are always better than by using the normal distribution.

The question which then occurs is: which correlation is most effective for achieving the highest back-testing results? Therefore, in figure 3.4 theoretical correlations are used for the simulations. In this example, volatility is calculated by using the GARCH model with Gaussian residuals. The results show that the best performance is achieved by using different correlations for each index. An optimal performance is achieved with a correlation of 10% for the Dax, 30% for the MDax and 30% to 50% for the SDax. This indicates that a correlation of one results in an overestimation of risk. Overestimation is increasing with a fall in the index capitalization. Also this chart shows that a perfect correlation leads to a significant fall in back-testing performance.

Figure 3.4: Back-testing results by using theoretical correlations

The following figure shows the back-testing results by using formula 3.20 and theoretical correlations. The results are based on a GARCH model with normally distributed residuals. For the Dax 3.0m, MDax 0.5m and for SDax 0.15m traded volume are focus.



Based on the above-discussed theoretical correlations which indicate the optimal back-testing results, we now want to look at the results based on empirical simulations. The average correlation can be seen in table 3.3 for each index and traded volume.

Table 3.3: Results of the different correlation models for Dax, MDax and SDax

The table shows the average correlations for the 16 VaR calculations by using different correlation models namely Dynamic Conditional Correlation (DCC), Constant Correlation (CC), Exponentially Weighted Moving Average Correlation (CEWMA) and the Pearson correlation coefficient. The calculation is done for the indices Dax, MDax and SDax and different traded volumes.

Index	No. of traded volume*	DCC		CC		EWMA_C		Pearson	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Dax	50	-21%	0.075	-20%	0.132	-23%	0.061	-22%	0.125
	500	-19%	0.085	-19%	0.145	-23%	0.07	-19%	0.136
	3,000	-16%	0.087	-15%	0.148	-20%	0.071	-14%	0.141
MDax	50	-14%	0.012	-14%	0.008	-16%	0.005	-13%	0.053
	100	-14%	0.011	-14%	0.007	-16%	0.004	-13%	0.046
	500	-12%	0.008	-12%	0.006	-14%	0.004	-10%	0.04
SDax	25	-9%	0.005	-9%	0.002	-8%	0.002	-10%	0.028
	75	-9%	0.007	-9%	0.004	-10%	0.002	-9%	0.032
	150	-7%	0.007	-8%	0.003	-10%	0.002	-7%	0.034

* Traded volume in 1,000 EUR

The results of the Dax indicate that among the different correlation models, no big fluctuation takes place. They are all at around 20% which shows that they are neither moving very concurrently nor independently. It can be seen that the correlation in general decreases with increasing traded volume. This is also valid for the standard deviation of the average correlation results. We assume that this is based on the fact that for higher traded volumes the spreads are already higher and have therefore not so often been adjusted than for smaller traded volumes. The comparison with theoretical correlations shows that the results are too high to be optimal. The average correlations of the MDax data are smaller compared to the one of the Dax. But here also, deviation results are not significant between the different models. Another common, but less strong behavior can be seen by looking at the different traded volumes. While for the first two traded volumes the results are equal, the highest traded volume shows a slightly lower correlation and standard deviation. The last results are based on the SDax. By comparing the average results with the results of the previous indices, the values are again smaller. This leads to the conclusion that the size of the market has an impact on behavior between spreads and returns. Also, the standard deviation decreases constantly from Dax to MDax and SDax. This statement is based mainly on the results of a trading volume of 50,000 EUR which are available in all three indices. By comparing the empirical results with the optimal correlation results (figure 3.4) it can be seen that they are contrary. While optimal correlation is increasing, from MDax to SDax the empirical results decrease. This shows that there are other factors which cannot be captured by the correlation.

The different VaR methodologies are calculated at the end of the total observation period. This is done to achieve stable results. Nevertheless, the different correlation models can be calculated continuously over the total observation period. In the following example we focus on the Index Dax. To capture the liquidity within the index we calculate a Market Liquidity Measure (MLM). This measure is defined as the equally weighted average over all XLM spread data of the focused Dax stocks.

$$MLM_{t,v} = \frac{1}{23}\sum_{i=1}^{23} XLM_{i,v,t} \tag{3.38}$$

Here the variable i stands for each of the 23 stocks which are focused on and t for each point in time. The parameter v defines the trading volume. In the same way the equally weighted returns are also calculated.

$$IndDax_t = \frac{1}{23}\sum_{i=1}^{23} r_{i,t} \qquad (3.39)$$

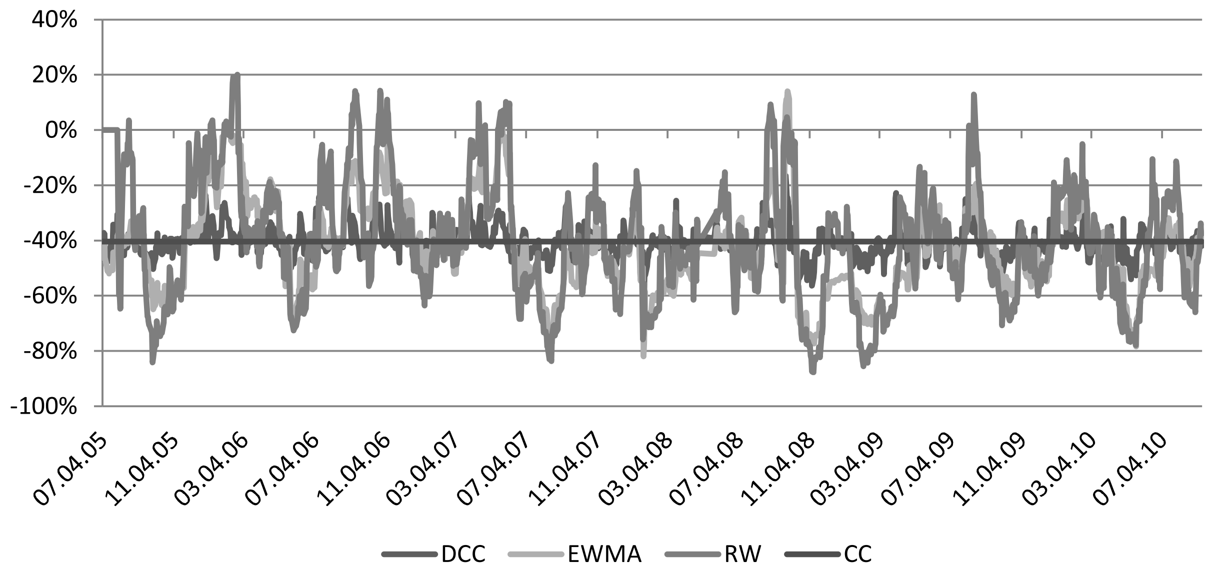
In this formula i stands for the stock, r for the periodic return and t for the point in time. We do not use the returns of the Dax index, published by the Deutsche Börse, because this measure is weighted by the market capitalization of each stock. To be consistent we would need to adjust the weights of the spread measure which cannot be performed due to missing data.

To create the following three figures, the different correlation models described in section 3.3.3 are used in combination with the MLM and $IndDax$ measures. We consider three different trading volumes. As well as the DCC, EWMA and CC correlation measure a 20 day rolling correlation is also calculated by using the Person correlation coefficient called RW (Rolling Window).

The results with a trading volume of 25,000 EUR can be found in the following figure.

Figure 3.5: Results of the different correlation models over the total observation period

In the following chart the result of the DCC, EWMA and CC correlation model is presented. The Pearson correlation coefficient is calculated by using a 20-day rolling time window named RW. The MLM is calculated by using a trading volume of 25,000 EUR.



By looking at figure 3.5 we can see that the correlation is negative overall. This shows that decreasing returns result in increasing spreads. The interpretation is that when stock prices are falling liquidity spreads are increasing. The CC measure is equal to -40%. In comparison, the other correlation coefficients show that there is a dynamic in the relationship between spreads and returns over time. By assuming a constant correlation this information is neglected. This justifies the usability of the advanced correlation DCC and EWMA model and the simple RW methodology.

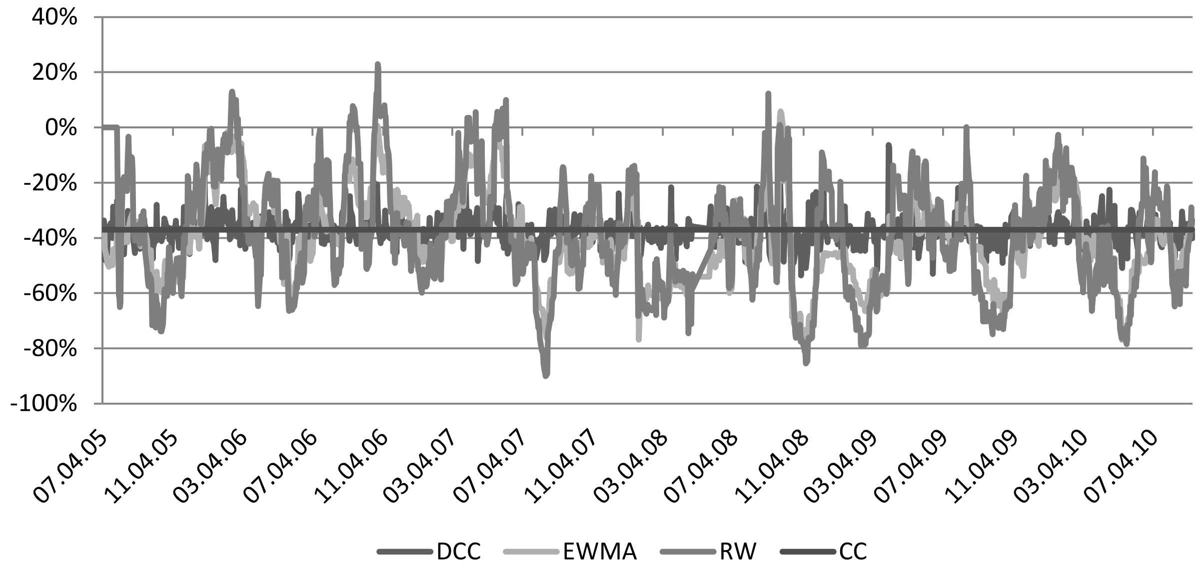
Comparing the dynamic correlation models it can be seen that highest volatility appears using the EWMA and the RW correlation. The difference is due to the methodology. While the RW always considers 20 days, the EWMA uses weights assigned to the different observations over a longer period. This results in a smoothing effect and, in general, slightly lower correlations. The range of both correlation results is between 0% and -80%. By looking at the correlations around the time of the collapse of Lehman Brothers in Sept. 2008 one can see the results are volatile. While in the pre-phase the correlation is around 0%, a jump appears to around -80%. This is influenced by the crisis when falling stock valuations led market makers to increase spreads based on concerns of being unable to sell shares at a "fair" price. The argument of Ernst et al. (2009) is that returns and spreads show perfect correlation during the crisis, but this is not born out completely when looking at the results. Even when this would be the case, the correlations before and after show that this basic assumption is not correct.

The DCC correlation is much less volatile compared to the EWMA and RW. The reason is based on the calculation method. As mentioned previously, the persistence of the covariance in the market is measured by λ in formula 3.28 and β in 3.29. For the EWMA model a fixed smoothing coefficient of $\lambda = 0.94$ is used. Within the GARCH and GJR model the α and β are determined by maximizing the MLE estimator. For the lowest trading volume, β is around 0.7 and decreases strongly with increasing trading volume. The α stays more or less constant at 0.04 for the three trading volumes. In comparison to that, the EWMA with 0.05 $(1 - \lambda)$ shows a close reaction to market shocks. The weight for the long run variance is equal to $1 - \alpha - \beta$. For the lowest trading volume the weight is 0.26. With increasing trading volume this value rises. The impact can be seen in figures 3.5, 3.6 and 3.7 where the DCC correlation fluctuates around the result of the CC model.

The following figure 3.6 shows the results using the higher volume of 250,000 EUR.

Figure 3.6: Results of the different correlation models over the total observation period

In the following chart, the result of the DCC, EWMA and CC correlation model is presented. The Pearson correlation coefficient is calculated using a 20-day rolling time window named RW. The MLM is calculated by using a trading volume of 250,000 EUR..

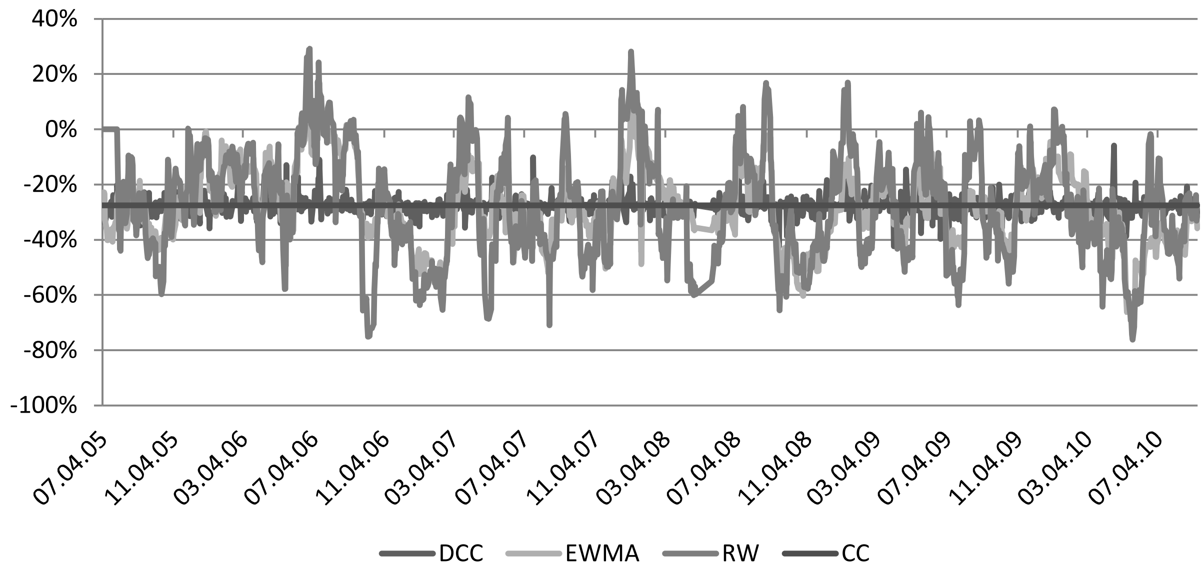


The results show that the CC results decreased slightly to -37%, demonstrating that decreasing stock prices result in smaller increases of liquidity spreads. The same result can be seen by looking at the average correlation of the DCC, EWMA and RW model and its standard deviation. This is in line with previously mentioned observations that spreads of higher traded volumes behave differently.

In figure 3.7 we look at a trading volume of 3 million EUR. The CC model shows a correlation of -27% over the total observation period. The trend of a decreasing correlation with increasing trading volume is also confirmed here. The highest correlation by comparing the trading volume of 25 thousand and 250 thousand EUR results in a decrease of around 10% during the crisis.

Figure 3.7: Results of the different correlation models over the total observation period

In the following chart the result of the DCC, EWMA and CC correlation model are presented. The Pearson correlation coefficient is calculated using a 20-day rolling time window named RW. The MLM is calculated using a trading volume of 3,000,000 EUR.



Within this chapter more sophisticated methods than the EWMA model are used for the first time to account for heteroscedasticity. The reason for taking these more advanced models is based on the results of the ARCH test (lags 1, 5 and 10) for log and squared log data. For example, by using the GARCH model with Gaussian residuals based on the Dax data the ARCH test[18] was rejected for spreads 91% (returns 90%) and after using the GARCH(1,1) model the values change to spreads 24% (returns 20%). This reduction of autocorrelation indicates that the models are appropriate for use.

In the following section we analyze advanced volatility models further. To determine the quality of the fit, we use mainly the common AIC and BIC criteria[19]. First we test different lags P and Q for the $GARCH(P,Q)$ and $GJR(P,Q)$ model. The best overall result is achieved when $P = 1$ and $Q = 1$. Afterwards we test the impact of different AR models on the

[18] The ARCH test of Engle assesses the null hypothesis that a series of residuals r(t) exhibits no conditional heteroscedasticity (ARCH effects), against the alternative that an ARCH(L) mode $r(t)^2 = a0 + a1 * r(t-1)^2 + \cdots + aL \times r(t-L)^2 + e(t)$ with at least one non zero $a(k)$ for $k = 1 \ldots L$ lags. H_o is that the underlying distribution is Chi-square distributed with L degree of freedom. The test can also be performed for the squared residuals. The chosen confidence level is 0.05%.

[19] Akaike information criterion (AIC) = $(-2 * \text{MLE}) + (2 * \text{CalcParameters})$ and Bayesian information criterion (BIC) = $(-2 * \text{MLE}) + (\text{CalcParameters} * \log(\text{NumOfObs}))$ are common information criteria to determine the quality of models which use the MLE function.

relevant results. The simulation results using the $GARCH(1,1)$ model in combination with $AR(0)$, $AR(5)$ and $AR(10)$ parameters can be found in table 3.4. The results of the AIC and BIC criteria show that the most negative is achieved by using the $AR(0)$ process. By using 5 lags a significant increase of both measures can be achieved. The comparison of the AIC and BIC measure by using 5 and 10 lags shows no big increase. By analyzing the different $GARCH$ parameters (which are a result of the MLE fitting process) the outperformance can be seen. The $GARCH$ term β (which measures the consistency of the conditional volatility in the market) is increasing on average and gets closer to the $EWMA$ shock of 94%. Also the volatility of the parameter is significantly reduced. In contrast to that is the average $ARCH$ parameter α decreasing with increases in the number of lags R. This results in lower reaction on market shocks. By summing both parameter α and β, this value indicates how quickly the process is converging to the conditional volatility. On average this value is 0.84 which shows that volatility is returning slowly to the long run variance. Another result using higher lags is that the conditional mean C of the process (formula 3.11) is increasing significantly. Overall it can be said that by using the $AR(5)$ process more stable results can be achieved which have a positive impact on the back-testing results. We also analyzed the relevant results for higher and lower traded volumes and these can be found in the appendix table 1.4 for Dax stocks, table 1.5 for MDax stocks, table 1.6 for SDax stocks. They are not discussed further because the above-mentioned results remain the same.

Table 3.4: GARCH fitting results by using log spreads and different lags for the conditional means

The table shows relevant results of an AR(0), AR(5) and AR(10) GARCH(1,1) model by using log spread changes. To determine quality, the Akaike AIC[19], Bayesian BIC[19] criterion and the Maximum Likelihood Estimator (MLE) are used. The results are calculated for the Dax, MDax and SDax and by assuming Gaussian distributed residuals.

