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Market Liquidity

An empirical analysis of the impact of the financial crisis, ownership structures and insider trading

Christoph G. Rösch

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Abstract[1]

This dissertation provides a solid and in-depth discussion of market liquidity in the financial markets; in particular, it focuses upon the empirical impact of the financial crisis, ownership structures and insider trading on market liquidity.

The empirical analysis uses a volume-weighted spread liquidity measure called XLM (Xetra liquidity measure) which is a relatively new liquidity measure that can be extracted from the limit order book of the Xetra trading platform and measures the order-size-dependent liquidity costs of a roundtrip. Our sample includes all companies listed in one of the four major German stock indices (DAX, MDAX, SDAX and TecDAX) during the period from July 2002 until December 2009.

The first part of this dissertation examines the dynamics and drivers of market liquidity during the financial crisis. We find that market liquidity is impaired when stock markets decline, implying a positive relationship between market and liquidity risk. This thesis furthermore sheds light on two puzzling features of market liquidity in the stock market, namely, liquidity commonality and flight-to-quality. We observe that liquidity commonality varies over time, increases during market downturns, peaks at major crisis events and becomes weaker as we look more deeply into the limit order book. Consistent with recent theoretical models that argue for a spiral effect between the financial sector's funding liquidity and an asset's market liquidity, we empirically show that funding liquidity tightness induces an increase in liquidity commonality that then leads to market-wide liquidity dry-

[1] The abstract is largely based on Rösch and Kaserer (2010), Rösch and Kaserer (2011) and Rösch and Kaserer (2012).

ups. Therefore we are able to prove that market liquidity can be a driving force of financial contagion. In accord with previous research that proposes a flight-to-quality, we demonstrate that there is a positive relationship between credit risk and liquidity risk, i.e., there is a spread between the liquidity costs of high- and low-credit quality stocks, and that in times of increased market uncertainty, the impact of credit risk on liquidity risk intensifies. This finding demonstrates that in times of crisis, investors become increasingly risk-avers and display a preference for less risky and more liquid instruments.

The second research topic addressed in this dissertation is an analysis of the relationship between market liquidity and ownership concentration and the effect of different types of blockholders on stock market liquidity in Germany. For the overall sample, high ownership concentration is negatively related to market liquidity. This result is due to an information asymmetry problem, as large shareholders possess economies of scale in the collection of information or have access to private, value-relevant information and may trade on this information to extract the private benefits of control. We scrutinized the effect of specific types of shareholders on market liquidity. We found that most blockholder types, particularly insider blockholders, have a deleterious effect on market liquidity. However, we also show that, in contrast, private blockholders and majority strategic blockholders alleviate the information asymmetry. This effect may be due to the fact that these blockholder types do not have access to private information, cannot leverage economies of scale in the acquisition of information, or simply do not engage in information-based trading, as they are typically long-term investors. Hence, private, and to some extent strategic, blockholders are able to improve stock market liquidity. We are therefore able to show that the often-promulgated tradeoff between the liquidity benefits obtained through dispersed corporate ownership and the benefits from efficient management control achieved by some degree of ownership concentration does not hold for all blockholder types.

The last part of this dissertation investigates the impact of reported insider trading on market liquidity. This relationship is scrutinized for the German market both in an event study framework and through a panel data analysis. Overall, we note that insiders appear to trade on days that are very active, most likely to hide their information-based trading in higher trading volumes. We discover that the liquidity impact of an insider transaction is highly dependent on the type of the transaction. Insider purchases impair market liquidity on and after the day of the insider transaction, whereas insider sales improve market liquidity on and after the day of the insider transaction. This liquidity impact is due to informational effects, as uninformed market participants price protect against the adverse selection generated by informed investors. Uninformed market participants use the share of insider ownership as a proxy for the level of information asymmetry induced by insiders. This price protection is therefore reflected in the market liquidity on and after the day of insider purchases. As a consequence, insider sales alleviate information asymmetry, as the share of insider holdings is decreased; thus, market liquidity is improved on and after the day of insider sales.

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List of Abbreviations

Abbreviation	Definition
AG	Aktiengesellschaft - German name for a certain type of a company with limited liabilities
a.m.	Ante meridiem
BaFin	Bundesanstalt für Finanzdienstleistungsaufsicht - financial regulatory authority for Germany
bn	Billion
bps	Basis points
CDS	Credit default swap
CET	Central European time
CRT	Cost of a round trip trade
EEC	European Economic Community
EONIA	Euro Over Night Index Average
et al.	Et alia
ETF	Exchange traded fund
EURIBOR	Euro Interbank Offered Rate
GWN	Gaussian white noise process
HRE	Hypo Real Estate - a German bank
IKB	IKB Deutsche Industriebank - a German bank
InsO	Insolvenzordnung - German insolvency statute
IPO	Initial public offering
ISIN	International Securities Identification Number

Abbreviation	Definition
LTCM	Long Term Capital Management
mio.	Million
NYSE	New York Stock Exchange
NASDAQ	National Association of Securities Dealers Automated Quotations
OLS	Ordinary least squares
p.m.	post meridiem
S.A.	Société Anonyme
SIC	Standard industrial classification
S&P	Standard & Poor's
thsd.	Thousand
U.K.	United Kingdom
U.S.	United States
VIF	Variance inflation factor
WpHG	Wertpapierhandelsgesetz - German Securities Trading Act
XLM	Xetra liquidity measure

List of Symbols

Symbol	Definition
a	Ask-price
A	Vector of regression variables
$AAWS$	Average abnormal volume-weighted spread
α	Regression coefficient
b	Bid-price
β	Liquidity beta
C	Total share of blockholdings
$C1$	Share of the largest blockholder
$C13$	Share of the three largest blockholders
$C15$	Share of the five largest blockholders
$CAWS$	Cumulative abnormal volume-weighted spread
CN	Number of blockholders
Cov	Covariance
d	Index d (DAX, MDAX, SDAX, TecDAX)
D_t	Dummy variable that represents the sign of the incoming order (+1 for a buy transaction and −1 for a sell transaction)
$D(q)$	Delay costs for an order with quantity q
e	Event period
ϵ	Stochastic disturbance term
ε	Error term

Symbol	Definition
γ	Price impact measure that measures the return reversal in response to the previous trading day's order-flow shock
h	Individual blockholder
HHI	Herfindahl index
i	Firm or stock of a firm i
IQE	Total number of insider transactions across all firms i and volume classes q
j	Order j
k	Order k
l	Firm or stock of a firm l
$LiqCom$	Measure of liquidity commonality
$L(q)$	Liquidity costs for an order with quantity q
λ	Price impact measure that measures the price impact of a unit of trade size
m	Month
MV	Market capitalization
$\mu(q)_n$	Volume and firm dependent constant
$\hat{\mu}(q)$	Sample mean of a volume-weighted spread of order quantity q
n	Number of shares of an order or traded in a transaction
p_h	Percentage share held by the individual blockholder h
P	Price
P_{mid}	Mid-price between the bid- and the ask-price
$PI(q)$	Price impact costs for an order with quantity q
ϕ	Regression coefficient
ψ	Fixed liquidity cost coefficient
q	Order quantity in currency units
r	Return of an asset
R^2	R^2 statistic
s	Time
$S_{eff.}$	Effective spread

Symbol	Definition
$S_{quo.}$	Quoted bid-ask-spread
$S_{rel.}$	Relative bid-ask-spread
$S(q)$	Search costs for an order with quantity q
$SAWS\,(q)$	Standardized abnormal volume-weighted spread of order quantity q
σ_r	Standard deviation of log-returns
$\hat{\sigma}\,(q)$	Sample standard deviation of a volume-weighted spread of order quantity q
t	Time
$T\,(q)$	Direct trading costs for an order with quantity q
Tn	Turnover rate
τ	Time period
θ	Regression coefficient
V	Traded volume
VO	Daily transaction volume (in number of shares)
$WS(q)$	Volume-weighted spread of order quantity q
$WS(q)_{M,i}$	Equal weighted average of the volume-weighted spreads of all stocks in the market excluding firm i
x	Transaction
X	Vector of regression coefficients
#	Number

Chapter 1

Introduction

1.1 Motivation[2]

Over the course of the last two decades, the financial markets worldwide were struck by several severe liquidity crises. Several of the most prominent examples of such events were the Asian financial crisis in 1997, the collapse of the Long Term Capital Management (LTCM) hedge fund in 1998, and the most recent financial crisis that was triggered by the downturn in the U.S. sub-prime mortgage market.[3] Particularly in the aftermath of the recent financial crisis the importance of market liquidity as a key factor for financial stability in the capital markets has been recognized, and even stressed, and has received a remarkable amount of attention from researchers, regulators and financial institutions. In 1999, recapping a speech of Myron Scholes[4] on the first anniversary of the collapse of LTCM, the Economist (1999) highlighted the relevance of market liquidity:

[2] This section is partly based on Rösch and Kaserer (2010), Rösch and Kaserer (2011) and Rösch and Kaserer (2012).
[3] See Elul (2008).
[4] Nobel prize laureate and co-founder of LTCM.

> "The possibility that liquidity might disappear from a market, and so not be available when it is needed, is a big source of risk to an investor."

In addition, only recently, in a review of the current financial crisis, Brunnermeier (2009) reaffirmed the importance of market liquidity in the financial markets by stating that

> "a relatively small shock can cause liquidity to dry up suddenly and carry the potential for a full-blown financial crisis".

As a response to the recent financial crisis, regulators also recognized the important role of market liquidity and revealed several shortcomings in the current liquidity risk management practice, which led to the revision and development of several guidelines for liquidity risk management and supervision[5], e.g., the "Principles for Sound Liquidity Risk Management and Supervision" developed by Basel Committee on Banking Supervision (2008a) demand that banks

> "establish a robust liquidity risk management framework that ensures it maintains sufficient liquidity, including a cushion of unencumbered, high quality liquid assets, to withstand a range of stress events"

and adjust

> "assumptions about the market liquidity of such positions [...] according to market conditions or bank-specific circumstances".

[5] See, e.g., Basel Committee on Banking Supervision (2008a), Basel Committee on Banking Supervision (2008b) and Basel Committee on Banking Supervision (2010) for guidelines for liquidity risk management and supervision.

However, despite the crucial role that market liquidity can play in the financial markets during times of financial turmoil[6], little is known about the dynamics and drivers of market liquidity, especially in these market conditions. Therefore, we seek to address this gap in the literature by focusing on three research topics centered around market liquidity that should deepen the understanding of market liquidity in the financial markets. In particular, our work contributes to the existing market liquidity literature by analyzing the properties and roles of market liquidity during the financial crisis, the relationship between market liquidity and ownership structures and the liquidity impact of insider trading activities.

First of all, we investigate and seek to understand the role of market liquidity during periods of financial distress. This thesis particularly endeavors to address two puzzling features of market liquidity in the stock market; namely, liquidity commonality and flight-to-quality (flight-to-liquidity). We extend the existing literature on liquidity commonality, such as Chordia et al. (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001), and Brockman and Chung (2002), by not solely focusing upon giving additional proof of the mere existence of liquidity commonality but also examining the dynamics and cause of liquidity commonality in an environment of increased market uncertainty. In our work, we further empirically analyze recent theories that propose dynamic and spiral interactions between the financial sector's funding liquidity[7] and the market liquidity that can lead to banking crises and market contagion, as described in Brunnermeier and Pedersen (2009). This analysis should help to prove that market liquidity, by amplifying financial market pro-cyclicality, can be a driving force for the transmis-

[6] For a more theoretical discussion on the role of liquidity as a promoter in economic crisis, see, e.g., Bookstaber (2000), and for an analysis and discussion of the more general relationship between business cycles and market liquidity, see, e.g., Næs et al. (2011).

[7] Funding liquidity describes the ease with which an investor, a company or a financial institution can obtain funding.

sion of shocks and financial contagion. To make our analysis of market liquidity during crises complete, we explore another phenomenon in market liquidity called flight-to-quality, which is also known as the flight-to-liquidity. This notion essentially states that market liquidity is positively correlated with credit risk and that investors tend to shift their portfolio towards less risky and more liquid assets in stressed market scenarios, as discussed in, e.g., Beber et al. (2009). The flight-to-quality theory, to the best of our knowledge, was never tested before for the stock market; therefore, we want to close this gap with this dissertation.[8]

Second, we examine the relationship between market liquidity and ownership concentration and the effect of different types of blockholders on stock market liquidity. There is a vast amount of literature that has investigated the effect of blockholders on corporate decision-making, corporate performance and firm valuation, e.g., Demsetz and Lehn (1985), Holderness and Sheehan (1988), Morck et al. (1988), Stulz (1988) and Kole (1995).[9] Theoretically, blockholders can produce two distinct effects. On the one hand, they can be beneficial to all of the company's shareholders, as they mitigate the classic agency problem between management and shareholders by controlling and monitoring the management, as described, for example, in Shleifer and Vishny (1986). This effect is known as the shared benefits of control. There is empirical evidence that supports the existence of shared benefits, see, e.g., Mikkelson and Ruback (1985) and Barclay and Holderness (1991). On the other hand, blockholders can generate an economic gain by exerting influence on a company, often at the expense of small shareholders, an effect known as the private benefits of control. There is also empirical evidence supporting the existence of private benefits of control, see, e.g., Barclay and Holderness (1989)

8 Thus far, this stream of research has focused mainly on the bond and CDS markets and on inter-market portfolio re-balancing between stock and bond markets.