		Dax			MDax			Sdax		
		AR(0)	AR(5)	AR(10)	AR(0)	AR(5)	AR(10)	AR(0)	AR(5)	AR(10)
C	Mean	-0.0001	-0.0002	-0.0003	0.0000	-0.0001	-0.0002	-0.0001	-0.0001	-0.0002
	STD	0.0001	0.0001	0.0001	0.0006	0.0002	0.0002	0.0002	0.0004	0.0004
ω	Mean	0.0000	0.0000	0.0000	0.0002	0.0001	0.0001	0.0003	0.0001	0.0001
	STD	0.0000	0.0000	0.0000	0.0002	0.0001	0.0001	0.0003	0.0001	0.0001
GARCH	Mean	0.7220	0.8737	0.8642	0.5149	0.8343	0.8141	0.5847	0.8354	0.8234
	STD	0.1591	0.0819	0.0870	0.2359	0.1447	0.1677	0.2382	0.0725	0.1186
ARCH	Mean	0.1180	0.0690	0.0716	0.2194	0.0793	0.0822	0.1786	0.1001	0.0957
	STD	0.0404	0.0289	0.0306	0.1252	0.0611	0.0625	0.0522	0.0671	0.0607
AIC[19]	Mean	-5,596	-5,813	-5,821	-4,800	-5,034	-5,045	-4,222	-4,475	-4,496
BIC[19]	Mean	-5,576	-5,769	-5,753	-4,781	-4,989	-4,977	-4,202	-4,430	-4,428
MLE	Mean	2,802	2,915	2,925	2,404	2,526	2,537	2,115	2,246	2,262
Calculated param.		4	9	14	4	9	14	4	9	14

The MLE fitting results using the $GARCH(1,1)$[20] model in combination with return data can be found in table 3.5. In contrast to the spreads, the AIC and BIC parameter do not improve when considering an autoregressive process. The $GARCH$ and $ARCH$ terms are as expected and show very little standard deviation. This results in stable conditional volatility. At the beginning, the conditional volatility of the GARCH model was significantly different to the EWMA model. The analysis shows that this is based on very few but extreme peaks within the log return data. Therefore we integrate a filter to cap and floor these values at $+2.5 * Standard\ Deviation$ and $-2.5 * Standard\ Deviation$. This reduces the gap between both volatilities and the back-testing performance increases.

Table 3.5: Average GARCH fitting results for log returns

The table shows the MLE fitting results of a AR(0), AR(5) and AR(10) GARCH(1,1) model by using log return changes. The results are calculated for Dax, MDax and SDax data by assuming Gaussian distributed residuals.

		Dax			MDax			SDax		
		AR(0)	AR(5)	AR(10)	AR(0)	AR(5)	AR(10)	AR(0)	AR(5)	AR(10)
C	Mean	0.0008	0.0009	0.0009	0.0009	0.0009	0.0010	0.0007	0.0007	0.0008
	STD	0.0004	0.0004	0.0004	0.0007	0.0007	0.0008	0.0004	0.0004	0.0004
ω	Mean	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	STD	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
GARCH (β)	Mean	0.8836	0.8831	0.8817	0.8584	0.8586	0.8540	0.8389	0.8678	0.8432
	STD	0.0434	0.0457	0.0449	0.0821	0.0847	0.0882	0.1278	0.0561	0.0937
ARCH (α)	Mean	0.1008	0.1012	0.1024	0.1175	0.1169	0.1212	0.1182	0.1065	0.1197
	STD	0.0323	0.0346	0.0340	0.0472	0.0475	0.0510	0.0555	0.0411	0.0499
AIC[19]	Mean	-5,019	-5,016	-5,009	-4,590	-4,590	-4,586	-4,654	-4,652	-4,648
BIC[19]	Mean	-4,999	-4,972	-4,940	-4,571	-4,546	-4,518	-4,634	-4,608	-4,579
MLE	Mean	2,513	2,517	2,519	2,299	2,304	2,307	2,331	2,335	2,338
Calculated parameter		4	9	14	4	9	14	4	9	14

The simulation results (which are discussed above) are based on the assumption of Gaussian distributed spreads and returns. By looking at table 3.1 the basic statistics show that spreads and returns are far from normal. This indicates that the Cornish Fisher (CF) approximation proposed by Ernst et al. (2012) can be used to account for the non-normality. Within this paper the normal distribution (confidence level 99%) is used instead of the CF methodology for the following reasons. First, it is easier to analyze the impact of the different volatility

[20] The AIC and BIC criterion is used to determine the best number of lags P and Q for the GARCH(P,Q) and GJR(P,Q) model. There best results are achieved by using $P = 1$ and $Q = 1$.

models[21] and secondly, by using the CF parameter the back-testing results show a huge drop. This is based on an overestimation of risk. In table 3.6 the average calculated CF parameters are listed. Having figure 3.3 in mind for example, it is clear that the CF parameter based on the log returns have a much higher impact on the L-VaR than the CF of the spreads. The CF values for the log returns are around 3.5 for all indices, which reflect the huge skewness and kurtosis of the statistical data analysis in table 3.1. On the other hand, the volatility of the models used is already high because of the market turmoil at the end of 2008 (see figure 2.3, 2.4 and 2.5). By calculating the product of both parameters (VaR formula 3.18) this resulted in an overestimation of risk. In the paper by Ernst et al. (2012) they introduced the CF and show the outperformance of this methodology, while in this paper the results indicate an underperformance after the market turmoil. This is a well-known problem, as mentioned by Alexander (2009). There the author shows that the error term between the CF expansion and the Student-T distribution becomes very large for extremely leptokurtic distributions.

Table 3.6: Estimated quantiles by using the Cornish Fisher approximation

The table shows the average Cornish Fisher (CF) approximation for spreads and returns. The CF is calculated by using formula 3.3. The results are calculated for Dax, MDax and SDax data.

	Dax					MDax					SDax				
	Vol.*	Mean	SD	Max	Min	Vol.*	Mean	SD	Max	Min	Vol.*	Mean	SD	Max	Min
Spreads	50	2.69	0.21	3.2	2.28	50	5.01	7.13	29.83	2.28	25	3.77	2.59	13.01	2.31
	500	2.62	0.18	3	2.36	100	4.8	6.77	29.28	2.33	75	3.5	1.48	8.62	2.41
	3,000	3.1	0.41	4	2.44	500	4.64	5.5	27.22	2.3	150	3.42	0.76	5.94	2.54
Returns		3.66	0.82	6.25	2.57		3.2	0.69	6.69	2.53		3.54	0.95	6.98	2.69

* Traded volume in 1,000 EUR

3.7 Conclusion

The aim of this chapter is to test different extensions of the basic $L-VaR$ models proposed by Bangia et al. (1999) and Ernst et al. (2012). For that reason, we use advanced conditional volatility models like the $AR-GARCH$ and $AR-GJR$ model. The back-testing results of the $L-VaR$ models indicate that, on average, a good performance can be achieved for the Dax and MDax while the performance by using the SDax data is still between 60% to 70%. The MLE fitting results of the different $GARCH$ models are stable and therefore it seems

[21] By combining different methodologies like CF or volatility models it is more difficult to interpret the results.

appropriate to use them for log return and log spread data. The log spread data show, in general, autoregressive behavior. Based on the AIC and BIC information criteria, we identified that the MLE gives the best results by using a $AR(5)$ process to adjust the conditional mean. Another focus within this paper are the new $CL - VaR$ models which we propose. These models account for correlation between log spread and log return data. This is new because in the current literature the correlation is assumed to be perfect like mentioned by Bangia et al. (1999). Based on our data, we could disprove the assumption and show that even during crisis no perfect correlation appears. To demonstrate this we use the DCC-, CC- and the $EWMA$ correlation models and the Pearson correlation coefficient. Overall the back-testing results indicate that the new $CL - VaR$ models always give a better performance than the basic $L - VaR$ models. The improvement is on average 10%.

Chapter Four

Impact of Regulatory Interventions on Stock Liquidity[22]

4.1 Motivation

During crisis, investors rebalance their portfolio because they fear losses. The common reaction is to reduce the volume invested in equity and to shift this into less volatile assets, such as government bonds. This behavior is named “flight to liquidity” (Næs, Skjeltorp, & Ødegaard, 2011). Depending on the scale of the crisis, this can lead to a significant imbalance between supply (sell) and demand (buy). Between the two parties stands the market maker, who takes the interim risk of buying the stock and subsequently selling it to another investor. Based on the market’s imbalance, he will then raise or lower the bid-ask spread to be compensated for the risk and to manage inventory (Chordia, Roll, & Subrahmanyamb, 2002).

The imbalance between supply and demand for securities is a fundamental self-regulating process that determines the "fair price" of a company. During crisis this mechanism fails. This can be seen when, for example, investors don’t buy company stocks even when they have good and stable results with a low price. This prevents the market reverting to equilibrium. At a later stage this will also influence the real economy and, in turn, the wealth of the country. To intervene when or before this happens, countries or groups of countries (such as the EU) have different methods for restoring stability. One example here is the SoFFin[23]. This organization’s goal is to stabilize the financial sector by providing the market with liquidity.

[22] This chapter is based on the working paper (Busch & Lehnert, 2012).
[23] The SoFFin (Sonderfonds für Finanzmarktstabilisierung) was created in Oct. 2008 to stabilize the financial system in Germany. The agency was able to grant guarantees and recapitalization. They were also authorized to establish their own resolution agencies under the protection of the federal agency for Financial Market Stabilization.

The aim of this chapter is to verify the impact of regulatory rescue interventions on financial markets at the announcement date. We therefore analyze whether these interventions restore stability, or whether they might even have a negative impact. The Xetra Liquidity Measure (XLM), provided by Deutsche Börse is used as a common indicator for stability and liquidity in the stock market (Stange & Kaserer, 2010). This measure is calculated based on volume-weighted bid-ask spreads for different traded volumes[24]. The market reaction is analyzed by focusing on return changes.

The chapter is structured as follows. In the next section 4.2, a literature review is performed. First we focus on papers discussing the impact of regulatory interventions on financial markets. Then we present papers offering different methodologies for performing event studies. In section 4.3, we present the event study methodology and in the following section 4.4, we define scenarios that are subsequently used for the event study. Following this, section 4.5 provides a statistical analysis of the underlying spread and return data. In the last section 4.6, the results are presented and discussed. Finally, section 4.7 concludes.

4.2 Literature Review

The financial crisis has driven a large number of researchers to publish various papers. One research area focuses on the impact of regulatory interventions on financial markets during the crisis. The intention is to evaluate whether certain interventions help to restore stability. Most of the papers focus on liquidity and returns of stocks as indicators. The first part of the following literature review presents the main papers that focus on event studies. The second part presents a short introduction of event-study methodologies.

The paper by Aït-Sahalia et al. (2012) analyzes the market response to regulatory interventions on the interbank market between 2007 and 2009. It considers the U.S., the U.K., the Euro area, and Japan. The researchers use, e.g., Libor rates (LIBOR), Overnight Index Swaps (OIS), and CDS spreads as an indicator for liquidity. They mention that, overall, the interbank market reacts positively to recapitalization programs and negatively to the decision to bail out individual banks.

[24] A more detailed description can be found in Section 2.5

Another paper published by Tong and Wei (2012) focuses on whether unconventional interventions unfreeze the credit market. The authors use an international dataset of 192 interventions from 15 countries between September 2008 and July 2010. The tested events focus on deposit insurance, debt guarantee, bank recapitalization, purchase of bank toxic assets, and central bank liquidity support. Their results show that interventions targeting the whole financial system are more significant than those that focus only on individual financial institutions. However, relative to the severity of the financial crisis, the quantitative effect of any given intervention is limited.

The paper published by King (2009) focuses on the impact that bank-rescue interventions have on the financial markets. The research analyzes 52 banks. As liquidity indicators, King uses CDS spreads and stock prices. The results show that, overall, the effect on the share price is negative. As one reason for this, he mentions that rescue packages were not designed to protect shareholders, whose capital is designed to bear losses.

A paper analyzing the impact of short-selling restrictions on institutional investors was published by Bohl et al. (2011). The paper states that, overall, the reaction to short-selling restrictions is negative. This result is in line with several other papers, such as Beber and Pagano (2013).

A number of other event studies analyzing the post-Lehman crisis from another perspective are also worthy of mention. In Neuhierl et al. (2010), the focus is on the impact of press releases considering corporate strategy, customers & partners, products & services, management changes, and legal issues relating to the stock liquidity and returns. Their results state that, in general, return volatility increases as liquidity decreases. They show that the crisis did not have an equal impact on all corporates. Another interesting study was carried out by Claudio et al. (2010); here, the researchers analyze the abnormality of returns based on corporate-responsibility ratings during the 2007–2008 financial crisis. They find that firms with more-independent boards and higher institutional ownership experienced worse stock returns during the crisis period.

Abnormal performance based on different events is a well-known topic of research. Many published papers have analyzed the impact of different events. Of particular note are publications by Balaban and Constantinou (2006) and Savickas (2003). These use different methodologies, such as the traditional basic approach described by Brown and Warner (1980), the standardized cross-sectional approach introduced by Boehmer et al. (1991), or the mean rank approach described by Corrado (1989). In the paper by Savickas (2003), the author tests all of the above-mentioned methodologies and concludes that they are not sufficient to capture the event-induced volatility for several reasons. Therefore, he proposes a GARCH-based approach, which is described and used later in this chapter. The advantage of this approach is that the volatility process is modeled directly.

4.3 Event Study Methodology

The test methodology in this paper is introduced by Savickas (2003). He proposes a $GARCH$-based test that accounts for time-varying conditional volatility.

For the test, we use the asymmetric $EGARCH$ model introduced by Nelson (1991). The dynamic conditional behavior of a symmetric normal $AR(R) - EGARCH(P,Q)$ process is given by the following formula:

$$\boldsymbol{y_t = C + \sum_{i=1}^{R} AR_i \, y_{t-1} + \varepsilon_t} \tag{4.1}$$

where the conditional mean for an $AR(R)$ is calculated as the r-th order autoregressive process:

$$\mathbb{E}(y_t|I_{t-1}) = C + \sum_{i=1}^{R} AR_i \, y_{t-1} \tag{4.2}$$
$$\varepsilon_t|I_{t-1} \sim N(0, \sigma_t^2)$$

The $EGARCH(P,Q)$ volatility is calculated using the following formula:

$$\sigma_t^2 = exp\big(\omega + g(z_{t-1}) + \beta ln(\sigma_{t-1}^2)\big) \tag{4.3}$$

Where

$$g(z_{t-1}) = \theta z_t + \gamma\left(|z_t| - \sqrt{2/\pi}\right) \tag{4.4}$$

is the asymmetric response function. The variable Z_t is assumed to be independent and identically distributed (iid) and standard normal distributed with the expected value $E(|Z_t|) = \sqrt{2/\pi}$. In contrast to this, $z_t = \left(\frac{s_t - \bar{s}}{\sigma_t}\right)$ is the standardized bid-ask spread changes or log return. The difference (the part in brackets on the right in formula 4.4) is the deviation between the expected and the realized log changes. The long-run variance can be calculated as $ln(\bar{\sigma}^2) = \frac{\omega}{1-\beta}$. For the $EGARCH(1,1)$ volatility model, the following constraints must be fulfilled: $\omega > 0$, $\alpha, \beta \geq 0$, and $\alpha + \beta < 1$. The required parameters are calculated using the following log-likelihood function:

$$lnL(\omega, \theta, \gamma, \beta) = -\frac{1}{2}\sum_{t=1}^{T}\left(ln(\sigma_t^2) + \left(\frac{\varepsilon_t}{\sigma_t}\right)^2\right) \quad (4.5)$$

A simple test for abnormal spreads or returns is to focus on the assumption made in formula 4.2. As the H_0 hypothesis, the residuals of the $GARCH$ process are assumed to be $N(0, \sigma_t^2)$ distributed. To measure the abnormal return, formula 4.1 must be extended by a dummy variable that can measure the deviation relative to the assumption at the event date. The formula is:

$$y_t = C + \sum_{i=1}^{R} AR_i\, y_{t-1} + \varepsilon_t + \gamma_i D_t \quad (4.6)$$

where the last part consists of the indicator variable D_t; this is 1 when an event happens and otherwise equals 0. The parameter γ_i contains the absolute excess, which is equal to $\gamma_i = y_t - C - \sum_{i=1}^{R} AR_i\, y_{t-1}$. This value is then standardized by the calculated conditional mean:

$$S_i = \frac{\gamma_i}{\sqrt{\sigma_t^2}} \quad (4.7)$$

The test static for abnormality is:

$$\tau = \sum_{i=1}^{N}\frac{S_i}{N} \Big/ \sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N}\left(S_i - \sum_{j=1}^{N}\frac{S_i}{N}\right)} \quad (4.8)$$

where the results are t-distributed with N-1 degrees of freedom. Induced abnormal spreads and returns are captured with this test cross-sectional event.

To test the robustness of the conditional volatility model we also calculate results using constant volatility and equal volatility.

4.4 Regulatory Events

In this chapter we analyze the impact of different events on abnormal bid-ask spreads and return changes. The selected events focus mainly on European countries after the Lehman default in 2008. The Federal Reserve Bank (FED) of New York published a timeline showing the main interventions in chronological order[25]. The FED subdivides these events into the following categories:

- Bank liability guarantees
- Liquidity and rescue interventions
- Unconventional monetary policy
- Other market interventions

Based on single category events, listed by the FED (Appendix: Table 2.1), we create 10 scenarios; these can be found in table 4.1. The timeline of the FED shows that events from different categories can happen at the same time. It is then impossible to allocate responsibility for the abnormality to one event, and we therefore exclude all events on this day.

[25] http://www.newyorkfed.org/research/global_economy/policyresponses.html

Table 4.1: Defined event scenarios

This table shows the defined scenarios based on the individual events presented in table 2.1 in the appendix.

	Event No.	No. of events	Event category
All events from the FED timeline (double events are excluded)	1	12	Bank Liability Guarantees
	2	21	Liquidity and Rescue Interventions
	3	6	Other Market Interventions
	4	7	Unconventional Monetary Policy
Only German events from the FED timeline (double events are excluded)	5	6	Bank Liability Guarantees
	6	4	Bank Liability Guarantees (only SoFFin)
	7	7	Liquidity and Rescue Interventions
	8	5	Liquidity and Rescue Interventions (only SoFFin)
Short sell restrictions / ban	9	18	All short sell restrictions / ban
	10	1	German short sell restriction

The first four scenarios correspond to the four categories proposed by the FED in table 2.1 of the appendix. To create scenarios 5 and 7, we extract from scenario 1 and 2 only the events that occur in Germany. Scenarios 6 and 8 are created by considering only the SoFFin events from scenarios 5 and 7. In scenario 9 we select international short-selling restrictions, and in scenario 10 we select only German short-selling restrictions. The last two scenarios are not created based on the FED timeline but by using the events mentioned in the paper by Beber and Pagano (2013).