9 For a review of literature on blockholder ownership, please see Holderness (2003).

and Mikkelson and Regassa (1991). In addition, empirical evidence suggests that typically both factors are at work and are not mutually exclusive. However, there have only been a few investigations of the effect of ownership concentration and structures on market liquidity. This topic, therefore, will be one focus of our thesis. It appears obvious that a certain degree of ownership dispersion is necessary for liquid stock markets, as otherwise there would not be investors that are willing to trade. Therefore, most of the existing literature claims that the monitoring of blockholders comes at the cost of a decrease in market liquidity. They propagate a tradeoff between the liquidity benefits from dispersed ownership and the benefits from efficient management control that are achieved by a certain degree of ownership concentration, see for example Bolton and von Thadden (1998), Holmström and Tirole (1993) and Bhide (1993). These theoretical arguments have also been backed by certain empirical evidence demonstrating that ownership concentration impairs market liquidity, see, e.g., Heflin and Shaw (2000) and further references in section 3.2. However, in this dissertation, we want to analyze whether this tradeoff holds for all types of blockholders or whether there are certain types of blockholders or blockholder characteristics that actually improve market liquidity. This information should shed further light on the impact of different ownership structures and corporate governance mechanisms on stock market liquidity.

Third, it has been acknowledged that information asymmetries have an adverse effect on the efficient functioning of markets.[10] This dissertation aims to further analyze a fundamental issue of information asymmetry in the financial market: the information asymmetry between insiders[11] and uninformed investors. We ex-

[10] See, e.g., Akerlof (1970).

[11] Although the term insider has sometimes been extended to all investors with an informational advantage, in our study, consistent with Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin) (2012), we restrict it to members of the management or supervisory board and other persons with executive duties, who have access to (value-relevant) insider infor-

amine whether reported insider transactions are associated with informational effects that are manifested in market liquidity, as posited by market microstructure theory.[12] Our study uses directors' dealings[13] provided by the German Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin) to investigate the impact of informed trading on the stock market liquidity of the stocks listed on the major German indices. Insider trading is a topic that has received enormous attention in law, economics and finance both in practice and in academia.[14] Recently, the Galleon case, which is deemed to be one of the largest cases of illegal insider trading in the U.S., has caused quite a stir in media and business. Considerable resources have been devoted to establishing and enforcing legal restrictions for insider trading[15], e.g., in Germany, insider trading restrictions came into effect in 1994 through the Securities Trading Act (Wertpapierhandelsgesetz – WpHG), which implemented the European Community Insider Trading Directive (Council Directive 89/592/EEC of November 13, 1989). Numerous research papers have focused on discussing the advantages and disadvantages of insider trading regulations from different perspectives. First and foremost, Bainbridge (2000) provides a comprehensive summary of the major arguments for and against insider trading restrictions. Those researchers in favor of insider trading restrictions at least partially justify these restrictions with the hypothesis that insider trading cre-

mation, along with their spouses, registered civil partners, dependent children and other relatives living with them in the same household.

12 See, e.g., O'Hara (1997).

13 The linguistic usage of the terms 'directors' dealings' and 'insider trading' is somewhat ambiguous. In the colloquial language used most of the time, the term 'insider trading' refers to both illegal and legal transactions conducted by corporate insiders in their company's own shares, whereas the term 'directors' dealings' refers to legal reported transactions by corporate insiders. In this study, we strictly use the terms 'insider trading' and 'directors' dealings' synonymously, referring to legal, publicly reported insider transactions.

14 A good overview of the discussion on the merits of insider trading can be found in Leland (1992).

15 See, e.g., Bhattacharya and Daouk (2002) for a summary of the existence and the enforcement of insider trading laws thoughout the world.

ates an adverse selection problem that impairs stock market liquidity.[16] This prominent argument is backed by theoretical models in the literature on market liquidity, which showed that, due to the adverse selection problem from informed traders, uninformed market participants will increase the spreads, which leads to poorer market liquidity, to compensate for the expected losses to these privately informed traders.[17] This can be linked to the impact of insider trading on market liquidity, as evidence and widespread belief suggest that insiders have access to price-sensitive information and are therefore well informed about the fundamental value of the security.[18] Hence, an observed insider trade can essentially have two fundamental motivations: insiders can either trade on value-relevant private information, or they, like any other market participant, can trade for liquidity reasons. Therefore, one would expect that uninformed market participants price protect against the perceived information risk induced by insider transactions to compensate for the expected losses. However, there have only been a few empirical research investigations into the effect of insider trading activity on market liquidity, and the empirical results in the existing literature are ambiguous, as discussed in section 3.3. Most of this ambiguity might be explained by the fact that much of the previous research fails to distinguish between insider purchases and sales. However, in this dissertation, we are able to separately analyze the effect of insider purchases and sales on market liquidity. We further seek to link our results on insider trading to our research on the relationship between insider

[16] See, e.g., Georgakopoulos (1993).

[17] See, e.g., Copeland and Galai (1983), Glosten and Milgrom (1985) and Easley and O'Hara (1987) for theoretical work on the adverse selection component and section 2.4 for a discussion of all three basic theoretical determinants or sources of friction that influence market liquidity costs.

[18] Existing research that confirms that insiders are able to earn abnormal returns when trading in their own company's securities and therefore fail to provide support for the strong-form market efficiency hypothesis, suggests that they trade on non-public value-relevant information, see, e.g., Jaffe (1974), Finnerty (1976), Demsetz (1986) and Seyhun (1986).

ownership and market liquidity (see above), as uninformed market participants appear to use the share of insider ownership as a proxy for the level of information asymmetry induced by insiders.

In summary, market liquidity attracted increasing attention from both academics and market paricipants in recent years. Despite the considerable attention devoted to liquidity, little is known about the role and impact of market liquidity in times of crisis, and there are only a few, surprisingly diverse perspectives regarding the impact of ownership structures and insider trading on market liquidity. The motivation for our analysis of market liquidity is to shed light on these questions.

1.2 Research questions and contribution[19]

This section summarizes the main research questions of this dissertation. This thesis seeks to deepen the understanding of the properties, role and impact of market liquidity in the financial markets. Our main focus is on the dynamics and the drivers of market liquidity during the financial crisis, the relationship between market liquidity and ownership concentration, the effect of different types of blockholders on liquidity and the liquidity impact of the trading activity of insiders. In particular, we will cover the following research questions during the course of this dissertation:

1. What is the role of market liquidity during periods of financial distress?
    a) Is market liquidity time-varying? Is market liquidity affected by market downturns?

[19] This section is partly based on Rösch and Kaserer (2010), Rösch and Kaserer (2011) and Rösch and Kaserer (2012).

   b) Is the individual market liquidity of an asset affected by system-wide interactions, i.e., does liquidity commonality exist? Is liquidity commonality time-varying and affected by the financial crisis? What are the drivers of liquidity commonality?

   c) Can the theoretical concept of funding and market liquidity spirals proposed by Brunnermeier and Pedersen (2009) be empirically validated?

   d) Do external rating agencies help to alleviate the information asymmetry in the market, and is this effect manifested in market liquidity? Is there a link between credit risk and market liquidity? Does the liquidity phenomenon of flight-to-quality or flight-to-liquidity exist in the stock market?

2. Is there a relationship between ownership concentration or different types of blockholders and stock market liquidity?

   a) How is ownership concentration linked to market liquidity?

   b) Do different types of blockholders, i.e., insiders, strategic investors, financial investors and private investors, affect stock market liquidity differently? How are the access to and the use of value-relevant information affecting market liquidity? Therefore, how are different ownership structures and corporate governance mechanisms impacting market liquidity?

3. Do insider transactions have an impact on market liquidity?

   a) Are reported insider transactions associated with informational effects that are manifested in market liquidity, as posited by market microstructure theory?

b) Do insider sales and insider purchases affect market liquidity differently?

On the basis of the general research questions presented above, we formulate testable hypotheses in Chapter 3 and empirically analyze these hypotheses using a highly representative data set of daily liquidity data for the sample period of July 2002 until December 2009 for the German market. In contrast to the existing literature on market liquidity, which largely focuses on the bid-ask spread or other, less precise market liquidity proxies, to assess liquidity costs, we use a volume-weighted spread liquidity measure[20] called XLM (Xetra liquidity measure), which is provided by Deutsche Börse. XLM is a relatively new liquidity measure that can be extracted from the limit order book of the Xetra trading platform and that measures the order-size-dependent liquidity costs of a roundtrip. The use of this order-size-dependent, volume-weighted spread measure gives us new insights into market liquidity and enables us to demonstrate that our presented liquidity effects hold for the whole depth of the limit order book.[21]

To the best of our knowledge, there has been no research in the field of market liquidity using such a sophisticated liquidity measure and taking such a holistic view of dynamics, drivers and phenomena. We add to the existing literature by clarifying the impact of insider trading, ownership structures and corporate governance mechanisms on stock market liquidity. These findings contribute to a better understanding of the impact, role and behavior of stock market liquidity in crisis scenarios and thereby provide additional insight into the characteristics

[20] For an overview on the liquidity literature and the different liquidity measures, see, e.g., Amihud et al. (2005) and section 2.5.

[21] This is especially interesting as our last two main research questions focus on the adverse section component of liquidity costs (see section 2.4) and Glosten and Harris (1988) find that the importance of the adverse selection component rises with trade size.

of market liquidity risk. These insights should be especially helpful for institutional investors, exchange officials, financial regulators, supervisory bodies and risk management practitioners in the context of a sophisticated risk management approach.

1.3 Structure of the analysis

In this section, we will provide a brief overview of the structure of this dissertation.

This chapter includes the motivation, the research questions and the contribution of this thesis as well as a description of its structure. The remainder of this dissertation is organized as follows.

Chapter 2 introduces the foundational knowledge and basic principles underlying market liquidity. We clearly delimit the different meanings of liquidity that can be found in the existing literature and provide a detailed definition of market liquidity in the context of this dissertation. This definition is followed by a description of key characteristics and associated theoretical concepts regarding liquidity, as well as a presentation of existing liquidity measures. We then provide a detailed introduction to the liquidity measure known as the Xetra liquidity measure (XLM), which will be the basis of our empirical analysis as well as a description of the associated electronic trading platform operated by Deutsche Börse called Xetra.

In Chapter 3, we provide an overview of the existing literature about market liquidity that relates to the three main research questions that we presented in section 1.2. Furthermore, we will derive testable research hypotheses based upon our main research questions.

Chapter 4 introduces our datasets in great detail, including a description of all of our different variables. We further give an overview of the descriptive statistics of our data sets and present the average daily liquidity costs for different order sizes for our sample stocks, which gives first insights on the magnitude and variance of liquidity costs and liquidity risk in the German market.

Chapter 5 is dedicated to the empirical analysis of our three main research questions and, more explicitly, the test of our more detailed research hypotheses. We discuss and interpret our empirical results and provide several robustness tests that support our findings.

In Chapter 6, we will sum up our work with a conclusion and provide an outlook for avenues for further research in adjacent areas of market liquidity.

Chapter 2

Background on market liquidity and market structure

This chapter provides foundational knowledge regarding market liquidity and establishes the basic principles used in our later discussions. As Goodhart (2008) put it,

> "the word liquidity has so many facets that it is often counter-productive to use it without further and closer definition."

Therefore, we first clearly delimit the different meanings of liquidity by providing an overview of what is implied by the term "liquidity" in the literature. After having differentiated market liquidity from other liquidity terms, we offer a detailed definition of market liquidity. We then present characteristics of market liquidity and discuss the theoretical explanation for the existence of liquidity costs. Furthermore, we summarize several different concepts of market liquidity measurement and discuss the definitions, properties and characteristics of each concept. To conclude the discourse upon the foundations of market liquidity, we introduce our liquidity measure, known as the Xetra liquidity measure (XLM), in great detail, and thoroughly explain the construction of this liquidity measure. Finally, we introduce the market model of the Xetra, which is the electronic trading platform that we focus upon in our research.

2.1 Delimitation of market liquidity

Before we define market liquidity, we need to first of all clearly delimit it from other liquidity definitions, as the term liquidity is commonly used in at least three different contexts, which we will now briefly discuss:

- First, liquidity can refer to a macroeconomic perspective on liquidity that focuses on the monetary liquidity of whole economies and is also often known as global liquidity. Recently, monetary liquidity and its impact on other macroeconomic factors, e.g., inflation, long-term real interest rates, risk premiums and cross-border flows, has attracted a lot of attention, especially in media and politics. However, there is no unique and widely accepted definition for this macroeconomic liquidity, although most of the offered definitions center around the different categories of the money supply of individual countries and monetary aggregates across major economies.[22]

- Second, in corporate finance, liquidity often refers to the funding liquidity of companies, especially financial institutions. There are several definitions for funding liquidity. The International Monetary Fund (2008) describes funding liquidity as "the ability of a solvent institution to make agreed-upon payments in a timely fashion". The Basel Committee on Banking Supervision (2008a) defines funding liquidity as "the ability to fund increases in as-

[22] See, e.g., Baks and Kramer (1999), Clark and Polak (2004) and Rüffer and Stracca (2006).

sets and meet obligations as they come due, without incurring unacceptable losses". Summarizing this, we can therefore essentially conclude that liquidity of this type has two dimensions: timing and funding capacity, i.e., the ease of obtaining financing[23] of cashflows to settle obligations. According to the German insolvency statute (Insolvenzordnung (InsO)), illiquidity[24] is, in addition to over-indebtedness[25] (the going concern value of the assets falls below the value of the obligations), one reason for the insolvency of a company.