Scenario 1 consists of 12 events where bank liability guarantees were announced (Appendix: Table 2.1). One example could be seen when Hypo Real Estate received EUR 25 billion from Germany on Sep. 29, 2008. In scenario 2, 21 events are selected to allow consideration of liquidity and rescue interventions. One example here is the EUR 8.2 billion loan for Commerzbank AG provided by the SoFFin. The third scenario contains six events and deals with other market interventions, such as interbank liquidity supply. This includes, for example, unlimited swap lines provided by the FED to various other central banks. Short-selling restrictions, which are also listed in the FED timeline in this category, are extracted and will be tested in the separate scenarios 9 and 10. Finally, scenario 4 captures unconventional monetary-policy interventions. These are events where sovereigns (regulators) change their normal policy based on the crisis. This can be, for example, when the national bank buys non-eligible assets (toxic papers) and therefore absorbs the risk and provides liquidity.

In scenarios 5 and 7, the intention is to focus on scenarios 1 and 2, as defined above, but only selecting events that occurred in Germany.

Scenarios 6 and 8 are subsamples of scenarios 5 and 7 and focus exclusively on SoFFin (*Sonderfonds für Finanzmarktstabilisierung*) interventions. The SoFFin was created in Oct. 2008 with the function of restoring stability to the financial markets. It is able therefore to provide various banks, such as Hypo Real Estate, with liquidity in the form of guarantees.

In scenarios 9 and 10, the intention is to analyze the impact of short-selling restrictions. The first scenario therefore only analyzes the impact of international short-selling restrictions. In contrast to this, the second scenario only contains the short-selling restriction imposed by Germany. Because of an inconsistency within the FED timeline, we decided to use the event dates stated in Beber and Pagano (2013).

4.5 Empirical Data Analysis

The empirical data focuses on stocks listed in the Dax for a five-year period (Jul. 1, 2005 – Sep. 30, 2010). Once new listings, de-listings, and data-quality problems were accounted for, we selected 23 remaining stocks that fulfilled the requirements.

The returns are calculated based on daily mid-price p:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \tag{4.9}$$

The weighted bid-ask spreads for different traded volumes are provided by Deutsche Börse. These values are calculated and offered on a daily basis under the name Xetra Liquidity Measure (XLM). The XLM is denoted in bps and is a measure for the costs arising through buying and directly selling a stock (round trip). An advantage of the XLM is that the costs of a round trip are calculated based on different quantities, q. In general it can be said that with increasing traded volumes, more missing XLM data appear because not many or no trades have taken place with this order size. This paper considers the following trading volumes for the Dax stocks: 25, 50, 100, 250, 500 thousand and 1, 2 and 3 million.

The XLM is calculated using the following formula, as stated by Kaserer and Stange (2008). The value at time t is:

$$\mathrm{XLM(q,t)} = \left[\frac{\frac{1}{v}(\sum_i b_{i,t}v_{i,t} - \sum_j a_{j,t}v_{j,t})}{P_{mid,t}}\right] * 10{,}000 \quad (4.10)$$

where b_i and a_i are different bid and ask prices for limit order volumes v_i and v_j.

A statistical analysis of the underlying mean corrected return and spread data is presented in table 4.2. On average, the return results for the Dax show a mean of zero, which indicates a stationary process. This is a prerequisite for subsequent use of the $EGARCH$ model. The data shows a high excess kurtosis. Compared to the excess kurtosis, the skewness shows behavior that is not far from normal. The Jarque-Berra (JB)[26] test (95% confidence level) is rejected for all Dax stocks, which proves that the data are not normally distributed.

Table 4.2: Summary statistics

The table shows a statistical analysis of the mean adjusted log spread and log return data. For all stocks, the mean, standard deviation, skewness and excess kurtosis are calculated. In addition, the percentage value is listed when the Jarque-Bera[26] is rejected.

		Dax Spread (23 stocks)				
		Mean	Median	SD	Max	Min
Return statistics						
	Mean*	-0.062	-0.026	0.404	0.587	-1.403
	SD	0.025	0.023	0.005	0.037	0.016
	Skewness	-0.027	0.129	0.456	0.613	-0.902
	Kurtosis	11.920	10.829	5.085	26.137	6.400
	JB-test (95%)	100%				
Spread statistics						
	Mean*	0.206	0.189	0.329	1.192	-0.504
	SD	0.187	0.183	0.037	0.285	0.086
	Skewness	-0.047	-0.062	0.131	0.306	-0.446
	Kurtosis	4.504	4.097	1.377	10.590	3.152
	JB-test (95%)	94%				

* values in 1,000

[26] The null hypothesis of the Jarque-Bera test assumes that the sample comes from a normal distribution with unknown mean and variance, against the alternative that it does not come from a normal distribution.

By looking at the statistical results of the spread data, one can see that, on average, the log spreads also have a mean that is close to zero. This fulfills the prerequisite of the $EGARCH$ model that the data must be stationary. Compared to the log returns, the log spreads show a much larger standard deviation. Another indicator for the abnormality is the excess kurtosis, which is around 9 on average. This shows that the spread data contains extreme values, which might present difficulties for the model used later. The JB test is rejected in nearly all cases, which indicates that the spread data does not exhibit a normal distribution. The spread data show a significant autoregression, also described by Chen and Poon (2008). The results of our analysis can be found in table 4.3. We use the common measures MLE, AIC, and BIC to identify the number of lags. The results show that no significant autocorrelation is observed for returns, whereas for spreads the effect is dominant until lag 5. For the spread volatility, we therefore use an $AR(5)$ $EGARCH$ $(1,1)$ model, as used by Busch and Lehnert (2011).

Table 4.3: Calculation results of different $\boldsymbol{AR(x)}$ $\boldsymbol{GARCH(1,1)}$ models

This table shows the results of different $AR(x)$ $GARCH(1,1)$ models by using log spread and log return data over the total observation period. In the first part, the GARCH parameters are calculated as stated in formula 4.1. For spreads, the numbers represent the average over the traded volumes 1-8. The second part lists the corresponding results of the Akaike information criterion (AIC)[27], Bayesian information criterion (BIC)[28], and Maximum Likelihood function.

		Dax Spread			Dax Return		
		AR(0)	AR(5)	AR(10)	AR(0)	AR(5)	AR(10)
C	Mean	0.0001	0.0001	-0.0001	0.0003	0.0004	0.0004
	STD	0.0004	0.0002	0.0002	0.0004	0.0004	0.0004
ω	Mean	-1.0390	-0.3072	-0.3618	-0.1691	-0.1716	-0.1728
	STD	1.4045	0.5006	0.5770	0.1117	0.1120	0.1130
GARCH	Mean	0.8719	0.9631	0.9568	0.9782	0.9779	0.9778
	STD	0.1717	0.0605	0.0693	0.0136	0.0137	0.0137
ARCH	Mean	0.2254	0.1118	0.1195	0.1574	0.1594	0.1608
	STD	0.1673	0.0995	0.1030	0.0496	0.0526	0.0546
AIC	Mean	-6,912	-7,198	-7,210	-6,709	-6,705	-6,699
BIC	Mean	-6,886	-7,146	-7,133	-6,683	-6,653	-6,621
MLE	Mean	3,461	3,609	3,620	3,359	3,362	3,364
Calculated param.		4	9	14	4	9	14

[27] $AIC = 2k - 2ln(L)$. Here, k is the number of parameters in the statistical model, and L is the result of the maximum likelihood function.

[28] $\mathrm{BIC} = -2 * \ln(\mathrm{L}) + \mathrm{k} * \ln(\mathrm{n})$, where L is the result of the maximum likelihood function, k is the number of parameters that have to be estimated, and n is the number of observations.

4.6 Empirical Performance and Discussion

This section discusses the test results, focusing on abnormal changes in bid-ask spreads and returns based on the scenarios defined in Section 4.4. The intention is to analyze whether certain market interventions are reflected in the market at the announcement date. In comparison to many other event studies, we also use volume-weighted bid-ask spreads in addition to returns to capture the impact of events on liquidity. According to our research, this is the first time this has been done.

The discussion is structured as follows. Firstly, we give an introduction to how spreads and returns behave during normal and crisis periods. Here, the focus is especially on how they influence one another. The information we gathered in the first part is then used to analyze the test results according to abnormal spread and return changes.

In general, a negative return is the result of a decreasing share price. This equates to a loss for the shareholder. The implication of a negative bid-ask spread change stands contrary to this. This is because bid-ask spreads are costs (approx. half of the spread) that the investor has to pay when the stock is sold. It is interesting to see not only the way that spreads and returns react individually to interventions, but also what interaction can be observed between the two.

In the paper published by Amihud and Mendelson (1980), they mention that spreads and returns exhibit a positive correlation. Increasing stock returns result in increasing illiquidity. Busch and Lehnert (2011) demonstrated that this is not the case even during the financial crisis that began in 2008. In the paper by Hameed et al. (2010), they show further that negative returns reduce liquidity more than positive returns raise liquidity.

Another paper written by Chordia et al. (2002) analyzes the relationship between spreads and returns, with a focus on order imbalances. The paper mentions that, especially during crisis, spreads and returns are strongly affected by extreme order imbalances, which influence the inventory of the market maker. The reaction of the market maker to such imbalances is to change spreads and revise quotations. Based on this research, one can argue that abnormal spreads and returns can be negatively correlated based on extreme order imbalances during the crisis starting in 2008. At that time, many investors wanted to or were forced to sell their stocks and therefore to create a demand for liquidity (liquidity effect).

On the other hand, the market maker faces constraints that prevent him from providing unlimited liquidity to the market. This includes, for example, the size of the stock position in his inventory. When one or more of these constraints are met, he may stop buying shares (Deutsche Börse AG, 2012). To reduce the market risk in his inventory he will also try to reduce the stock position; this creates even more demand for liquidity. This spiral effect results in the financial market increasingly drying up, as described by Hameed et al. (2010). But, of course, the market maker will not wait until his constraints are hit or the market dries up.

This brings us to the research papers written by Yakov (2002) and Bookstaber (1999), which show that spreads and returns can exhibit acyclic behavior. The first paper states that the market maker uses spreads and returns to influence and manage supply/demand and that therefore these also include the expectations of the future development of the market. This can also be seen in our results: for some events, for example, abnormal negative returns can appear with abnormal negative spread changes. This would indicate that the market is decreasing but that expectations are positive.

The simulation results of the event study can be found in table 4.4. These results are calculated using formula 4.8 and consider different volume-weighted bid-ask spread and return data. The results follow a Student-T distribution with $n-1$ degrees of freedom. Positive and negative significant values are highlighted by using a 95% confidence level.

Table 4.4: Test results of abnormal spread and return data

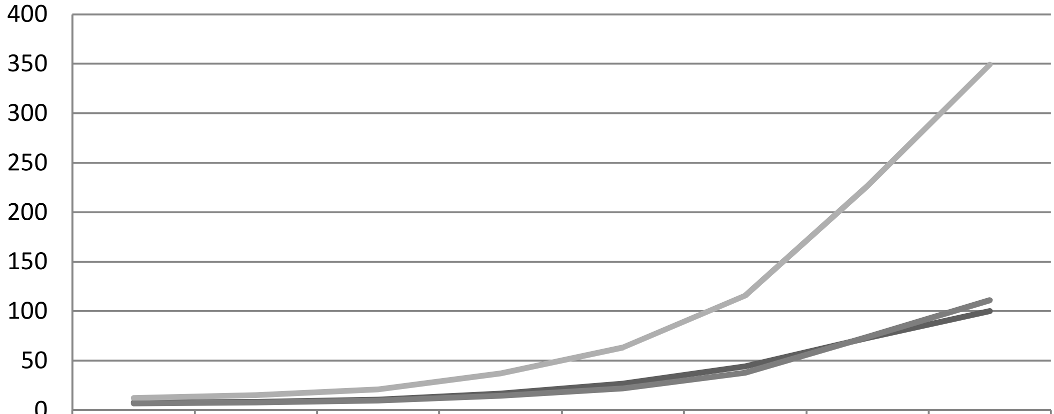
The table contains the t-test results for abnormal spread and return changes at the announcement date calculated by using formula 4.8. The colors indicate significant positive or negative change based on a 95% confidence level.

Dax		Volume 1	2	3	4	5	6	7	8	Return
Event	1	8.1	8.62	8.8	7.43	5.77	3.84	3.77	3.13	-4.15
	2	-8.47	-8.43	-6.73	-4.69	-3.08	-2.92	-4.42	-3.69	3.03
	3	3.21	3.53	3.67	2.84	1.34	-0.88	-1.18	-1.21	-3.25
	4	1.41	1.34	1.08	1.29	2.16	2.76	1.26	0.61	-1.63
	5	5.5	6.62	6.94	5.55	4	2.88	2.12	1.43	-1.44
	6	5.93	7.13	6.64	3.1	1.42	0.39	0.23	-0.09	0.23
	7	1.27	1.74	1.55	1.07	0.7	0.21	-0.61	-0.56	-0.93
	8	2	2.89	3.32	2.95	2.16	1.33	0.61	1.04	-2.67
	9	-7.69	-17.13	-17.34	-16.25	-10.36	-5.9	-4	-3.91	7.21
	10	-0.88	-1.31	-1.76	-1.79	-0.6	0.33	1.32	1.12	-3.59

As defined in Section 4.4, the first four scenarios consider all events from the four categories. The result of the first scenario indicates that market reaction is negative when **bank liability guarantees** are given. This is based on a significant increase in abnormal spreads and significant decrease in abnormal returns. The imbalance of the order book, where the demand of liquidity is dominant, leads to a drying-up of the financial market. This reaction to the intervention is in line with the observations made by King (2009). He further mentions that, in general, banks that are involved in rescue intervention suffered more than those that are not. In contrast to his analysis, which focused on banking stocks, our results show that the negative reactions to the intervention is not limited to financial companies. This spillover effect between different industries shows that investors anticipate negative cross-effects. Based on uncertainty in the market, they change their portfolio composition and step out of the stock markets, shifting into safer investments (they "fly to quality") (Næs, Skjeltorp, & Ødegaard, 2011). By looking at the average abnormal spreads of the different traded volumes it can be seen that higher volumes react more weakly than smaller volumes at the event date. This observation is contrary to the information given in Figure 4.1. Here it can be seen that, on average, the spreads increase almost exponentially with the traded volume. Our conclusion is that, with increasing trading volume, the spreads become so high already that no large adjustments are necessary. This means that the market maker is already risk-averse for higher traded volumes before the event occurs. Table 4.5 presents the results of a t-test, comparing high (Volumes 6 and 8) versus low (Volume 1) traded volumes. The numbers show that there is an asymmetric increase in the spreads at the event date.

Figure 4.1: Mean spreads of pre-crisis, crisis and post-crisis

The following chart is created based on Figure 2.1 and shows the different reactions of average spreads (in bps) considering different trading volumes in pre-crisis, crisis and post-crisis periods. The volumes Vol. 1 to Vol. 8 are equal to the trading volumes 25, 50, 100, 250, 500 thousand and 1, 2, and 3 million.



	Vol. 1	Vol. 2	Vol. 3	Vol. 4	Vol. 5	Vol. 6	Vol. 7	Vol. 8
Pre-crisis	7.63	8.58	10.55	16.77	26.85	44.30	72.98	100.29
Crisis	12.22	15.19	20.96	37.16	63.47	115.63	226.69	349.25
Post-crisis	6.84	7.88	9.79	14.66	22.00	37.77	74.11	111.02

The results of scenario 2 provide a good example of the ability of market intervention to restore stability. Here **different liquidity and rescue interventions are** announced. The results show, on average, a significant increase in returns and a decrease in spreads. This implies that the financial market is more stable. The same result is described by Bohl et al. (2011), although that study focuses on liquidity in the banking sector. As a liquidity measure, the authors use Libor-OIS rates that indicate the future expected liquidity supply in the interbank market. A low Libor-OIS reduces funding pressure and counterparty risk (Aït-Sahalia, Andritzky, Jobst, Nowak, & Tamirisa, 2012). It is interesting to see that, for this scenario too, the whole Dax market is significantly affected even though most of the events focus only on the financial sector (e.g., SoFFin gives EUR 8 billion loan to Commerzbank or the government of Switzerland injects CHF 6 billion into UBS). This kind of overall co-movement typically appears during crisis and reduces the efficiency of the diversification effect within portfolios (also according to liquidity), as stated by Markowitz et al. (2009) and Bissantz et al. (2010). By considering the higher traded volumes, one can see a significantly positive reaction to liquidity. The comparison shows that the effect decreases with increasing traded volume. This is the same behavior as we detected in the first scenario, albeit simply in reverse. The spreads of the higher traded volumes will still remain at a high level.

Furthermore, based on the results in table 4.4, an asymmetric increase of spreads can be found in this scenario.

The third scenario shows significant negative returns by focusing on **other market interventions**[29]. By looking at the spreads, we observe a different response. For small traded volumes, significant positive abnormal spreads appear; these result in an increase in market illiquidity. In contrast, higher traded volumes show a slightly negative abnormality. The results indicate that FED and other central bank interventions helped to bring back stability. Most of these interventions focused on liquidity support from the FED to the ECB, SNB, and BoE by, e.g., providing unlimited U.S. dollar swap lines. The reason for this intervention is that, after the Lehman collapse, international financial institutions in particular were hit by the phenomenon of dollar shortage. In the papers by Beba and Packer (2009) and McAndrews (2009), they mention the positive feedback to the Libor and federal fund rates. This is also recognized by the financial market, which shows a positive reaction to the intervention.

In scenario 4, the Dax data did not exhibit significant behavior overall. While, on average, the returns decreased, the spreads showed a positive response (two of eight are significant) to **unconventional interventions.** Most of the events focus on buying governmental bills or bonds from commercial banks and therefore providing liquidity. The research published by Aït-Sahalia et al. (2012) shows, by focusing on the financial sector, that no significant results are detected either. It states that there are only small improvements in liquidity. Another paper focusing on the impact on stock prices was published by Tong and Wei (2012). Here, the researchers state a slightly positive impact on liquidity. Furthermore, they find that companies that had high liquidity needs before the announcement benefited especially from the interventions. Given all Dax data, our results again show, on average, equal behavior across all stocks and industries. Compared to the aforementioned scenarios, there is, on average, no significance between bid-ask spreads of the different traded volumes. This is also confirmed by the t-test results in the following table 4.5.

[29] We exclude short selling restrictions. They are dealt with separately in scenarios 9 and 10.

Table 4.5: T-stats of abnormal returns by comparing different trading volumes

This table shows t-test results obtained by comparing mean bid-ask spreads of the traded Volumes 1 & 6 and 1 & 8. The grey color indicates a significant deviation based on a 95% confidence level.