- Third, liquidity can refer to the trade characteristics of an asset, and is frequently termed asset or market liquidity if used in this context. In brief, market liquidity or asset liquidity describes the marketability or ease of trading an asset (see, e.g., Longstaff (1995)). A more applied definition specifies market liquidity as the cost of trading an asset relative to its fair value (see, e.g., Dowd (2001) and Amihud and Mendelson (2006)).

Despite the clear distinctions between these three forms of liquidity, these three concepts are also closely intertwined, albeit in a rather complex way. This dissertation primarily focuses on market liquidity. However, in section 5.1.2.5, we will also discuss the nexus between funding and market liquidity. We will elaborate upon the definition of market liquidity in the next subsection.

[23] See Brunnermeier and Pedersen (2009).
[24] § 17 InsO.
[25] § 19 InsO.

2.2 Definition of market liquidity

From the brief description above, we can already see that market liquidity is a complex and often elusive concept. According to Crockett (2008), "liquidity is easier to recognize than to define". Despite this statement, we try to give a definition of market liquidity in the following paragraphs, which should serve as a foundation for the remainder of our work.

As we already stated above, in general, market liquidity or asset liquidity describes the marketability or ease of trading an asset (see, e.g., Longstaff (1995)). To make this concept of marketability or ease of trading more accesible, we will provide more concrete definitions.

Early definitions of asset or market liquidity are centered upon an asset's ability to be (quickly) converted into cash or another asset without a loss of value. An asset is therefore said to be liquid if it can be easily bought or sold. A consequence of these definitions of asset liquidity is that cash is one of the most liquid assets. Of the more standardized assets that are continuously traded on regulated financial markets, investments in instruments such as, e.g., stocks, bonds or futures are considered to be more liquid than investments in, e.g., real estate or rare art. This rather simple definition provides an initial practical impression of what market liquidity means and permits broad differentiation between the liquidity of different asset categories: however, it fails to distinguish either between the liquidity of different assets of the same asset category (e.g., the liquidity of different DAX stocks traded on Xetra) or between the liquidity of different markets for the same asset.

We will now further develop the definition of market liquidity. According to one of the first definitions of a liquid market by Black (1971),

> "a liquid market is a continuous market, in the sense that almost any amount of stock can be bought or sold immediately; and an efficient market, in the sense that small amounts of stock can always be bought or sold very near the current market price, and in the sense that large amounts can be bought or sold over long periods of time at prices that, on average, are very near the current market price".

This leads us to the conclusion that two main factors of market liquidity can be determined: the immediacy of trading and its associated costs (e.g., in the form of price concessions). Thus, we can define market liquidity as the ability of an asset to be bought or sold quickly at any time and in any quantity in the market without a significant loss in value (compared with its fair value).

For a liquid market, it is therefore essential that there is an abundance of market participants in the market that are ready and willing to buy or sell. Therefore, liquidity is often associated with a high level of trading activity. Depending on the architecture of the market studied the following different market participants that contribute to the liquidity in the market may all potentially exist: specialists, floor brokers, market makers, dealers, designated sponsors and traders placing limit orders.[26] In the case of an order-driven market, like the Xetra-market that is the focus of this dissertation, limit orders placed by traders provide liquidity, whereas market orders placed by traders consume liquidity.[27] Therefore, to tailor the definition of market liquidity to an order-driven market, we follow the definition of Hollifield et al. (2001), who state that

> "a liquid limit order market has a large volume of limit orders in

[26] See, e.g., Hollifield et al. (2001).

[27] In addition to traders, there are also so-called designated sponsors active in the Xetra-market to enhance liquidity. They quote binding ask and bid limits for those securities that are sponsored by them, which largely consist of less-liquid shares.

> the book, a small bid/ask spread, a relatively large quantity of shares offered close to the bid and ask quotes, and a limit order book which rebounds quickly after a market order is submitted."

Thus, this definition of market liquidity emphasizes once again the rapid matching of demand and supply of an asset at low costs of transaction. However, to make the market liquidity definition more practical and less elusive, and to make the resulting assessment of market liquidity more comparable, all components of market liquidity, including, in particular, the immediacy of trading, can be translated into the costs that they generate. Therefore, market liquidity, as already stated above, can also be defined as the cost of trading an asset in the capital markets relative to its fair value[28] (see, e.g., Dowd (2001) and Amihud and Mendelson (2006)). This market liquidity cost definition is the foundation for this dissertation. In accordance with Aitken and Comerton-Forde (2003), Amihud and Mendelson (2006) and Stange and Kaserer (2011), we can effectively distinguish between the four order-size-dependent explicit and implicit liquidity cost components of price impact costs $PI(q)$, search costs $S(q)$, delay costs $D(q)$ and direct trading costs $T(q)$. These components, in total, represent the market liquidity costs $L(q)$ and therefore define the market liquidity of an asset:

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

The four liquidity cost components are described in the following paragraphs:

- **Price-impact** (or **market-impact)** measures how much the transaction itself will impact the current price of the asset underlying the transaction

[28] In most definitions and concepts, the fair value of an asset is set to the mid-price of the bid-ask-spread. This makes the application of the concept rather simple, but leads by definition to a continuous fluctuation of the fair value of an asset, which is a bit counter-intuitive.

in the market in which the transaction takes place. Therefore, price impact costs $PI(q)$, as a liquidity cost component, can be defined as the difference between the realized transaction price and the fair value of an asset at the time of the transaction. In more concrete terms, the price impact costs comprise the price concession (discount when selling, premium when buying) that a trader has to make to secure an immediate transaction and is therefore often referred to as the price for immediacy. For small order sizes[29], the calculation of the price impact is straightforward: For purchases, it is the difference between the (best) ask-price and the fair value of the asset, which is often set at the mid-price of the bid-ask-spread, and for sales it is the difference between the (best) bid-price and the fair value of the assets. For larger order sizes, orders cannot be fulfilled at the (best) bid or ask price, and therefore the price impact costs depend on the (presumably inelastic) demand and supply curves[30] (bid- and ask-price functions) of the asset at the time of the transaction, and thus increase with order size. Figure 2.1 illustrates the price impact as a function of the order size. We will introduce a measure capturing the price impact as a function of the order size in section 2.6. By now, we can summarize that price impact is time-varying, order-size-dependent and can be quite substantial[31], especially for larger order sizes, and therefore will be the main focus of this dissertation.

- **Search costs** $S(q)$ include all costs involved in searching for a counter-

[29] A small order size refers to an order volume up to the quoted depth of the bid-ask spread or the order size of the best ask and bid prices in the limit order book.
[30] See, e.g., Shleifer (1986) and Greenwood (2005) for empirical evidence on inelastic demand curves for stocks.
[31] In chapter 4, we provide empirical evidence on the size of the price impact for German standard stocks at several different order sizes in Tables 4.1, 4.2 and 4.3.
[32] Cf. Bangia et al. (1999) and Domowitz et al. (2005).