	Vol. 1 vs. Vol. 6	Vol. 1 vs. Vol. 8
Event 1	0.893	2.162
Event 2	2.74	2.539
Event 3	3.116	3.274
Event 4	0.583	0.519
Event 5	0.811	2.026
Event 6	2.798	3.419
Event 7	0.567	1.245
Event 8	0.145	0.402
Event 9	3.858	4.767
Event 10	0.827	1.417

Up till now, we have discussed the results of the four scenarios, considering all events within the FED timeline. In the next part, we will analyze the impact of domestic events on the local stock market. This can be achieved by comparing scenario 1 versus scenario 5 and scenario 2 versus scenario 7, focusing on bank liability guarantees and liquidity and rescue interventions (Scenarios 6 and 7 are a subsample of scenarios 1 and 2 that only considers SoFFin events).

The comparison of scenarios 1 and 5 shows that there are differences between the average spread and return values. In scenario 1, the spreads are higher and the returns are lower compared to scenario 5, indicating that the German financial market experiences a greater effect based on international bank-liability interventions. This is called the spillover effect, which is also described by Aït-Sahalia et al. (2012). In their paper, the researchers analyze the impact of this effect on market interventions before and after the crisis. They find that the spillover effect is significantly higher during crisis. Similar results are described by the International Monetary Fund (2009), which analyzes the impact of U.S. crisis interventions on the European market. Comparing, in particular, the change in abnormal spreads between low and high volume allows an asymmetric behavior to be observed. Starting from scenario 5, where only German events are considered, the abnormal spread of the lowest trading volume increased by 147%, while for the highest trading volume the abnormal spread increased by 219% on average. Contrary to this, the abnormal returns decreased by 287%. In scenario 6, only the SoFFin events are considered. As already mentioned in section 4.3, the task of the SoFFin is to restore stability to the financial system by, e.g., providing liquidity to different banks in the form of guarantees. The results show that the abnormal spreads for the lower traded volumes are small, while for higher traded volumes these events show no significant abnormality. The abnormal returns slightly increased based on these events. Based on the results it can be said that the Dax did not react positively to the intervention. At the announcement date the spreads showed an asymmetric increase of abnormality, which can be seen in table 4.5.

An even more significant difference can be seen by comparing scenarios 2 and 7, which both focus on liquidity and rescue interventions. The results indicate that international interventions significantly decreased the abnormal spreads and restored liquidity to the market. Whereas when focusing only on German events one can even observe a slight (not significant) increase of abnormal spreads. The abnormal returns also show the same behavior. Comparing the traded volumes, the lowest decreased by 667% while the highest decreased by 659%, based on scenario 7. By analyzing just the SoFFin events within scenario 7, the results are visible in scenario 8. It can be seen that the abnormal spreads increase significantly in 4 out of 8 traded volumes and that the returns decrease significantly. This is a clear sign that the market reacts negatively to SoFFin interventions and that liquidity dries up.

The above results show a huge spillover effect that appeared during the crisis. Based on the results, it is important that market interventions should not be managed by each sovereign individually, but rather on a more global level. This is also stated by various other papers, such as Aït-Sahalia et al. (2012). In addition, we could see in nearly all cases that the log changes of different traded volumes react asymmetrically to the same events. This should be considered in future risk methodologies.

The last scenarios, scenarios 9 and 10, are used to analyze the impact of short-selling restrictions based on international interventions and then, separately, on German intervention. The results show that there are significant abnormal positive changes in returns and mainly significant negative changes in the abnormal spreads (all eight volumes are significant). This indicates that the financial market reacts positively and, consequently, increases liquidity. The interpretation of the results is still difficult because they differ from those of other papers published by, e.g., Beber and Pagano (2013) or Battalio and Schultz (2011). The paper by Battalio and Schultz (2011) finds that, at the announcement date, the market reacts negatively because short selling is only part of the overall trading activity. For them, trading is equal to liquidity. After the interventions, the number of market participants and trades decreases.

Our interpretation is based on order imbalances described by Chordia et al. (2002). The situation before the announcement is that liquidity supply (investors want to sell stocks) is not a problem but the liquidity demand (investors want to buy stocks) is. Based on the announcement, investors are now buying stocks to close their positions, which increase liquidity in the market. In the last scenario (scenario 10) only the impact of the German short-selling restriction on the Dax is analyzed. The results for abnormal spreads are negative overall while the abnormal returns are slightly positive. It is interesting to see that the domestic financial market reacts much more weakly to local interventions than to international action. This again shows the spillover effect. We believe that the German market already expected this to happen as a result of the announcements by, e.g., the U.S., Canada, the U.K., Switzerland, Luxembourg and Ireland a day beforehand. This would explain why reaction to local intervention shows such a different result.

Until now we only focused on the advance-event study methodology which models the volatility process by using a $E-GARCH$ model. To test the robustness of the results, we repeated the calculations with different volatility assumptions. In the results presented in appendix table 2.2 a constant volatility and in appendix table 2.3 an equal volatility is assumed. The comparison shows that for the returns the number of significant results stays the same. For spreads they are slightly different. This can be seen in scenario 7 which focuses on liquidity and rescue interventions only in Germany. Here the event methodology shows with constant volatility two positive significant results and with equal volatility three positive significant results for lower traded volumes. This indicates that the market has a significantly negative reaction after these interventions. Overall it can be said that the test results are (including for spreads) pretty much the same. When there are changes in significance they are mainly based on small changes of the test results. Therefore our general findings remain and seem to be robust. Based on the underlying data it is more accurate to use the advanced event study methodology.

4.7 Conclusion

In this chapter we use volume-weighted bid-ask spread and return data to test the abnormality of stocks within the Dax, based on interventions starting in 2008 during the financial crisis. To this end, we define different scenarios focusing on the following categories: bank liabilities guarantees, liquidity and rescue interventions, unconventional monetary policy and other market interventions. These interventions were aimed at restoring stability to the financial market. Based on the test results, different conclusions can be made. Overall, it can be said that the market reacts differently to these events with the same purpose: e.g., the market reacts positively to liquidity and rescue interventions and negatively to bank liabilities guarantees. Furthermore, we analyze the impact of international interventions on the domestic financial market. In this respect, we find that market interventions, which are triggered from abroad, have a significant spillover effect on the local financial market. This result shows that market interventions should be managed on a global level. Another interesting effect is that all stocks within the Dax are closely linked to the reaction of financial institutions within the index. Therefore even diversified portfolios suffered during the crisis. We also examine closely the impact of regulatory interventions on different traded volumes. Here the results show that in most cases a significant asymmetry appears. Overall, the spreads for lower traded volumes react more strongly than those for higher volumes at the announcement date. We also performed a robustness check of the conditional volatility model by performing the same calculations with constant and equal volatility approaches. The results remained the same overall.

Chapter Five

Liquidity Commonality and Option Prices[30]

5.1 Motivation

Equity markets and option markets are directly linked to each other. While in the last two chapters (3 and 4) the focus is mainly on stock market liquidity, in this chapter we want to concentrate more on option market liquidity. Therefore we analyze the relationship between stock liquidity and option implied volatility. The following questions are focused on:

1) What impact does stock market liquidity have on option implied volatility?
2) What is the impact of market (systematic) liquidity versus single stock (idiosyncratic) liquidity?
3) How does the relationship change during the Lehman crisis in 2008?

The structure of the chapter is as follows. First, we take a closer look at the data used, including a detailed description of the advanced liquidity measure XLM. Afterwards we test different hypothesis on a daily and monthly basis to analyze what impact stock liquidity and market liquidity have on implied volatility. In this context, we also focus on the time-varying liquidity commonality. In the last section the findings are summarized.

5.2 Literature Review

In various papers different liquidity measures are proposed. They can be separated roughly into one-dimensional and multi-dimensional measures (von Wyss, 2004). While the first

[30] This chapter is based on the working paper (Busch & Lehnert, 2013).

group focuses only on single attributes (e.g. daily traded volume or market capitalization (Sarr & Lybek, 2002)) the second group combines single measures from the first group. One frequently-used one-dimensional measure is the bid-ask spread (Amihud & Mendelson, 1986). The weakness of this is that with increasing trading volume the spread increases exponentially, as mentioned by Kaserer and Stange (2008). Therefore the liquidity risk of higher traded volumes is neglected. One measure which also considers this is provided by the Deutsche Börse and is called the Xetra Liquidity Measure (XLM). This multi-dimensional measure is based on volume-weighted bid-ask spreads[31]. In the paper by Kaserer and Stange (2010) they demonstrate the outperformance of this measure compared to others. Based on the above mentioned advantages, we use the XLM to capture liquidity in this chapter.

Beside liquidity in stock markets, it also plays an important role in option markets. Here we can mention Vijh (1990) who analyzes the liquidity of CBOE stock options compared with NYSE stocks. Based on the observation that large trading volumes can be absorbed without big changes in price, he assumes this market to be liquid. In the same direction there are the results by Kalondera and Schlag (2004). They find a positive relationship between stock market activity (measured by the transaction volume) and option market liquidity. This is in line with the results by George and Francis (1993) which show that trading activity and the bid-ask spreads have a negative correlation.

Another indicator for option liquidity or the option price is to focus on implied volatility. The link between liquidity and the "implied volatility smile" has been described by Rubinstein (1985). In the papers by Chou et al. (2011) and Christoffersen et al. (2012) they mention that a reduction in spot liquidity results in an increase in the implied volatility curve. This is in line with the argumentation of Cetin et al. (2006). They show that increasing illiquidity in the underlying stock results in higher hedging costs in the option market. By analyzing only data within the option market Chou et al. (2011) can find a positive link between implied volatility and option illiquidity. These findings are supported by the suggestion of Amihud and Mendelson (1986) and Christoffersen et al. (2012) that there is an illiquidity premium in the option market. In the paper by Bollen and Wahley (2004) they analyze the relationship between net buying pressure and implied volatility. They find that changes in the implied volatility for index options are affected by net buying pressure for index puts while stock

[31] A detailed description of this measure can be found in the following section 2.5

options are affected by the demand of call options. Also we can mention here the publication by Ammann et al. (2010). They discover a relationship between stock returns and lagged implied volatilities for the US equity option market. The results of the above mentioned papers show that implied volatility is a good indicator for option prices and liquidity. Therefore we focus on implied volatility as a measure for option market liquidity in the chapter.

Beside research papers which describe the impact of liquidity on option prices, other papers extend the classical arbitrage pricing theory to incorporate liquidity (Jarrow & Protter, 2007). One possibility is to model a stochastic supply curve for security prices depending on the trade size. In the paper by Certin et al. (2006) this model is used to incorporate illiquidity into an extended Black Scholes model. The results show that liquidity costs are a significant component in option prices especially with increased trading volume of the underlying security.

One often-neglected topic is the analysis of liquidity commonalities in stocks. As described by Chordia et al. (2000) liquidity risk is not only limited to the single stock level. In their paper they detect co-movements in stock liquidity which indicates market liquidity. They raise further research questions regarding external shocks such as political events, macroeconomic conditions or even hysteria. Their methodology is used by Rösch and Kaserer (2012) in combination with the Xetra Liquidity Measure (XLM). They support the existence of liquidity commonality between the market liquidity and stock returns. This commonality varies over time and shows a strong relationship with negative return changes. The impact of liquidity commonality within the equity option market has been studied by Duan and Wei (2009). By using S&P 100 data they demonstrate that systematic risk leads to higher implied volatility and a steeper slope in the implied volatility curve. In the publication by Datar et al. (1998) they focus on the equity market and demonstrate that liquidity plays an important role in cross-sectional returns.

5.3 Empirical Data Analysis

The empirical data used in this chapter are stocks and options listed in the Dax index. Based on data quality problems, new listings or de-listings, 23 stocks are selected for our research. The observation period is between 11.17.2005 – 09.30.2010 (1,216 observations).

We want to have a specific focus on different market situations in terms of pre-crisis, crisis and post-crisis periods. Therefore the summery statistic shows a detailed analysis for each period:

- Pre-crisis 11.17.2005 – 08.29.2008
- Crisis 09.01.2008 – 12.30.2009
- Post-crisis 01.04.2010 – 09.30.2010

These crisis time periods are used in Rösch and Kaserer (2012).

To measure liquidity we use volume-weighted bid-ask spreads. This measure is provided by the Deutsche Börse under the name "Xetra Liquidity Measure" (XLM). The XLM is denoted in bps and is a measure of the costs arising through buying and subsequently selling the stock (round trip). An advantage of the XLM is that the costs of a round trip are calculated using different quantities q (Gomber & Schweikert, 2002). In general it can be said that with increasing trading volume, more missing XLM data appear because few or no trades have taken place with this order size at that day. Because of this we consider 8 out of 10 volumes which are: 25 (Vol. 1), 50 (Vol. 2), 100 (Vol. 3), 250 (Vol. 4), 500 thousand (Vol. 5) and 1 (Vol. 6), 2 (Vol. 7), 3 million (Vol. 8). The XLM is calculated using the following formula (Gomber & Schweikert, 2002). The value at time t is:

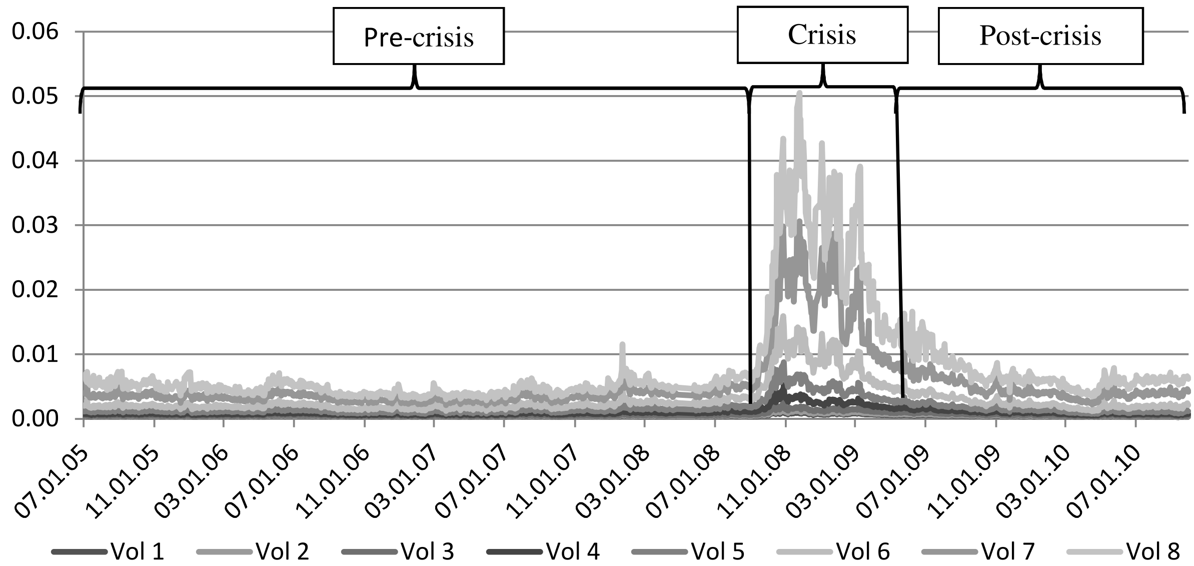
$$\mathrm{XLM(q,t)} = \left[\frac{\frac{1}{v}(\sum_i \mathrm{b}_{i,t}\mathrm{v}_{i,t} - \sum_j \mathrm{a}_{j,t}\mathrm{v}_{j,t})}{P_{mid,t}}\right] * 10{,}000 \tag{5.1}$$

where $\mathrm{b_i}$ and $\mathrm{a_j}$ are different bid and ask prices for limit order volumes $\mathrm{v_i}$ and $\mathrm{v_j}$.

In figure 5.1 we can see that the bid-ask spreads increase with trading volume. Additionally there is a difference between pre-crisis, crisis and post-crisis times. During the crisis the spreads are higher overall. Between the crisis and no crisis periods the spreads increase exponentially with traded volume.

Figure 5.1: Average spread changes of 23 selected Dax stocks by considering different traded volumes

The following table shows the average volume-weighted bid-ask spread changes for different traded volumes[32] over the total observation period of 5 years. In addition, the time period is subdivided into pre-crisis, crisis, and post-crisis periods.



A summary statistic for the attributes can be found in table 5.1. By looking at the periodic changes in table 5.1 we can see that with higher trading volumes the average change and the corresponding standard deviation increase. The comparison between the different crisis periods shows that pre-crisis the average changes are nearly equal to those during the crisis. In the post-crisis period there is a drop in these values.

[32] The different volumes, Vol. 1 – Vol. 8, correspond to 25, 50, 100, 250, 500 thousand and 1, 2, and 3 million traded volume.

Table 5.1: Summary statistics

The following table gives an overview of the attributes which we use in this paper. The values are average periodic changes. A special focus is on different market situations like pre-crisis (11.17.2005 – 08.29.2008), crisis (09.01.2008 – 12.30.2009) and post-crisis (01.04.2010 – 09.30.2010) times. Overall 1216 observations are considered over a period of around 5 years.

		Liquidity Spreads								Prices	Impl. Volatility			DTV	P/C ratio**
		Vol. 1	Vol. 2	Vol. 3	Vol. 4	Vol. 5	Vol. 6	Vol. 7	Vol. 8		110%	100%	90%		
Pre-crisis	Mean	0.013	0.013	0.015	0.018	0.021	0.024	0.023	0.024	0.039*	0.008	0.005	0.010	0.129	2.001
	SD	0.084	0.086	0.088	0.095	0.099	0.101	0.097	0.094	0.011	0.040	0.038	0.043	0.379	2.694
	Skew	0.537	0.528	0.508	0.454	0.393	0.324	0.345	0.477	-0.358	1.023	1.397	1.293	2.356	3.116
	Kurt	1.788	1.886	1.960	1.716	1.128	0.615	0.463	0.910	2.856	4.015	6.758	5.035	11.134	11.947
Crisis	Mean	0.012	0.012	0.013	0.014	0.016	0.020	0.026	0.030	0.025*	0.011	0.004	0.009	0.089	1.784
	SD	0.093	0.097	0.099	0.098	0.095	0.102	0.117	0.125	0.026	0.057	0.053	0.054	0.281	2.428
	Skew	0.896	1.047	1.222	1.115	0.591	0.499	0.775	0.900	0.518	0.949	0.548	0.442	1.085	3.819
	Kurt	7.027	8.572	10.313	8.829	3.230	1.102	1.536	1.875	4.676	1.787	2.590	1.208	2.506	19.154
Post-crisis	Mean	0.006	0.005	0.004	0.004	0.006	0.009	0.011	0.012	0.052*	0.013	0.004	0.014	0.125	1.220
	SD	0.087	0.085	0.081	0.077	0.081	0.091	0.094	0.088	0.012	0.054	0.048	0.053	0.384	1.452
	Skew	0.690	0.675	0.647	0.607	0.568	0.620	0.813	0.916	-0.043	1.493	1.391	1.265	1.391	3.829
	Kurt	1.886	1.971	2.309	2.332	1.590	1.643	2.537	2.967	1.683	3.370	4.488	2.608	3.562	21.529
Overall	Mean	0.012	0.012	0.012	0.015	0.017	0.020	0.022	0.024	0.037*	0.010	0.004	0.010	0.118	1.819
	SD	0.087	0.089	0.090	0.093	0.095	0.100	0.103	0.103	0.017	0.048	0.045	0.048	0.355	2.478
	Skew	0.679	0.734	0.792	0.697	0.484	0.419	0.594	0.778	0.467	1.178	1.013	0.955	2.065	3.466
	Kurt	3.673	4.501	5.380	4.170	1.761	0.858	1.298	2.033	10.240	3.370	4.633	3.028	9.440	15.319

* in 100, ** in 1,000

In the following analysis we will use periodic changes of returns and implied volatilities. They are calculated as

$$\Delta\left(Return_{s,t}\right) = \frac{Price_{s,t} - Price_{s,t-1}}{Price_{s,t-1}} \qquad \Delta\left(IV_{s,t}\right) = \frac{IV_{s,t} - IV_{s,t-1}}{IV_{s,t-1}} \tag{5.2}$$

In table 5.1 the results show the lowest changes of stock prices during the crisis followed by the post-crisis and the pre-crisis. The standard deviations of the changes are highest during the crisis.

The changes in implied volatility indicate that the out-of-money calls and out-of-money puts have higher volatility than at-the-money options. It can be seen that from the pre-crisis through to the crisis and post-crisis periods, the average periodic change increases. Only the average changes of the at-the-money options stay nearly constant. In this chapter we only focus on at-the-money implied volatilities.

Another attribute which we consider is the daily traded volume (DTV) of the underlying stock. This value is defined as the cumulated volume of all single trades during the day. It can be seen that the highest average periodic change and standard deviation can be seen before and after the crisis.

The put/call ratio is calculated by dividing the cumulated number of traded puts by the cumulated number of traded calls at the end of each day.

$$P/C\ ratio = \frac{Number\ of\ traded\ Puts}{Number\ of\ traded\ Calls} \tag{5.3}$$

In table 5.1 the results show that the change of the put/call ratio has the highest value pre-crisis followed by the crisis and post-crisis periods. The standard deviation of this variable shows the same behavior.

5.4 Empirical Performance and Discussion

In the section we focus on two liquidity measures. The first is *Stock Liquidity Measure (SLM)* which is based on volume-weighted bid-ask spreads. We received these data from the Deutsche Börse who provide them under the name "Xetra Liquidity Measure" (XLM). The second is the *Market Liquidity Measure (MLM)*. This is defined as an equally weighted cross sectional average over the SLMs[33].

$$MLM_t = \frac{1}{23} \sum_{i=1}^{23} SLM_{i,t} \quad (5.4)$$

We use the MLM based on the research by Chordia et al. (2000). They find that when liquidity risk is analyzed, not only single stock liquidity but also market liquidity risk should be considered. Therefore we subdivide liquidity risk into idiosyncratic liquidity risk measured by the SLM and systematic liquidity risk measured by the MLM. Idiosyncratic liquidity risk means that changes in single stock liquidity are triggered mainly by its own specifics. In contrast, systematic liquidity risk is when single stock liquidity is more affected by a common movement of market liquidity. In the following we analyze if idiosyncratic liquidity or systematic liquidity risk can better explain implied volatility changes.

The following regression formula (5.5) is calculated without considering liquidity. Based on the results we want to identify the interaction between the independent variables and the at-the-money implied volatility. This helps us to identify later if the MLM or the SLM can better explain implied volatility changes. As is common in regressions we use periodic changes of all data to have more stationary data.

$$\Delta(IV_{s,t}) = \beta_0 + \beta_1 \Delta(IV_{s,t-1}) + \beta_2 \Delta(Return_{s,t}) + \beta_3 \Delta(DTV_{s,t}) + \beta_4 \Delta(P/C\ ratio_{s11,t}) + \varepsilon \quad (5.5)$$

In the formula, the variables $\Delta(IV_{s,t})$ and $\Delta(IV_{s,t-1})$ contain the daily periodic changes of implied volatility and lagged implied volatility of stock s. The variable $\Delta(Return_{s,t})$ stands for periodic changes of stock prices. Additionally we add the control variables $\Delta(DTV_{s,t})$ and $\Delta(P/C\ ratio_{s,t})$. The daily trading volume accounts for transaction based liquidity as

[33] This can be done, in our opinion, because of the homogeneity of the stocks listed in the Dax.

mentioned by Kalodera and Schlag (2004). They mention that with increasing trading volume option liquidity increases. The $put\ /\ call\ ratio$ is a common measure on the option side for trading activity and liquidity.

The results can be found in table 5.2. There, lagged implied volatility shows significant behavior, indicating an autocorrelation in implied volatilities. Also, the return changes of 96%[34] represent significant behavior. All beta values are negative, which means that decreasing returns result in increasing implied volatilities. This is also described by Smales (2012). In the paper by Ammann (2010) they show that lagged implied volatility can be used to predict stock market returns.

[34] The value is equal to the sum of all significant single stocks divided by the total number of stocks (overall 23 stocks). A single stock is significant based on a confidence level of 90%.

Table 5.2: Basic regression without liquidity

To following table is calculated by using regression formula 5.5. The intention is to detect the impact of different attributes on implied volatility. In the regression, liquidity risk is neglected.

Panel A: Without Liquidity						
			Parameter Estimates			
	R^2	Adj. R^2	lag IV	Returns	DTV	P/C ratio****
ADIDAS AG O.N.	0.1308	0.1276	-0.2856 ***	-0.7787 ***	-0.0041	-0.0062
ALLIANZ SE VNA O.N.	0.2368	0.2340	-0.2459 ***	-1.407 ***	0.0122 **	-1.2616
BASF AG O.N.	0.1544	0.1513	-0.2886 ***	-1.0504 ***	0.0106 **	0.3139
BAY.MOTOREN WERKE AG ST	0.1540	0.1509	-0.2667 ***	-0.8722 ***	0.0071 *	-0.5389
BAYER AG NA	0.1276	0.1244	-0.2483 ***	-1.0124 ***	0.0106 **	-0.0054
COMMERZBANK AG O.N.	0.1983	0.1954	-0.2694 ***	-1.0393 ***	0.02 ***	0.1325
DAIMLER AG NA O.N.	0.1644	0.1613	-0.2943 ***	-0.9625 ***	0.0017	-0.2052
DEUTSCHE BANK AG NA O.N.	0.2079	0.2050	-0.2305 ***	-1.2394 ***	0.0122 **	-0.1615
DEUTSCHE BOERSE NA O.N.	0.1646	0.1615	-0.2938 ***	-0.6817 ***	0.0178 ***	0.0836
DEUTSCHE POST AG NA O.N.	0.1119	0.1086	-0.2972 ***	-0.6866 ***	-0.0073	-0.1848
DT.TELEKOM AG NA	0.1120	0.1087	-0.27 ***	-0.8505 ***	0.0264 ***	0.9136
FRESEN.MED.CARE AG O.N.	0.1247	0.1214	-0.3207 ***	-0.9093 ***	0.0083	-0.0017
HENKEL AG+CO.KGAA VZO	0.1171	0.1137	-0.2615 ***	-0.9336 ***	0.0061	-0.003
LINDE AG O.N.	0.0375	0.0340	-0.1633 ***	-0.5637 ***	0.0117 *	-0.3741
LUFTHANSA AG VNA O.N.	0.2071	0.2042	-0.3135 ***	-1.2766 ***	0.0062	0.0086
MAN AG ST O.N.	0.1219	0.1187	-0.3086 ***	-0.4957 ***	0.0155 ***	-0.0904
METRO AG ST O.N.	0.0698	0.0664	-0.232 ***	-0.7574 ***	0.0149 **	0.0158
MUENCH.RUECKVERS.VNA O.N.	0.1975	0.1945	-0.252 ***	-1.5984 ***	0.0056	0.003
RWE AG ST O.N.	0.1206	0.1174	-0.3169 ***	-0.773 ***	0.0252 ***	-0.0698
SAP AG O.N.	0.1578	0.1547	-0.309 ***	-1.7197 ***	0.0114 *	0.1178
SIEMENS AG NA	0.1752	0.1722	-0.2348 ***	-1.1005 ***	0.0106 **	-1.3678
THYSSENKRUPP AG O.N.	0.0989	0.0956	-0.3104 ***	-0.1676 *	0.0006	0.0078
VOLKSWAGEN AG ST O.N.	0.0167	0.0131	0.0139	-0.0831	0.0104 ***	-0.0934 **

* 90%, ** 95%, *** 99% , **** in 1,000

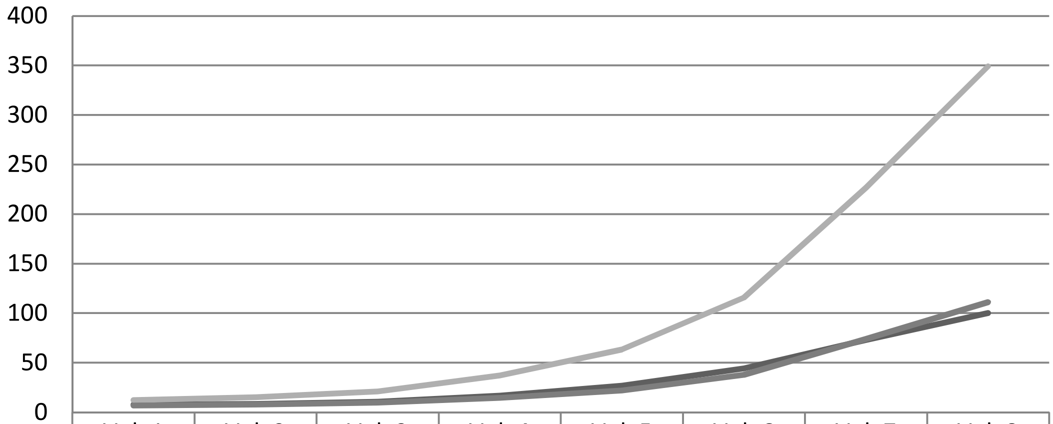
The results of the $\Delta(DTV_{s,t})$ indicate overall that with increasing trading volume implied volatility also rises. This is in line with the observations by Kalodera and Schlang (2004) and Cho and Engle (1999). They detect a relationship between stock market activity, measured by the transaction volume, and option liquidity. With 65%[34] the stocks showed significant behavior. It can be seen that financial institutions like Commerzbank or Deutsche Bank and the Deutsche Börse are especially significant. This is because after the Lehman default world financial markets were unsure which institution could be hit next. The increasing uncertainty is therefore reflected in implied volatility and higher option prices.

The $put\ /\ call\ ratio$ shows the lowest significance in the first regression. Also the prefix is mixed positive and negative which indicates that implied volatility is affected differently by this ratio.

In the following regressions we want to analyze what impact stock liquidity has on implied volatility. Therefore the basic regression formula (formula 5.5) is extended by integrating either the SLM or MLM. Additionally we subdivide the complete observation period into pre-crisis (11.17. 2005 – 08.29.2008), crisis (09.01.2008 – 12.30.2009) and post-crisis (01.04.2010 – 09.30.2010) periods. The intention is to identify the impact liquidity has on implied volatility during the financial crisis in 2008. By doing this we follow the research suggestion paper by Chordia et al. (2000). They mention that it would be interesting to analyze how liquidity commonality changes over time.

Figure 5.2: Mean spreads of pre-crisis, crisis and post-crisis

MLM in bps by considering different trading volumes and the following market situations: pre-crisis, crisis and post-crisis periods. The different trading volumes are: 25 (Vol. 1), 50 (Vol. 2), 100 (Vol. 3), 250 (Vol. 4), 500 thousand (Vol. 5)and 1 (Vol. 6), 2 (Vol. 7) and 3 million (Vol. 8).



	Vol. 1	Vol. 2	Vol. 3	Vol. 4	Vol. 5	Vol. 6	Vol. 7	Vol. 8
Pre-crisis	7.63	8.58	10.55	16.77	26.85	44.30	72.98	100.29
Crisis	12.22	15.19	20.96	37.16	63.47	115.63	226.69	349.25
Post-crisis	6.84	7.88	9.79	14.66	22.00	37.77	74.11	111.02

In figure 5.2 it can be seen that the MLM (resp. average SLM) is available for different traded volumes. On one side, we do not want to use the smallest trading volume because liquidity risk is not critical for an investor in this case. On the other side, fewer trades are made with higher traded volumes. Based on that, the impact of single trades on the SLM (resp. MLM) increases, which can distort the measure. Therefore we choose volume 4 which is equal to 250 thousand traded volume.

$$\Delta(IV_t) = \beta_0 + \beta_1\Delta(IV_{t-1}) + \beta_2\Delta(Return_t) + \beta_3 D_{pre\ crisis}\Delta(SLM_t) + \beta_3 D_{crisis}\Delta(SLM_t) + \beta_3 D_{after\ crisis}\Delta(SLM_t) + \beta_3\Delta(DTV_t) + \beta_6\Delta(P/C\ \ ratio_t) + \varepsilon \quad (5.6)$$

$$\Delta(IV_t) = \beta_0 + \beta_1\Delta(IV_{t-1}) + \beta_2\Delta(Return_t) + \beta_3 D_{pre\ crisis}\Delta(MLM_t) + \beta_3 D_{crisis}\Delta(MLM_t) + \beta_3 D_{after\ crisis}\Delta(MLM_t) + \beta_3\Delta(DTV_t) + \beta_6\Delta(P/C\ \ ratio_t) + \varepsilon \quad (5.7)$$

First we look at the results of the SLM regression formula (formula 5.6). The results are presented in table 5.3. Overall it can be said that the average adjusted R^2 value increases from

0.136 (without liquidity) to 0.143 (with SLM)[35]. This shows that changes in implied volatility can be better explained by also considering the SLM. The effect is based on idiosyncratic liquidity risk.

[35] On single stock level 22 out of 23 stocks (96%) show an increase of the adjusted R^2 value.

Table 5.3: Impact of SLM on implied volatility

The impact of stock liquidity (SLM) on implied volatility is calculated by using regression formula 5.6. The results show which impact idiosyncratic liquidity risk has on implied volatility.

Panel B: SLM									
			Parameter Estimates						
	R^2	Adj. R^2	lag IV	Returns	Pre-crisis	Crisis	Post-crisis	DTV	P/C ratio****
ADIDAS AG O.N.	0.1376	0.1320	-0.2839 ***	-0.7245 ***	-0.0254 *	0.0628 *	0.0328	-0.0046	-0.0067
ALLIANZ SE VNA O.N.	0.2437	0.2389	-0.249 ***	-1.2951 ***	0.0537 **	0.0697	0.0623	0.0154 ***	-1.3109
BASF AG O.N.	0.1721	0.1668	-0.288 ***	-0.8745 ***	0.0278	0.0817	0.1841 ***	0.0136 **	0.3283
BAY.MOTOREN WERKE AG	0.1632	0.1578	-0.2699 ***	-0.811 ***	0.0399 **	0.059 *	0.0454	0.0107 **	-0.5353
BAYER AG NA	0.1509	0.1455	-0.2439 ***	-0.9383 ***	0.0342 *	0.2064 ***	0.0409	0.0126 ***	0.0024
COMMERZBANK AG O.N.	0.2279	0.2229	-0.271 ***	-0.8866 ***	0.0149	0.279 ***	0.0214	0.0214 ***	0.3292
DAIMLER AG NA O.N.	0.1753	0.1700	-0.294 ***	-0.8611 ***	-0.0054	0.1089 **	0.1299 ***	0.0038	-0.1313
DEUTSCHE BANK AG NA O.N.	0.2161	0.2111	-0.2322 ***	-1.1395 ***	0.04 *	0.1221 ***	0.0421	0.0153 ***	-0.1468
DEUTSCHE BOERSE NA O.N.	0.1685	0.1632	-0.2892 ***	-0.6496 ***	-0.0012	0.0345	0.0528 **	0.0188 ***	0.1172
DEUTSCHE POST AG NA O.N.	0.1161	0.1104	-0.2993 ***	-0.6476 ***	0.0019	0.0833 **	0.0005	-0.0071	-0.1711
DT.TELEKOM AG NA	0.1214	0.1158	-0.2727 ***	-0.7089 ***	0.0584	0.0735	0.1311 ***	0.0286 ***	0.897
FRESEN.MED.CARE AG O.N.	0.1426	0.1368	-0.3149 ***	-0.7714 ***	0.0096	0.1356 ***	0.1343 **	0.0105	-0.0012
HENKEL AG+CO.KGAA VZO	0.1256	0.1197	-0.2621 ***	-0.891 ***	-0.0092	0.0466	0.0639 **	0.0061	-0.0025
LINDE AG O.N.	0.0411	0.0350	-0.1634 ***	-0.5201 ***	-0.0121	0.0892 *	-0.0146	0.0105	-0.3843
LUFTHANSA AG VNA O.N.	0.2109	0.2058	-0.3138 ***	-1.2142 ***	0.0222	0.0679 *	0.0114	0.0075	0.0093
MAN AG ST O.N.	0.1279	0.1223	-0.3108 ***	-0.4498 ***	-0.0089	0.0948 **	0.0453	0.0152 ***	-0.0938
METRO AG ST O.N.	0.0734	0.0674	-0.2304 ***	-0.677 ***	0.0303	0.1076	0.053	0.0177 **	0.0175
MUENCH.RUECKVERS.VNA O.N.	0.2063	0.2012	-0.2571 ***	-1.4651 ***	0.0263	0.0706	0.1023 ***	0.0085 *	0.0703
RWE AG ST O.N.	0.1298	0.1242	-0.3215 ***	-0.6122 ***	-0.0045	0.1258 *	0.1931 ***	0.0283 ***	-0.0779
SAP AG O.N.	0.1658	0.1605	-0.3127 ***	-1.5934 ***	0.0741 **	0.0505	0.1035 *	0.0173 **	-0.0184
SIEMENS AG NA	0.1908	0.1856	-0.2437 ***	-0.9721 ***	-0.0182	0.1256 ***	0.1397 ***	0.012 **	-1.5918
THYSSENKRUPP AG O.N.	0.0994	0.0937	-0.3101 ***	-0.1713 *	-0.013	0.0051	0.0055	0	0.0084
VOLKSWAGEN AG ST O.N.	0.0222	0.0159	0.0171	-0.0939	0.0617 **	-0.0276	0.0024	0.0113 ***	-0.0727 **

* 90%, ** 95%, *** 99% , **** in 1,000

The detailed results indicate that the lagged implied volatility and returns have a significant behavior. This is in line with the results already presented in table 5.2. The prefix for the return changes are, as expected, negative again.