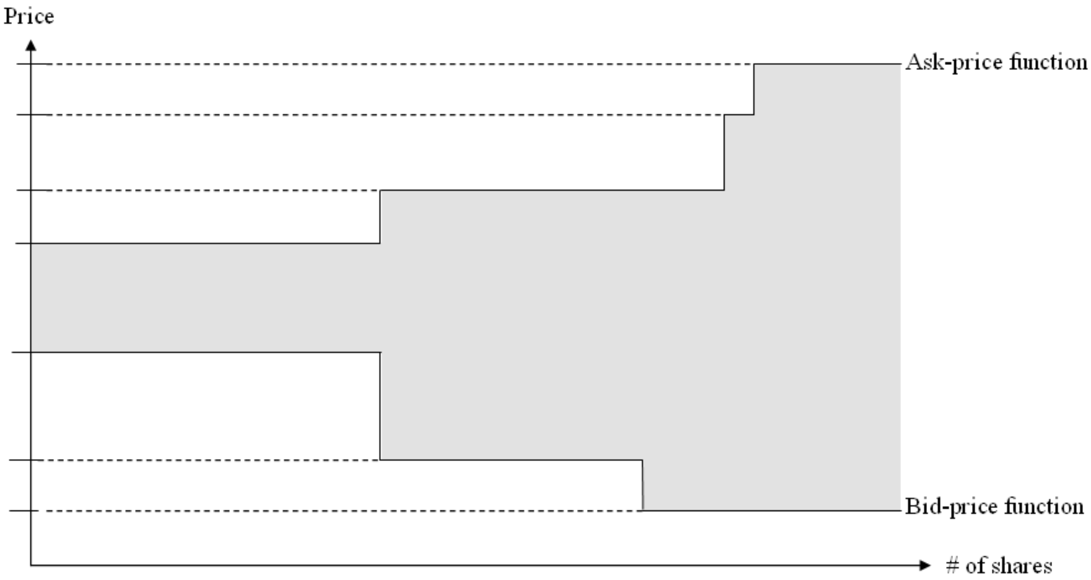

Figure 2.1: Price impact[32]

part for transactions. Search costs can be a significant part of liquidity costs, especially for rather unique assets like rare art or real estate, but for many other assets, like stocks and bonds, that are continuously traded on exchanges, the search costs are negligible. However, stocks can be associated with significant search costs in case of block trades of large quantities of shares. In such trades, investors typically search for a counterpart with whom they can privately negotiate the transaction instead of dumping the whole order on the market, which would lead to a significant price impact.

- **Delay costs** $D(q)$ basically describe the risk of an adverse change in asset prices or price impact costs during transaction delays. We can distinguish between two different types of delays, forced and unforced delays. An unforced delay describes the situation that occurs if a trader deliberately delays (parts of) the transaction in the hopes of receiving better prices or reducing price impact costs. Particularly for large orders, there are trading strate-

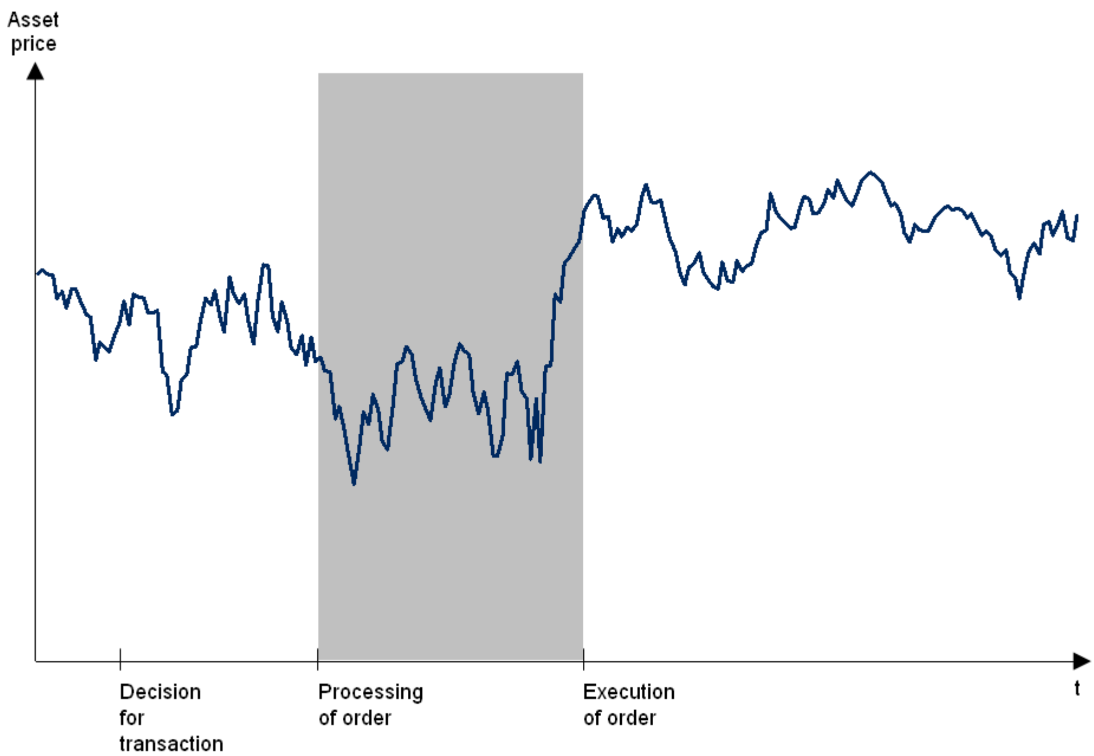

Figure 2.2: Delay costs

gies that split orders to optimize the tradeoff between price impact costs and delay costs.[33] If an order cannot be immediately and fully executed, then (parts of) the order experiences a forced delay. In this case, the forced delay costs comprise the price risk incurred during the processing time of the order (see Figure 2.2). Furthermore, forced delays result if there are not enough traders on the other side of the transaction and therefore the whole order cannot be fulfilled immediately, causing parts of the transaction to be delayed. Delay costs can be substantial.

33 For research on trading strategies that optimize the tradeoff between delay costs and price impact costs see, e.g., Bertsimas and Lo (1998), Almgren and Chriss (1999), Almgren and Chriss (2000), Konishi and Makimoto (2001), Subramanian and Jarrow (2001), Almgren (2003) and Rosu (2009).

- **Direct trading costs** $T(q)$ summarize all the explicit liquidity costs that are related to the transaction including exchange fees, brokerage commissions and government taxes. Only exchange fees can be controlled by the exchange itself (and are often used as a selling proposition in the competition among different exchanges), whereas the others are exogenous. Direct trading costs are rather simple to quantify, as they are deterministic and are typically relatively small compared to the other liquidity cost components listed above (especially for most standardized assets, such as stocks). Due to their deterministic nature, direct trading costs are often neglected in academic research.

By relating all the liquidity cost components to the fair value of the asset, liquidity costs and hence market liquidity are represented as a fraction of the asset's fair value, which makes a comparison of market liquidity across different assets and markets very straightforward.

2.3 Characteristics of market liquidity

In the previous section, we gave a definition of market liquidity and stressed the importance of the price impact as a liquidity component. Several researchers in the field of market liquidity followed the work of Kyle (1985) by describing three main characteristics of market liquidity. More precisely, these are characteristics of the price impact, which we defined above. As these characteristics play a central role in the existing research and help us to better understand the concept of price impact, we will briefly describe these three characteristics, which are illustrated in summary in Figure 2.3.

[34] Cf. Bervas (2006).

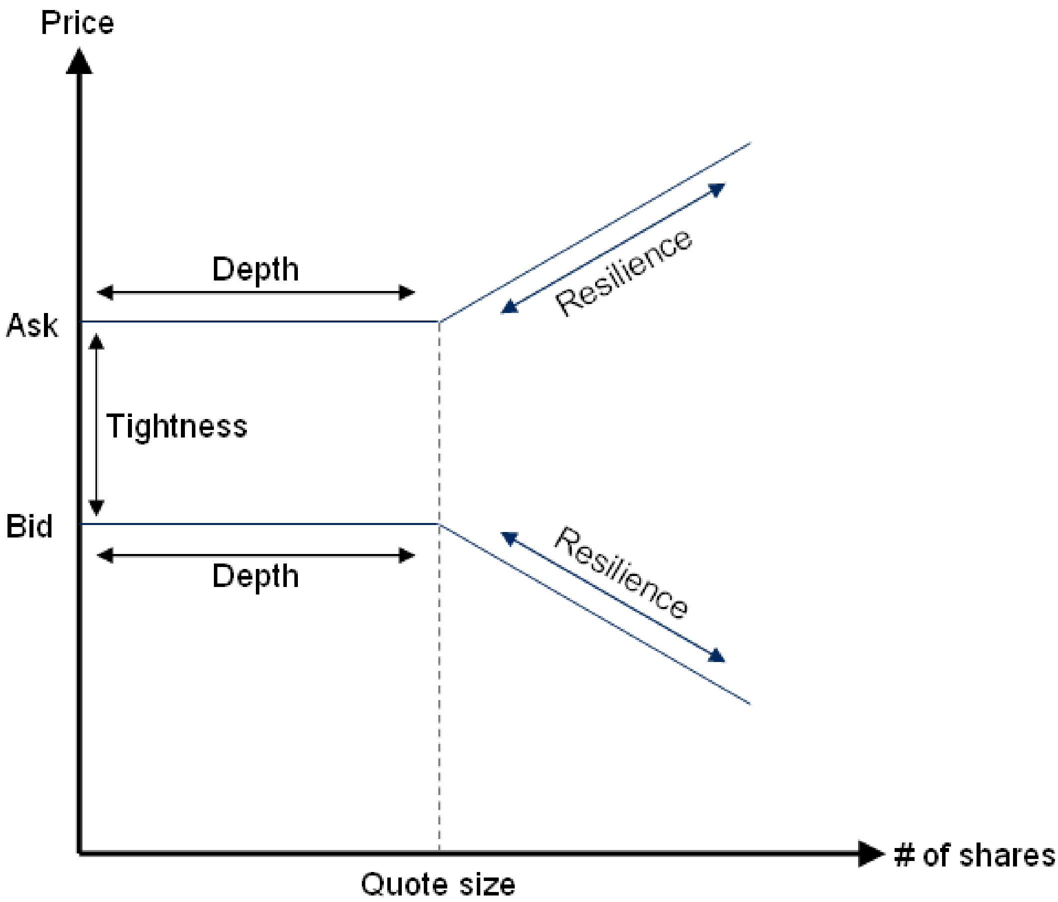

Figure 2.3: Liquidity characteristics[34]

The three basic characteristics of market liquidity or price impact are:

- **Tightness,** or **breadth**, which describes the ability to trade assets close to the fair value of the asset. In a more concrete manner, one can say that tightness is measured as the spread between the best bid and the best ask price.

- **Depth**, which is the ability to buy and sell large order sizes without an excessive adverse impact on the price of the asset. More precisely, depth measures the volume that can be transacted (either sold or bought) at the best quoted price. The concepts of tightness and depth can be combined by stating that a tight and deep market is a market in which even large orders (both purchases and sales) can be fulfilled immediately at close to the current market price.

- **Resilience** refers to the speed at which prices recover from the impact of a transaction or a random shock, like temporary order imbalances. It is therefore closely linked to the order flow that is required to counterbalance these price effects.

All of these three characteristics play a crucial role in the evaluation of the liquidity of a financial market.

2.4 Theoretical explanations for the existence of liquidity costs[35]

After having focused on the definition and characteristics of market liquidity (costs), we now seek to derive a better understanding for the driving forces underlying the existence of market liquidity costs. The existing market microstructure literature on market liquidity distinguishes three basic theoretical determinants or sources of friction that influence market liquidity costs (see, e.g., Stoll (1989), Stoll (2000) or Amihud et al. (2005)). A solid understanding of these factors is essential for any further empirical research that focuses on effects on market liquidity, as these form the theoretical underpinnings of that concept. The three sources of friction are:

- **Order handling costs** or **order processing costs** (see, e.g., Demsetz (1968), Tinic (1972) and Roll (1984)) relatively straightforwardly reflect the compensation required for the intermediation processes of transacting an order.

- **Inventory costs** comprise the compensation for the price risk and opportunity costs of holding a position (see, e.g., Stoll (1978b), Amihud and Mendelson (1980) and Ho and Stoll (1981)). This theory is based on a market structure with some sort of market maker[36]. Market makers stand ready to buy and sell from investors to provide immediacy of trading. As a result, a market maker may have to buy an asset from an investor with the anticipation of being able to unwind the position by selling it to another investor in the future. In the interim, by holding the position in his inventory, he is

[35] This section is partly based on Rösch and Kaserer (2011).
[36] Designated sponsors in the case of the Xetra.

exposed to the risk of adverse price changes. He therefore must be compensated for taking this risk. This compensation is implemented through the use of a spread; thus, the magnitude of this risk influences the size of the spread.