By looking at the results of the dummy SLM variables, a different behavior can be seen. The significance pre-crisis is around 30%[36]. During the crisis the value increases to 56%[36] and drops afterwards to 43%[36]. This shows that the impact of liquidity becomes stronger during the 2008 financial crisis. The betas of the pre-crisis variables show mixed positive and negative prefixes. During the crisis this changes. Now all prefixes are positive, indicating that with a step up of illiquidity (increasing SLM measure) implied volatility is also higher. The average value of the beta increases from 0.02 to 0.09. This is in line with observations by Chou et al. (2011) where they mention that a reduction in stock liquidity results in an ascending implied volatility curve. In the paper by Cetin et al. (2004) they argue that this increased volatility is based on hedging transactions. Given the uncertainty of a crisis, investors seek to hedge against potential market declines and therefore buy protection. In the paper by Christoffersen et al. (2012) they mention that a shock to a stock's illiquidity results in higher option prices. This would also be reflected in increasing implied volatility. After the crisis, the betas are still positive overall but the average value changes from 0.09 to 0.06. An increase of the SLM measure has therefore a lower impact on implied volatility. Based on the results we can demonstrate that idiosyncratic liquidity risk has an impact on implied volatility and changes over time. The highest impact appears during the crisis.

The results of the control variables $\Delta(DTV_{s,t})$ and $\Delta(P/C\ ratio_t)$ are close, as described previously. The daily traded volume, at 65%[36], demonstrates significant behavior. The beta is positive overall, in line with the observation by Kalodera and Schlang (2004). Increasing market trading activity results in increasing implied volatility. On the other side, the put/call ratio shows only one significant stock. The prefixes of the betas are mixed positive and negative.

[36] The value is equal to the sum of all significant single stocks divide by the total number of stocks (overall 23 stocks). A single stock is significant based on a confidence level of 90%.

In the following section we focus on the impact of the MLM on implied volatility changes. The results can be found in table 5.4. By looking at the average R^2 value it can be seen that by substituting the SLM with the MLM this value changes from 0.143 (with SLM) to 0.150 (with MLM)[37]. This shows that systematic liquidity risk (MLM) better explains implied volatility changes than idiosyncratic liquidity risk (SLM). We further investigate this point by looking at the detailed results.

[37] On single stock level 21 out of 23 stocks (91%) show an increase of the adjusted R^2 value.

Table 5.4: Impact of MLM on implied volatility

By using regression formula 5.7 we analyze what impact market liquidity (MLM) has on implied volatility. The MLM is an indicator for systematic liquidity risk.

Panel C: MLM									
			Parameter Estimates						
	R^2	Adj. R^2	lag IV	Returns	Pre-crisis	Crisis	Post-crisis	DTV	P/C ratio****
ADIDAS AG O.N.	0.1546	0.1492	-0.2839 ***	-0.5671 ***	-0.0058	0.258 ***	0.158 ***	-0.0046	-0.0082
ALLIANZ SE VNA O.N.	0.2492	0.2444	-0.2519 ***	-1.2486 ***	0.04	0.207 ***	0.1453 **	0.0114 **	-1.3613
BASF AG O.N.	0.1814	0.1762	-0.2885 ***	-0.8276 ***	0.0467	0.1921 ***	0.2703 ***	0.0099 *	0.2994
BAY.MOTOREN WERKE AG ST	0.1667	0.1614	-0.268 ***	-0.7609 ***	0.0297	0.135 ***	0.123 **	0.0062	-0.5611
BAYER AG NA	0.1597	0.1544	-0.2426 ***	-0.8565 ***	0.0341	0.3175 ***	0.1234 **	0.009 **	-0.0047
COMMERZBANK AG O.N.	0.2130	0.2079	-0.2792 ***	-0.9328 ***	0.0481	0.3046 ***	0.0279	0.0198 ***	0.2074
DAIMLER AG NA O.N.	0.1810	0.1758	-0.2928 ***	-0.789 ***	0.0436	0.2504 ***	0.1471 **	0.0013	-0.0801
DEUTSCHE BANK AG NA O.N.	0.2180	0.2130	-0.2422 ***	-1.1314 ***	0.0378	0.2023 ***	0.1051	0.0116 **	-0.1533
DEUTSCHE BOERSE NA O.N.	0.1806	0.1753	-0.2954 ***	-0.5674 ***	-0.008	0.1967 ***	0.1565 ***	0.0174 ***	0.0842
DEUTSCHE POST AG NA O.N.	0.1256	0.1200	-0.2979 ***	-0.5054 ***	0.0361	0.2486 ***	0.0772	-0.0077 *	-0.156
DT.TELEKOM AG NA	0.1218	0.1162	-0.2723 ***	-0.6013 ***	0.0553	0.2301 ***	0.087	0.0258 ***	0.7945
FRESEN.MED.CARE AG O.N.	0.1515	0.1458	-0.3168 ***	-0.6295 ***	0.0453	0.4108 ***	0.0745	0.0049	0.0005
HENKEL AG+CO.KGAA VZO	0.1389	0.1331	-0.2608 ***	-0.7221 ***	0.0038	0.2342 ***	0.1455 **	0.0058	-0.0035
LINDE AG O.N.	0.0510	0.0449	-0.1621 ***	-0.3167 *	0.0839 *	0.2387 ***	0.135 *	0.012 *	-0.3322
LUFTHANSA AG VNA O.N.	0.2150	0.2099	-0.314 ***	-1.1536 ***	0.0349	0.1605 ***	0.0655	0.0051	0.0102
MAN AG ST O.N.	0.1307	0.1252	-0.3087 ***	-0.4064 ***	0.0061	0.1656 **	0.1274 *	0.0151 ***	-0.0892
METRO AG ST O.N.	0.0755	0.0695	-0.232 ***	-0.5755 **	0.0713	0.1389	0.2183 *	0.0156 **	0.0178
MUENCH.RUECKVERS.VNA O.N.	0.2085	0.2035	-0.2561 ***	-1.4108 ***	0.041	0.1365 **	0.1691 ***	0.0053	0.0787
RWE AG ST O.N.	0.1340	0.1284	-0.3183 ***	-0.5309 **	0.0115	0.1805 *	0.3378 ***	0.0248 ***	-0.0752
SAP AG O.N.	0.1645	0.1592	-0.31 ***	-1.568 ***	0.0805	0.0975	0.1868 **	0.0116 *	0.0541
SIEMENS AG NA	0.2021	0.1970	-0.2348 ***	-0.8887 ***	0.0251	0.2486 ***	0.2241 ***	0.0101 **	-1.6158
THYSSENKRUPP AG O.N.	0.0998	0.0940	-0.31 ***	-0.1625 *	-0.0259	0.0369	0.0067	0.0002	0.0086
VOLKSWAGEN AG ST O.N.	0.0501	0.0439	0.0064	-0.0593	0.0125	0.4537 ***	0.0166	0.0094 ***	-0.071 **

* 90%, ** 95%, *** 99%, **** in 1,000

Overall, we see for lagged implied volatility and return changes the same highly significant results, as mentioned before.

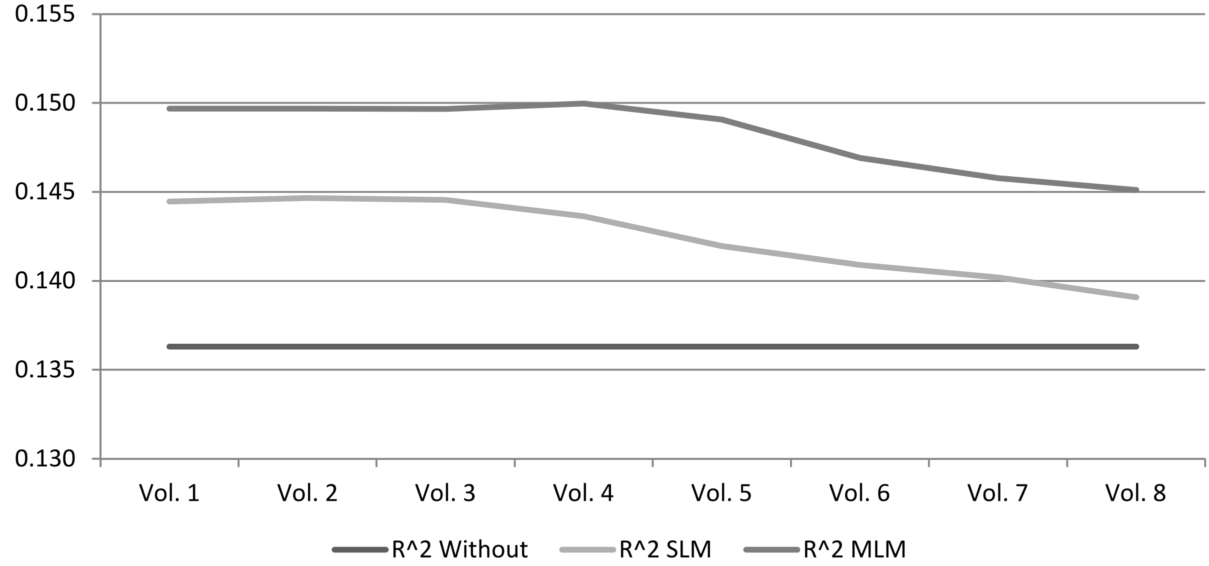
The dummy regressions show that the rate for significant stocks is around 4%[36] pre-crisis and increases during the crisis to 86%[36]. In the post-crisis period the value decreases to 65%[36]. It is also worth mentioning that significance rose during the crisis (using a 99% confidence level) from 22% (with SLM) to 74% (with MLM). This shows that not only are the number of significant stocks increasing but also the significance itself. The results of the betas are positive overall, which is in line with the observations presented in table 5.3. By looking at absolute values of the betas we can see that pre-crisis the average value is 0.03. During the crisis there is a strong increase of the average value to 0.22 and in the post-crisis period this value decreases to 0.14. Also here we can see that MLM changes during the crisis have a higher influence on implied volatility changes than before and after the crisis. The detailed results confirm our finding that systematic liquidity risk dominates the idiosyncratic one. This is in line with the results from Chordia et al. (2000) because the liquidity commonality is equal to systematic liquidity risk.

Until now we only focused on a trading volume of 250,000 EUR. In the following section we want to analyze the impact of higher and lower traded volumes on the regression results. Therefore we calculate regression formula 5.6 and 5.7 by using SLM and MLM of all 8 trading classes. These are 25 (Vol. 1), 50 (Vol. 2), 100 (Vol. 3), 250 (Vol. 4), 500 thousand (Vol. 5) and 1 (Vol. 6), 2 (Vol. 7), and 3 million (Vol. 8) traded volume.

The average R^2 values are presented in figure 5.3. We can see that the MLM displays higher overall R^2 values than that for the SLM. The R^2 of regression formula 5.5 without liquidity is the lowest. The results indicate that especially from trading volume 5 on the R^2, values of the SLM and MLM values are decreasing. This shows that liquidity risk cannot explain changes in implied volatility as well as before.

Figure 5.3: Impact of different trading volume

The following figure represents the average $\mathbf{R^2}$ by using different trading volumes of the SLM and MLM measure. For the calculation we used regression formula 5.5 (without liquidity), 5.6 (with SLM) and 5.7 (with MLM).



Going further into detail we look at the result presented in table 5.5. Here we present the ratios of significant stocks of the dummy variables[35]. Overall it can be seen that the highest significance for SLM and the MLM is reached during the crisis. Similarly, the value is lower pre-crisis and higher in post-crisis times. Besides the pre-crisis period, all results are more significant when using the MLM rather than the SLM. This is in line with our results as discussed previously. In the paper by Chou et al. (2011) they mention that decreasing spot liquidity is linked to an increase of implied volatility. What they do not test is the impact different trading volumes have on implied volatility. In their paper they use proportional bid-ask spreads[38]. The same is discussed by Christoffersen et al. (2012) where they show that an illiquidity premium is reflected in the option price. Their results are in line with our observations for lower trading volumes. But by looking at the higher trading volumes we can now go further than their research and state that for higher traded volume this link becomes weaker. This result becomes clear if we look at the rising SML spreads for higher trading volumes in figure 5.2 in the knowledge that trading volume has no direct impact on implied volatility. There are other papers like Certin et al. (2006) which integrate the impact of

[38] They use the proportional spreads which are calculated as the difference between closing bid and ask prices divided by the average price of the bid and ask. There is no impact of trading volume.

liquidity in the basic Black Scholes formula via a supply curve. The supply curve closes the gap between trading volume and liquidity costs as with the SLM (respectively XLM). For further research, it would be interesting to see how our regression results change by calculating the implied volatility based on the new framework as mentioned by Certin et al. (2006).

Table 5.5: Impact of different trading volumes on implied volatility

In the following table we use higher trading volumes via the SLM and MLM measure to analyze explanatory power on implied volatility changes. Each value is equal to the sum of all significant single stocks divided by the total number of stocks (overall 23 stocks). A single stock is based significantly on a confidence level of 90%.

		Vol. 1	Vol. 2	Vol. 3	Vol. 4	Vol. 5	Vol. 6	Vol. 7	Vol. 8
SLM	pre-crisis	17%	17%	26%	17%	17%	13%	4%	4%
	crisis	43%	43%	48%	39%	35%	35%	39%	35%
	post-crisis	26%	35%	43%	43%	39%	17%	22%	17%
MLM	pre-crisis	13%	13%	4%	0%	0%	0%	4%	9%
	crisis	87%	87%	87%	83%	83%	74%	65%	57%
	post-crisis	61%	61%	57%	61%	57%	39%	43%	43%

Another analytical perspective is to focus on a more granular time-varying liquidity commonality. Therefore a one-factor market model is used by Duan and Wei (2009), Cordia et al. (2000) and Rösch and Kaserer (2012). The regression is calculated on a monthly basis for each stock s.

$$\Delta(SLM_{st}) = \alpha_s + \beta_s \Delta(MLM_t) + \varepsilon_s \quad (5.8)$$

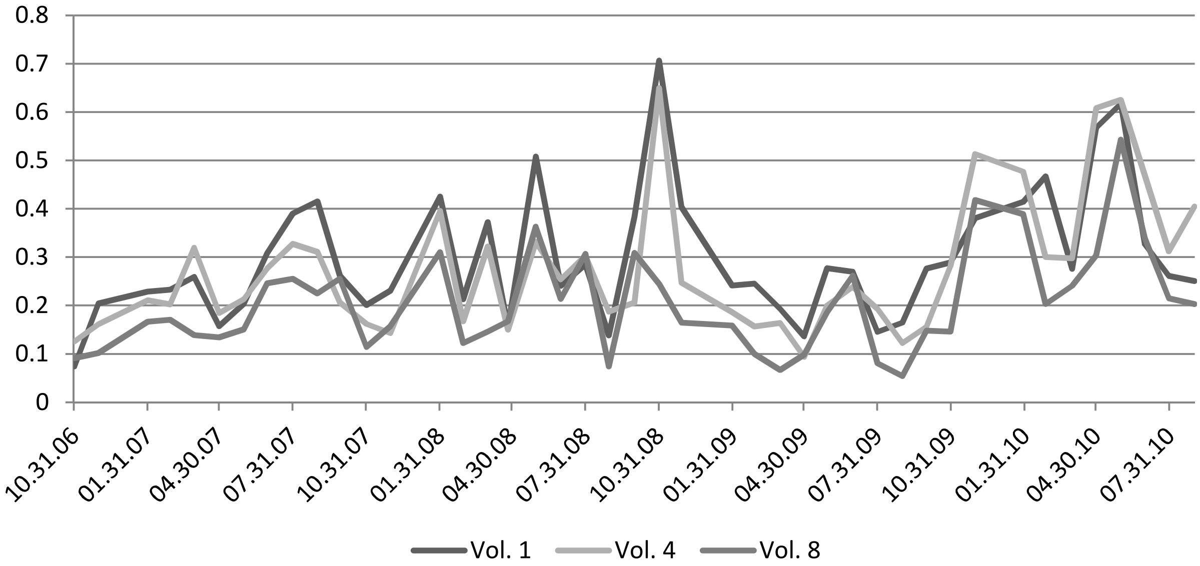
Based on the R^2 results for each stock s we calculate an equally weighted Liquidity Commonality measure ($LiqCom$) (Rösch & Kaserer, 2012).

$$LiqCom_t = \sum_{s=1}^{23} R_{s,t}^2 \quad (5.9)$$

The result is presented in figure 5.4. As suspected by Chordia et al. (2000) the commonality in liquidity changes over time.

Figure 5.4: Commonality of liquidity

The following chart is calculated on a monthly basis and shows the communality between market liquidity and stock liquidity measured by the average R^2 values of regression formula 5.8. Also, to capture the impact of different trading volumes we use: 25k (Vol. 1), 250k (Vol. 4), 3m (Vol. 8).



Based on the SLM and MLM data we can see that trading volume has a huge impact on commonality. In this chart we use 25k (Vol. 1), 250k (Vol. 4) and 3m (Vol. 8) traded EUR. The lowest trading volume shows that pre-crisis and post-crisis commonality is lower than during the crisis. This confirms our suggestion that systematic liquidity risk is especially high during the crisis. By increasing the trading volume the results show that commonality is decreasing during the crisis. Based on that, implied volatility is less affected by bid-ask spreads of higher trading volumes. This result is an extension of the work by Cordia et al. (2000) where they mentioned this commonality but did not consider different trading volumes of the limit order book. The reason for the decreasing result is based on the increased risk to the market maker, as mentioned by Amihud and Mendelson (1980). The market maker's task is to provide liquidity to the market by buying and selling stocks. Between the buy and the sell, the market maker risks making losses. This risk increases with greater trading volume, so he requires a reward in the form of a higher bid-ask spread (see figure 5.2). The results show that for higher trading volumes, idiosyncratic liquidity is more important than systematic liquidity risk. This is contrary to the experience with lower trading volume.

Finally, we test the robustness of our results. The intention is to show that the discussed results can also be found using monthly data of the advanced commonality measure LiqCom. Therefore the following regression is calculated:

$$\Delta(IV_t) = \beta_0 + \beta_1\Delta(IV_{t-1}) + \beta_2\Delta(ReturnDax_t) + \beta_3 D_{pre\ crisis}\Delta(LiqCom_t) + \beta_4 D_{crisis}\Delta(LiqCom_t) + \beta_5 D_{post\ crisis}\Delta(LiqCom_t) + \beta_6\Delta(AvgDTV_t) + \beta_7\Delta(P/C\ ratio_t) + \varepsilon \quad (5.10)$$

One characteristic of the R^2 value is the limited range between 0 and 1. This makes the measure questionable for a regression. Therefore we make the following transformation as performed by Rösch and Kaserer (2012):

$$AdjR^2{}_t = \frac{R_t^2}{1-R_t^2} \quad (5.11)$$

The R^2 in formula 5.9 is exchanged by the $Adj.R^2$.

The results can be found in table 5.6. The lagged implied volatility does not show a significant result, which demonstrates no significant autocorrelation. Overall, the return changes have the same negative prefix and significant behavior. This is in line with our results based on regression formulas 5.6 and 5.7.

Table 5.6: Liquidity commonality

In the following table we use the $LiqCom$ measure to check the robustness of our results. Therefore we use regression from formula 5.10 and transformation described in formula 5.11.

Panel A: LiqCom									
			Parameter Estimates						
	R^2	Adj. R^2	lag IV	Returns	Pre-crisis	Crisis	Post-Crisis	DTV	P/C ratio****
ADIDAS AG O.N.	0.4603	0.3523	-0.016	-0.815	-0.0163	0.149 ***	0.1335 *	0.1328	0.9673
ALLIANZ SE VNA O.N.	0.6601	0.5921	-0.0838	-1.6837 ***	-0.0311	0.1233 **	0.079	0.1471	-19.9909
BASF AG O.N.	0.6380	0.5656	0.0992	-1.6881 ***	-0.0141	0.0803	0.0346	0.2582 *	-7.5802
BAY.MOTOREN WERKE AG ST	0.5703	0.4843	0.0249	-1.0462 ***	-0.0289	0.0445	0.0262	0.3455 ***	-1.2976
BAYER AG NA	0.6159	0.5391	0.0972	-1.1664 **	-0.007	0.1421 ***	0.0291	0.1478	0.4606
COMMERZBANK AG O.N.	0.4571	0.3485	0.0328	-0.3025	-0.0047	0.1511 ***	0.0241	0.1237	-15.0538
DAIMLER AG NA O.N.	0.6015	0.5217	0.1603	-1.1011 **	-0.0076	0.1551 ***	-0.0174	0.398 ***	1.2238
DEUTSCHE BANK AG NA O.N.	0.5862	0.5034	-0.0096	-0.9461 ***	-0.0392	0.165 ***	0.0628	0.209	2.5312
DEUTSCHE BOERSE NA O.N.	0.3241	0.1890	0.0757	-0.2018	-0.05	0.0993 **	0.0469	0.1898 *	17.6567
DEUTSCHE POST AG NA O.N.	0.4553	0.3464	-0.2234	-1.4628 ***	-0.0101	0.1103 *	0.1249	0.0129	11.6155
DT.TELEKOM AG NA	0.5912	0.5094	0.1698	-0.0317	-0.0312	0.1079 **	0.0455	0.4572 ***	26.7955
FRESEN.MED.CARE AG O.N.	0.4939	0.3927	0.1531	-1.126 *	-0.0104	0.0479	0.0367	0.2634 ***	-1.754
HENKEL AG+CO.KGAA VZO	0.4631	0.3557	0.0361	-0.8879 **	0.0025	0.1082 ***	0.0867	0.1079	-0.4538
LINDE AG O.N.	0.5671	0.4806	0.1226	-1.8232 ***	-0.0003	0.1183 **	0.0309	0.2596 *	-4.2537
LUFTHANSA AG VNA O.N.	0.5207	0.4248	-0.0212	-0.8264 ***	-0.0058	0.1005 ***	0.0931 *	0.119	1.111
MAN AG ST O.N.	0.5599	0.4719	0.1967	-0.3472	-0.0003	0.1568 ***	0.0801	0.1025	0.9951
METRO AG ST O.N.	0.4257	0.3109	-0.044	-0.9235 **	-0.0407	0.0866 *	0.0782	0.1612	-0.9556
MUENCH.RUECKVERS.VNA O.N.	0.5428	0.4514	0.1362	-2.4382 ***	-0.0351	0.2014 ***	0.1104	-0.0924	-17.024
RWE AG ST O.N.	0.4185	0.3022	0.1441	-0.5681	-0.0257	0.1879 ***	0.029	0.2121	-3.4724
SAP AG O.N.	0.7424	0.6909	0.0639	-3.0238 ***	-0.0493	0.1717 ***	0.0528	0.2434 *	-8.479
SIEMENS AG NA	0.6616	0.5939	0.0856	-1.1809 ***	-0.0063	0.1514 ***	0.0826	0.2424 **	-58.5745
THYSSENKRUPP AG O.N.	0.0728	-0.1126	0.0694	0.2084	0.0293	-0.017	-0.0461	-0.0906	-14.5224
VOLKSWAGEN AG ST O.N.	0.4781	0.3737	0.1824	-0.2391	-0.0297	0.3145 ***	-0.0154	0.0082	-2.2789

* 90%, ** 95%, *** 99% , **** in 1,000

The results of the dummy variables show no significance during the pre-crisis period (0%[35]). During the crisis this value jumps to 83%[35] and afterwards drops to 9%[35]. This is the same behavior we could also see in the MLM and SLM regressions (tables 5.3 and 5.4). All betas are negative in the pre-crisis, with an average of –0.017. This is contrary to our previous results. In the first regressions we had just one or two stocks which showed a negative prefix. This mean that with increasing spreads, implied volatility falls. The reason for this misleading effect might be the use of monthly data. The betas during and after the crisis were on average respectively 0.128 and 0.052. This is in line with the results we found previously. In the robustness check the highest betas also appear during the crisis.

In regression formula 5.10 we also integrate the daily traded volume and put/call ratio as control variables. The results are in line with the data presented in table 5.3 and 5.4. In 39%[35] of the results, the DTV shows significant behavior. Also with an overall positive beta, the results are in line with the previously mentioned observations. The $put\ /\ call\ ratio$ still does not show any significance and has a mixed positive and negative prefix.

5.5 Conclusion

In this chapter we analyze the impact of stock liquidity on the implied volatility. We focus on 23 stocks listed in the Dax over an observation period of around 5 years. To measure liquidity we use the single Stock Liquidity Measure (SLM) and Market Liquidity Measure (MLM). The measures are based on the Xetra Liquidity Measure (XLM) which is a volume-weighted bid-ask spread measure provided by the Deutsche Börse. To determine the impact of the financial crisis in 2008 we integrate dummy variables which consider the pre-crisis, crisis and post-crisis periods.

Our first result is that stock liquidity plays an important role in explaining at-the-money implied volatility changes. Therefore we calculate regressions with and without liquidity and, in the first case, we see overall higher average R^2 values. This is in line with the result mentioned by Chou et al. (2011). We were able to show that the link is strong, especially during the financial crisis in 2008. The reason is that investors hedge their investments as mentioned by Certin et al. (2006).

Based on the paper by Chordia et al. (2000) we analyze the impact of market liquidity on implied volatility changes. To measure market liquidity we calculate an equally weighted liquidity measure called MLM. The results show that systematic liquidity risk (MLM) is better able to explain implied volatility changes than idiosyncratic liquidity risk (SLM). The average R^2 increased from 0.143 (with SLM) to 0.150 (with MLM). This relationship is especially strong during the crisis. This result indicates that market liquidity should also be considered, for example, when designing risk management systems.

Another focus is on different trading volumes. Here we demonstrate that with increasing traded volume the explanatory power of implied volatility changes decreases. This result is in line with the paper by Certin et al. (2006) and shows that, in particular, the liquidity risk of higher traded volumes is not reflected in the option price. Underestimating this risk can lead, for example, to higher hedging costs.

Based on the results using the MLM, we analyze further the time varying behavior of liquidity commonality. Therefore the $LiqCom$ measure is calculated on a monthly basis as described by Chordia et al. (2000). The measure shows (especially during the crisis) a co-movement of the cross-sectional single stock spreads. This commonality decreases with increasing trading volume. We argue that this is based on the increasing risk taken by the market maker as mentioned by Amihud and Mendelson (1980). For higher traded volumes, the risk of being unable to resell shares is higher. Therefore with increased trading idiosyncratic liquidity risk is bigger than systematic liquidity risk.

In the last part of this paper we demonstrate the robustness of our results. For this we use monthly data and the advanced liquidity commonality measure $LiqCom$. The results show the same behavior.

Chapter Six

General Conclusion

In this thesis we focus on stock liquidity risk from different perspectives. To measure stock liquidity we use the Xetra Liquidity Measure which is calculated by the Deutsche Börse. The advantage of this volume-weighted measure is that different trading volumes are taken into account.

The aim of chapter three is to test different VaR methodologies which also account for liquidity risk. A basic $L - VaR$ model is proposed by Bangia et al. (1999) and this is the starting point of the research. In the first step, we extend the model by integrating advanced volatility models like the $AR - GARCH$ and $AR - GJR$. The results show (especially for the Dax and MDax) a significant increase in Kupiec back-testing compared to the basic model. Within the spread data, we find an autoregressive process which is significant up to lag 5. In the next step, we integrate the correlation between spreads and returns into the standard $L - VaR$ and present a new Correlation Liquidity adjusted VaR $(CL - VaR)$ model. Based on our results, we show that the correlation is a time-varying component which is increasing during the crisis. We use a Constant Correlation (CC), Dynamic Conditional Correlation (DCC) and the Exponentially Weighted Moving Average correlation $(CEWMA)$ model. Contrary to the basic approach by Bangia et al. (1998), where a perfect positive correlation of spreads and returns is assumed, we can demonstrate that overall this assumption is not valid. Our argumentation is that liquidity risk is overestimated by simply summing both single VaR measures. The results confirm our hypothesis by reducing the number of back-testing results where the test is rejected based on an overestimation of risk, while the rate for underestimation stays constant. Overall, the results improve around 10%. The overall results show that, on one side, the $(CL - VaR)$ has slightly higher complexity, but on the other side, a higher back-testing result. This might help to better manage liquidity risk.

Risk management is driven by the fear of unknown events and their impact on the financial market. In chapter four we analyze what impact regulatory interventions had on stock market liquidity during the financial crisis in 2008. Therefore we focus on the following categories: bank liability guarantees, liquidity and rescue interventions, unconventional monetary policy and other market interventions. These interventions were aimed at restoring stability to the financial market. Based on the test results, different conclusions can be made. Overall, it can be said that the market reacts differently to these actions even if they have similar aims: e.g., the market reacts positively to liquidity and rescue interventions and negatively to bank liability guarantees. Furthermore, we analyze the impact of international interventions on the domestic financial markets. In this respect, we find that market interventions triggered from abroad have a significant spillover effect on local financial markets. This result shows that market interventions should be managed on a global level. Another interesting effect is that all stocks within the Dax are closely linked to the reaction of financial institutions within the index. Therefore, even portfolios diversified across different industries suffer during the crisis. We also examine closely the impact of regulatory interventions on different traded volumes. Here the results show that in most cases a significant asymmetry appears. Overall, the spreads for lower traded volumes react more strongly than those for higher volumes at the announcement date.

In chapter five we analyze the impact of stock liquidity on implied volatility. To measure liquidity we use the single Stock Liquidity Measure (SLM) and Market Liquidity Measure (MLM). The measures are based on the Xetra Liquidity Measure (XLM) which is a volume-weighted bid-ask spread measure provided by the Deutsche Börse. To determine the impact of the financial crisis in 2008 we integrate dummy variables to enable a focus on the pre-crisis, crisis and post-crisis periods.

Our first result is that stock liquidity plays an important role in explaining at-the-money implied volatility. Therefore we calculate regressions with and without liquidity and get overall higher average R^2 values in the first case. This is in line with the result mentioned by Chou et al. (2011). We were able to show that the link is strong, especially during the financial crisis in 2008. The reason is that investors hedge their investments, as mentioned by Certin et al. (2006).

Based on the paper by Chordia et al. (2000) we analyze the impact of market liquidity on implied volatility changes. To measure market liquidity we calculate an equally weighted liquidity measure called MLM. The results show that systematic liquidity risk (MLM) is better able to explain implied volatility changes than idiosyncratic liquidity risk (SLM). The average R^2 increased from 0.143 (with SLM) to 0.150 (with MLM). This relationship is especially strong during the crisis. These results show that market liquidity should also be considered e.g. in risk management systems.

Another focus is on different trading volumes. The results indicate that with increased traded volume the explanatory power of implied volatility changes decreases. This result is in line with the paper by Certin et al. (2006) and indicates that the liquidity risk of higher traded volumes is, in particular, not reflected in the option price. Underestimating this risk can lead to higher hedging costs.

Based on the results using the MLM, we analyze further the time varying behavior of liquidity commonality. Therefore we calculate the $LiqCom$ measure on a monthly basis as described by Chordia et al. (2000). The measure shows (especially during the crisis) a co-movement of the cross sectional single stock spreads. This commonality decreases with increasing trading volume. We argue that this is based on the increasing risk born by the market maker as mentioned by Amihud and Mendelson (1980). For higher trading volumes, there is a greater risk of being unable to resell shares. Therefore with increasing trading idiosyncratic liquidity risk is greater than systematic liquidity risk.

Appendix

1. Appendix for Chapter Three

Table 1.1: Simulation results based on Dax data by using the Kupiec test

The following table shows the back-testing results by using the Kupiec test (95% confidence level) in combination with different correlation models and trading volumes. The percentage indicates in how many cases the test was not rejected. Overall 23 stocks from the Dax index are considered. The abbreviations are DCC (Dynamic Conditional Correlation) CC (Constant Correlation) and Corr is prefect correlation.

	GARCH (Gaussian residuals)			GARCH (t - residuals)			GJR (Gaussian residuals)			GJR (t - residuals)			EWMA	
Trade Vol. 50,000	DCC	CC	Corr = 1	DCC	CC	Corr = 1	DCC	CC	Corr = 1	DCC	CC	Corr = 1	EWMA Corr.	Corr =1
Overestimation	9%	9%	13%	9%	9%	13%	17%	17%	17%	17%	17%	17%	4%	4%
Correct	91%	91%	87%	91%	91%	87%	83%	83%	83%	83%	83%	83%	96%	96%
Underestimation	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Trade Vol. 500,000														
Overestimation	9%	9%	13%	9%	9%	13%	17%	17%	17%	17%	17%	17%	0%	4%
Correct	91%	91%	87%	91%	91%	87%	83%	83%	83%	83%	83%	83%	100%	96%
Underestimation	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Trade Vol. 3,000,000														
Overestimation	4%	4%	26%	4%	4%	35%	9%	9%	35%	9%	9%	39%	0%	9%
Correct	96%	96%	74%	96%	96%	65%	91%	91%	65%	91%	91%	61%	96%	91%
Underestimation	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	4%	0%

Table 1.2: Simulation results based on MDax data by using the Kupiec test

The following table shows the back-testing results by using the Kupiec test (95% confidence level) in combination with different correlation models and trading volumes. The percentage indicates in how many cases the test was not rejected. Overall 45 stocks from the index Dax are considered. The abbreviations are DCC (Dynamic Conditional Correlation) CC (Constant Correlation) and Corr is prefect correlation.

	GARCH (Gaussian residuals)			GARCH (t - residuals)			GJR (Gaussian residuals)			GJR (t - residuals)			EWMA	
Trade Vol. 50,000	DCC	CC	Corr = 1	DCC	CC	Corr = 1	DCC	CC	Corr = 1	DCC	CC	Corr = 1	EWMA Corr.	Corr = 1
Overestimation	2%	2%	9%	2%	2%	9%	4%	4%	9%	4%	4%	7%	2%	9%
Correct	98%	98%	91%	98%	98%	91%	96%	96%	91%	91%	91%	93%	98%	91%
Underestimation	0%	0%	0%	0%	0%	0%	0%	0%	0%	4%	4%	0%	0%	0%
Trade Vol. 100,000														
Overestimation	2%	2%	11%	2%	2%	11%	4%	4%	9%	4%	4%	7%	2%	11%
Correct	98%	98%	89%	98%	98%	89%	96%	96%	91%	89%	89%	93%	98%	89%
Underestimation	0%	0%	0%	0%	0%	0%	0%	0%	0%	7%	7%	0%	0%	0%
Trade Vol. 500,000														
Overestimation	0%	0%	31%	0%	0%	31%	0%	0%	29%	0%	0%	27%	0%	36%
Correct	93%	93%	69%	93%	93%	69%	93%	93%	71%	84%	84%	73%	91%	64%
Underestimation	7%	7%	0%	7%	7%	0%	7%	7%	0%	16%	16%	0%	9%	0%

Table 1.3: Simulation results based on SDax data by using the Kupiec test

The following table shows the back-testing results by using the Kupiec test (95% confidence level) in combination with different correlation models and trading volumes. The percentage indicates in how many cases the test was not rejected. Overall 23 stocks from the index Dax are considered. The abbreviations are DCC (Dynamic Conditional Correlation) CC (Constant Correlation) and Corr is prefect correlation.

	GARCH (Gaussian residuals)			GARCH (t - residuals)			GJR (Gaussian residuals)			GJR (t - residuals)			EWMA	
Trade Vol. 25,000	DCC	CC	Corr = 1	DCC	CC	Corr = 1	DCC	CC	Corr = 1	DCC	CC	Corr = 1	EWMA Corr.	Corr = 1
Overestimation	0%	0%	17%	0%	0%	17%	0%	0%	26%	0%	0%	26%	0%	26%
Correct	91%	91%	83%	91%	91%	78%	91%	91%	74%	91%	91%	70%	74%	74%
Underestimation	9%	9%	0%	9%	9%	4%	9%	9%	0%	9%	9%	4%	26%	0%
Trade Vol. 50,000														
Overestimation	0%	0%	39%	0%	0%	26%	0%	0%	39%	0%	0%	26%	0%	39%
Correct	87%	87%	61%	78%	83%	74%	87%	87%	61%	87%	87%	74%	74%	61%
Underestimation	13%	13%	0%	22%	17%	0%	13%	13%	0%	13%	13%	0%	26%	0%
Trade Vol. 150,000														
Overestimation	0%	0%	48%	0%	0%	39%	0%	0%	43%	0%	0%	35%	0%	43%
Correct	78%	78%	52%	65%	70%	61%	78%	78%	57%	70%	65%	65%	78%	57%
Underestimation	22%	22%	0%	35%	30%	0%	22%	22%	0%	30%	35%	0%	22%	0%

Table 1.4: GARCH fitting results by focusing on log spreads of Dax stocks

The table shows fitting results of an AR(0), AR(5) and AR(10) GARCH(1,1) model by using log spread changes and different trading volumes. To determine the quality the Akaike AIC[19], Bayesian BIC[19] criterion and the Maximum Likelihood Estimator (MLE) are used. The results are calculated for the Dax, MDax and SDax and by assuming Gaussian distribute residuals.

		Vol 2			Vol 4			Vol 8		
		AR(0)	AR(5)	AR(10)	AR(0)	AR(5)	AR(10)	AR(0)	AR(5)	AR(10)
C	Mean	-0.0001	-0.0002	-0.0003	-0.0001	-0.0003	-0.0004	-0.0001	-0.0002	-0.0003
	STD	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
ω	Mean	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000
	STD	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000
GARCH	Mean	0.7220	0.8737	0.8642	0.7565	0.8987	0.8972	0.6565	0.8531	0.8423
	STD	0.1591	0.0819	0.0870	0.1992	0.0892	0.0809	0.2506	0.1239	0.1374
ARCH	Mean	0.1180	0.0690	0.0716	0.1140	0.0644	0.0658	0.1701	0.0783	0.0813
	STD	0.0404	0.0289	0.0306	0.0532	0.0329	0.0304	0.0996	0.0490	0.0484
AIC	Mean	-5,596	-5,813	-5,821	-5,390	-5,603	-5,608	-4,976	-5,180	-5,187
BIC	Mean	-5,576	-5,769	-5,753	-5,370	-5,559	-5,540	-4,956	-5,135	-5,118
MLE	Mean	2,802	2,915	2,925	2,699	2,810	2,818	2,492	2,599	2,607
Calculated param.		4	9	14	4	9	14	4	9	14

Table 1.5: GARCH fitting results by focusing on log spreads of MDax stocks

The table shows fitting results of an AR(0), AR(5) and AR(10) GARCH(1,1) model by using log spread changes and different trading volumes. To determine the quality the Akaike AIC[19], Bayesian BIC[19] criterion and the Maximum Likelihood Estimator (MLE) are used. The results are calculated for the Dax, MDax and SDax and by assuming Gaussian distribute residuals.

		Vol 2			Vol 4			Vol 8		
		AR(0)	AR(5)	AR(10)	AR(0)	AR(5)	AR(10)	AR(0)	AR(5)	AR(10)
C	Mean	0.0000	-0.0001	-0.0002	0.0000	-0.0001	-0.0002	-0.0001	-0.0002	-0.0002
	STD	0.0006	0.0002	0.0002	0.0004	0.0002	0.0002	0.0002	0.0002	0.0003
ω	Mean	0.0002	0.0001	0.0001	0.0002	0.0000	0.0001	0.0001	0.0001	0.0001
	STD	0.0002	0.0001	0.0001	0.0002	0.0001	0.0001	0.0002	0.0001	0.0001
GARCH	Mean	0.5149	0.8343	0.8141	0.5822	0.8569	0.8420	0.7117	0.8521	0.8391
	STD	0.2359	0.1447	0.1677	0.2597	0.1301	0.1510	0.1955	0.1216	0.1445
ARCH	Mean	0.2194	0.0793	0.0822	0.1738	0.0716	0.0736	0.1476	0.0778	0.0795
	STD	0.1252	0.0611	0.0625	0.1013	0.0601	0.0607	0.0610	0.0398	0.0414
AIC	Mean	-4,800	-5,034	-5,045	-4,616	-4,842	-4,853	-4,305	-4,507	-4,516
BIC	Mean	-4,781	-4,989	-4,977	-4,597	-4,798	-4,785	-4,285	-4,463	-4,448
MLE	Mean	2,404	2,526	2,537	2,312	2,430	2,441	2,157	2,263	2,272
Calculated param.		4	9	14	4	9	14	4	9	14

Table 1.6: GARCH fitting results by focusing on log spreads of SDax stocks

The table shows fitting results of an AR(0), AR(5) and AR(10) GARCH(1,1) model by using log spread changes and different trading volumes. To determine the quality the Akaike AIC[19], Bayesian BIC[19] criterion and the Maximum Likelihood Estimator (MLE) are used. The results are calculated for the Dax, MDax and SDax and by assuming Gaussian distributed residuals.

		Vol 1			Vol 4			Vol 6		
		AR(0)	AR(5)	AR(10)	AR(0)	AR(5)	AR(10)	AR(0)	AR(5)	AR(10)
C	Mean	-0.0001	-0.0001	-0.0002	0.0001	-0.0001	-0.0001	0.0000	-0.0002	-0.0002
	STD	0.0002	0.0004	0.0004	0.0002	0.0003	0.0003	0.0003	0.0002	0.0003
ω	Mean	0.0003	0.0001	0.0001	0.0003	0.0000	0.0001	0.0004	0.0001	0.0001
	STD	0.0003	0.0001	0.0001	0.0003	0.0001	0.0001	0.0004	0.0002	0.0002
GARCH	Mean	0.5847	0.8354	0.8234	0.6451	0.8786	0.8634	0.6207	0.8134	0.8143
	STD	0.2382	0.0725	0.1186	0.2399	0.0556	0.0817	0.2577	0.1846	0.1719
ARCH	Mean	0.1786	0.1001	0.0957	0.1652	0.0827	0.0910	0.1503	0.0871	0.0875
	STD	0.0522	0.0671	0.0607	0.0663	0.0459	0.0615	0.0512	0.0375	0.0373
AIC	Mean	-4,222	-4,475	-4,496	-4,027	-4,229	-4,247	-3,844	-4,014	-4,028
BIC	Mean	-4,202	-4,430	-4,428	-4,007	-4,184	-4,179	-3,824	-3,970	-3,959
MLE	Mean	2,115	2,246	2,262	2,017	2,123	2,138	1,926	2,016	2,028
Calculated param.		4	9	14	4	9	14	4	9	14

2. Appendix for Chapter Four

Table 2.1: Selected events from the FED timeline

This table is based on the FED crisis timeline published by the FED. The various regulatory interventions are listed chronologically, starting in Sept. 2008. Furthermore, the events are subdivided into the following groups: Bank liability guarantees, Liquidity and rescue interventions, Unconventional monetary policy, and Other market interventions.

Events	Category	Date	Country	Act
1	Bank Liability Guarantees	10.23.08	Canada	Canadian Lenders Assurance Facility announced to guarantee debt up to three years
		10.31.08	Germany	SoFFin provides Hypo Real Estate with an additional EUR 15 billion in guarantees
		11.05.08	Switzerland	Deposit insurance increased to CHF 100
		12.03.08	Germany	SoFFin provides BayernLB with EUR 15 billion in guarantees
		12.15.08	United Kingdom	Credit Guarantee Scheme guarantee lengthened to five years
		12.22.08	Germany	SoFFin provides IKB with EUR 5 billion in guarantees
		04.02.09	Sweden	Guarantee scheme extended until end of October
		04.14.09	Germany	SoFFin extends EUR 52 billion in guarantees to Hypo Real Estate until mid-August
		07.03.09	Germany	IKB receives an additional EUR 7 billion in guarantees
		07.31.09	Italy	Banco Popolare becomes the first bank to use the Italian bank liability guarantee program
		09.09.09	Germany	Commerzbank announces it will return all of its unused debt guarantees
		10.08.09	Sweden	Guarantee scheme extended an additional six months to April 30th
2	Liquidity and Rescue Interventions	10.16.08	Switzerland	Government injects CHF 6 billion into UBS and creates an SPV to buy illiquid assets, funded by UBS capital and a central bank loan
		10.28.08	Sweden	Carnegie liquidity facility increased to SEK 5 billion
		11.10.08	Sweden	Carnegie seized by the government, as collateral on the liquidity facility that cannot be repaid
		11.28.08	Germany	BayernLB receives EUR 7 billion of capital from Bavaria, requests 3 billion more from SoFFin
		01.08.09	Germany	SoFFin gives another EUR 8.2 billion of loans to Commerzbank, and buys 1.8 billion worth of equity
		01.15.09	Ireland	Anglo Irish bank nationalized due to weak funding position and “unacceptable practices”
		02.11.09	Ireland	New terms for recapitalization for two banks announced
		02.24.09	Germany	Two German states recapitalize the state-owned HSH Nordbank
		02.25.09	Italy	EUR 12 billion recapitalization plan approved
		03.17.09	Japan	Bank of Japan announces a subordinated loan program of JPY 1 trillion
		03.30.09	Germany	SoFFin purchases 8.7% of Hypo Real Estate for EUR 60 million
		04.07.09	Ireland	Government announces it will swap government bonds for EUR 90 billion face value of toxic assets
		04.09.09	Germany	SoFFin makes a bid for Hypo Real Estate, will nationalize if investors do not accept by May
		06.03.09	Germany	Hypo Real Estate shareholders, led by SoFFin at 47% ownership, vote for a EUR 3 billion capital injection giving government full control
		07.10.09	Germany	Bad bank plan passed by legislature: trades toxic assets for guaranteed debt, but firms must repay any losses over 20 year period
		07.30.09	Ireland	Bad bank draft proposal released, legislative debate to begin mid-September
		08.20.09	Switzerland	Government converts its stake in UBS to shares and sells them, in addition to a cash payment from UBS in lieu of coupon payments
		10.06.09	France	Societe Generale follows BNP Paribus, announcing a rights handover to repay government aid
		11.03.09	United Kingdom	Lloyds exits the Asset Protection Scheme for a fee; RBS will continue participating under new conditions
		12.14.09	Ireland	Finance Ministry announces EUR 10 billion will be made available for recapitalization
		12.21.09	Ireland	Subject to shareholder vote, three banks will receive EUR 5.5 billion in preference shares
3	Other Market Interventions	10.15.08	Switzerland	Central bank will begin issuing its own debt to absorb excess liquidity
		02.02.09	Switzerland	Central bank will now also issue debt denominated in USD
		04.06.09	ECB, U.K., Japan, Switzerland	Foreign central banks agree to provide the Federal Reserve with foreign currency liquidity
		06.25.09	ECB, U.K., Sweden, Switzerland	Swap lines with the Federal Reserve extended until February 1st
		07.15.09	Japan	Swap line with the Federal Reserve extended until February 1st
		12.17.09	Sweden	Government announces it will purchase SEK 15 billion against EUR, in foreign exchange, given a historically weak krona
4	Unconventional Monetary Policy	01.22.09	Japan	Bank of Japan will purchase JPY 3 trillion of CP and asset-backed CP
		03.05.09	United Kingdom	Asset Purchase Plan increased to GBP 75 billion, will include purchases of gilts
		03.18.09	Japan	Purchases of Japanese government bonds increased to JPY 1.8 trillion per month
		06.08.09	United Kingdom	Asset purchases to be expanded to include secured commercial paper
		08.06.09	United Kingdom	Asset purchase plan increased to GBP 175 billion in assets
		11.05.09	United Kingdom	Asset purchase plan increased to GBP 200 billion in assets

Events	Category	Date	Country	Act
		03.17.10	Japan	Bank of Japan expands fixed rate loans to JPY 20 trillion from JPY 10 trillion
5	Bank Liability Guarantees	10.31.08	Germany	SoFFin provides Hypo Real Estate with an additional EUR 15 billion in guarantees
		12.03.08	Germany	SoFFin provides BayernLB with EUR 15 billion in guarantees
		12.22.08	Germany	SoFFin provides IKB with EUR 5 billion in guarantees
		04.14.09	Germany	SoFFin extends EUR 52 billion in guarantees to Hypo Real Estate until mid-August
		07.03.09	Germany	IKB receives an additional EUR 7 billion in guarantees
		09.09.09	Germany	Commerzbank announces it will return all of its unused debt guarantees
6	Bank Liability Guarantees	10.31.08	Germany	SoFFin provides Hypo Real Estate with an additional EUR 15 billion in guarantees
	(only SoFFin events)	12.03.08	Germany	SoFFin provides BayernLB with EUR 15 billion in guarantees
		12.22.08	Germany	SoFFin provides IKB with EUR 5 billion in guarantees
		04.14.09	Germany	SoFFin extends EUR 52 billion in guarantees to Hypo Real Estate until mid-August
7	Liquidity and Rescue Interventions	11.28.08	Germany	BayernLB receives EUR 7 billion of capital from Bavaria, requests 3 billion more from SoFFin
		01.08.09	Germany	SoFFin gives another EUR 8.2 billion of loans to Commerzbank, and buys 1.8 billion worth of equity
		02.24.09	Germany	Two German states recapitalize the state-owned HSH Nordbank
		03.30.09	Germany	SoFFin purchases 8.7% of Hypo Real Estate for EUR 60 million
		04.09.09	Germany	SoFFin makes a bid for Hypo Real Estate, will nationalize if investors do not accept by May
		06.03.09	Germany	Hypo Real Estate shareholders, led by SoFFin at 47% ownership, vote for a EUR 3 billion capital injection giving government full control
		07.10.09	Germany	Bad bank plan passed by legislature: trades toxic assets for guaranteed debt, but firms must repay any losses over 20 year period
8	Liquidity and Rescue Interventions	11.28.08	Germany	BayernLB receives EUR 7 billion of capital from Bavaria, requests 3 billion more from SoFFin
	(only SoFFin events)	01.08.09	Germany	SoFFin gives another EUR 8.2 billion of loans to Commerzbank, and buys 1.8 billion worth of equity
		03.30.09	Germany	SoFFin purchases 8.7% of Hypo Real Estate for EUR 60 million
		04.09.09	Germany	SoFFin makes a bid for Hypo Real Estate, will nationalize if investors do not accept by May
		06.03.09	Germany	Hypo Real Estate shareholders, led by SoFFin at 47% ownership, vote for a EUR 3 billion capital injection giving government full control
9	Short Sell Restrictions	09.19.08	Canada	Short sale restriction
		09.19.08	Ireland	Short sale restriction
		09.19.08	Luxembourg	Short sale restriction
		09.19.08	Switzerland	Short sale restriction
		09.19.08	U.K.	Short sale restriction
		09.19.08	U.S.	Short sale restriction
		09.22.08	Belgium	Short sale restriction
		09.22.08	France	Short sale restriction
		09.22.08	Italy	Short sale restriction
		09.22.08	Netherlands	Short sale restriction
		09.22.08	Portugal	Short sale restriction
		09.24.08	Spain	Short sale restriction
		10.08.08	Norway	Short sale restriction
		10.10.08	Denmark	Short sale restriction
		10.10.08	Greece	Short sale restriction
		10.26.08	Austria	Short sale restriction
		10.30.08	Japan	Short sale restriction
		07.28.09	Japan	Short sale restriction
10	Short Sell Restrictions	09.20.08	Germany	Short sale restriction

Table 2.2: Test results of abnormal spread and return data with fixed volatility

This table contains the t-test results for abnormal spread and return changes at the announcement date calculated using formula 4.8. The colors indicate significant positive or negative change based on a 95% confidence level.

Dax		Volume								Return
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	
Event	**1**	7.69	8.86	9.59	8.37	5.83	3.93	3.64	3.37	-4.62
	2	-7.78	-8.6	-7.24	-5.53	-3.82	-2.97	-3.71	-2.25	5.31
	3	5.81	6.5	7.18	5.66	2.53	-0.42	-0.52	-0.34	-3.68
	4	2.12	1.89	1.67	2.08	3.27	4.38	2.27	1.4	-1.85
	5	5.33	6.39	7.07	5.48	3.71	2.54	1.69	0.92	-0.31
	6	4.85	5.77	6	3.19	1.54	0.57	0.34	0.09	0.8
	7	1.74	2.24	2.09	1.55	1.06	0.59	-0.01	0.11	-0.56
	8	2.59	3.43	3.82	3.42	2.54	1.73	1.38	1.76	-2.05
	9	-18.4	-20.88	-19.13	-16.58	-10.17	-5.85	-3.95	-3.13	9.83
	10	-0.4	-0.99	-1.43	-1.56	-0.49	0.44	1.47	1.34	-3.37

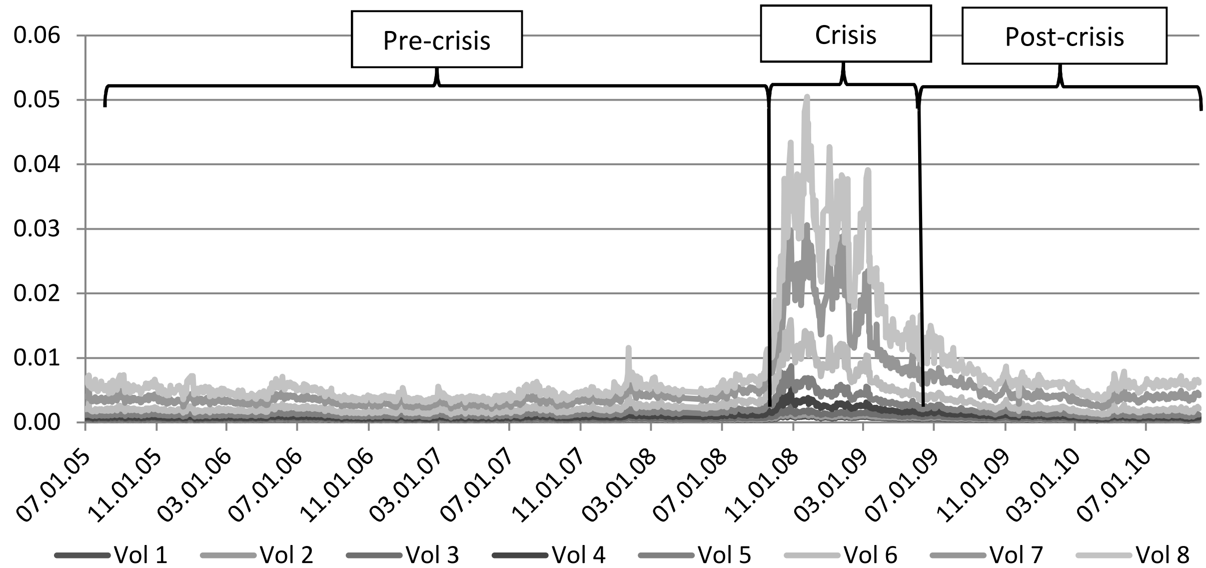
Table 2.3: Test results of abnormal spread and return data with equal volatility

This table contains the t-test results for abnormal spread and return changes at the announcement date calculated using formula 4.8. The colors indicate significant positive or negative change based on a 95% confidence level.

Dax		Volume								Return
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	
Event	**1**	7.94	8.59	9.19	8.42	5.83	3.75	3.41	2.87	-3.96
	2	-7.32	-8.32	-7.03	-5.53	-3.75	-2.97	-3.77	-1.94	5.00
	3	4.63	6.51	6.90	5.42	2.36	-0.56	-0.55	-0.28	-4.19
	4	2.13	1.91	1.68	2.14	3.34	4.33	1.99	1.05	-1.88
	5	5.57	6.56	7.35	6.09	3.99	2.45	1.48	0.65	-0.48
	6	5.38	6.34	6.54	3.43	1.44	0.38	0.21	-0.06	0.53
	7	2.09	2.42	2.18	1.59	0.99	0.51	-0.04	0.22	0.01
	8	2.92	3.68	3.94	3.50	2.55	1.72	1.39	1.76	-1.68
	9	-17.39	-17.14	-15.76	-15.73	-11.70	-6.25	-3.87	-3.04	10.04
	10	-0.69	-1.21	-1.69	-1.67	-0.42	0.50	1.41	1.10	-3.49

Figure 2.1: Average spread changes of Dax stocks by considering different traded volumes

The following table shows the average volume-weighted bid-ask spread changes for different traded volumes[39] over the total observation period. In addition, the time period is subdivided into pre-crisis, crisis, and post-crisis periods.



[39] The different volumes, Vol. 1 – Vol. 8, correspond to 25, 50, 100, 250, 500 thousand and 1, 2, and 3 million traded shares

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