- **Adverse selection costs** refer to theories demonstrating that asymmetric information is a driver for liquidity costs and therefore explain the spread as compensation for losses incurred by trading with (privately) informed investors. This notion can be derived from theories of Copeland and Galai (1983), who demonstrated that due to the adverse selection problem from informed traders, uninformed market participants will increase the spreads, which leads to poorer market liquidity, to compensate for the expected losses to these privately informed traders. Thus, market makers will gain from trading with uninformed liquidity traders while they lose money to the privately informed traders (see, e.g., Bagehot (1974)). The private information in question can stem from either confidential data regarding the fundamentals of the asset, e.g., a potential buyer has private information that a company is about to take off, justifying a higher asset price, or data regarding the order flow, e.g., a trader has private information that another large institutional investor is going to dump a large position of a security in the market, which will depress the price of this asset in the market, at least in the short term. This phenomenon was later referred to as the "adverse selection component" by Glosten and Milgrom (1985). Further fundamental theoretical works on the adverse selection component include the sudies of Kyle (1985) and Glosten and Harris (1988). Furthermore, Stoll (1989) and George et al. (1991) provide empirical evidence for the existence of the adverse selection component in the financial markets.

An understanding of the sources of liquidity costs is essential for regulators, exchange officials, market makers, traders, etc. to develop mechanisms, e.g., better disclosure to reduce the extent of private information, to improve market liquidity.

2.5 Measures of market liquidity

Given its definition and characteristics, a holistic measurement of liquidity seems to be nearly impossible. As a consequence, a vast number of different measures have been used as a proxy for market liquidity, indicating that there is no established consensus regarding the most appropriate measure. One major empirical constraint for the construction and use of a market liquidity measure is data availability. Financial data recorded on a high-frequency level, which enables liquidity measurement based on the actual sequence of orders, quotes and trades, only recently became available for developed financial markets such as those of the U.S.. For less developed markets or longer periods of time, one is therefore restricted to the use of low-frequency data to measure market liquidity. This section surveys and discusses the most prominent existing market liquidity measures and sets the foundation for the introduction of the market liquidity measure that we will use for our empirical research, which will be discussed in the next section. In this presentation of the liquidity measures, we broadly categorize them as liquidity measures that only roughly act as proxies for market liquidity, i.e., they give a general sense of the liquidity of an asset and enable a liquidity ranking of assets but do not have a clear linkage to liquidity costs (indirect measures); and those liquidity measures for which liquidity costs can be directly inferred from the respective liquidity measure (direct measures).

2.5.1 Indirect measures

We begin our discussion by considering the indirect liquidity measures of traded volume, turnover rate and proportion of zero-trading days.

- **Traded volume**

Traded volume V represents a rather simple and rough liquidity measure, although it does have very limited data requirements.[37] It measures the amount transacted either between investors of a single asset or by an entire market for a certain period of time (usually a day, a week, a month or a year). It is therefore a measure that acts as a proxy for the activity and the existence of participants in the market. It is calculated by aggregating the product of the price of a transaction P_x with the quantity transacted n_x for all transactions for a specified period of time:

$$V = \sum_x P_x \cdot n_x \tag{2.2}$$

- **Turnover rate**

  The traded volume by itself is hard to compare across securities and markets, as it does not account for the number of shares outstanding or the shareholder bases. Thus, Datar et al. (1998) propose an adaption that uses the turnover rate as a proxy for liquidity. The turnover rate Tn is constructed by relating the traded volume V (as calculated in equation (2.2)) to the outstanding volume of the asset MV, which is the product of the number of shares outstanding and the average price of the traded shares.

$$Tn = \frac{V}{MV} \tag{2.3}$$

- **Proportion of zero-trading days**

  Lesmond et al. (1999) propose a liquidity measure that is based on the inci-

[37] However, Stoll (1978a) shows that traded volume is the most important determinant of the bid-ask spread and therefore, if data availability precludes the use of other liquidity measure, this metric is often used as a liquidity proxy. For instance, Brennan et al. (1998) use trading volume as a measure of liquidity in a multi-factor asset pricing model.

dence of trading days with a zero return. They argue that there is a direct link between liquidity costs and the number of days with zero returns. In their view, an asset with higher liquidity costs exhibits less frequent price movement and, in turn, more days with zero returns, as liquidity costs constitute a threshold to transact, and given the adverse selection model introduced by Glosten and Milgrom (1985) and Kyle (1985), market participants will only trade if this threshold is outweighed by the value of an informational signal.[38] Lesmond et al. (1999) further demonstrate that this measure is highly correlated with more conventional direct liquidity measures, like the bid-ask-spread, which makes it a good liquidity proxy. The calculation of the proportion of zero-trading days is simply the number of days with zero returns as a fraction of the total number of trading days in a month (see equation (2.4)). The construction of this liquidity measure already implies that it is a rather low frequency measure. Indeed, perhaps the most important advantage of this liquidity measure is that it requires very little data, i.e., it only requires time-series data of returns, and therefore it can be a useful liquidity proxy in contexts for which volume data or more sophisticated high-frequency price data are unavailable, as is the case for many emerging markets.

$$Zero = \frac{\# \; of \; days \; with \; zero \; returns}{\# \; of \; trading \; days \; in \; a \; month} \tag{2.4}$$

Certain studies use a slightly different definition of the proportion of zero-trading days that counts only zero-return days with a positive trading volume:

[38] See, e.g., Goyenko et al. (2009) and Bekaert et al. (2007).

$$Zero = \frac{\#\ of\ positive\ volume\ days\ with\ zero\ return}{\#\ of\ trading\ days\ in\ a\ month} \tag{2.5}$$

After having presented some indirect liquidity measures, we will now focus on direct liquidity measures, which can be converted rather straightforwardly into estimates of particular liquidity costs.

2.5.2 Direct measures

In the following section, we will discuss the direct liquidity measures of quoted bid-ask-spread, relative bid-ask-spread, effective spread, lambda λ, gamma γ, ILLIQ, liquidity ratio and volume-weighted spread.

- **Quoted and relative bid-ask-spread**

  The quoted and the relative bid-ask spread are among the most widely used measures of market liquidity, see, e.g., Amihud and Mendelson (1986). The quoted bid-ask spread $S_{quo.}$ is the difference between the quoted bid (b) and ask (a) price and is therefore a direct measure for the cost of an immediate transaction (see equation 2.6).[39]

  $$S_{quo.} = a - b \tag{2.6}$$

  It measures the price for immediacy that a small investor[40] has to pay, i.e., to purchase a stock he has to pay the ask-price, whereas he only receives the bid-price when selling the same stock, and therefore a small investor has to pay the spread as a liquidity cost for a roundtrip. To make the bid-

[39] Cf. Amihud and Mendelson (1986).

[40] A small investor, in this context, is an investor that trades order sizes that are smaller than the quote size.

ask spread more comparable across different assets (especially with different prices), the quoted bid-ask-spread is often expressed as a fraction of the mid-price P_{mid} between the bid- and the ask-price.

$$P_{mid} = \frac{a+b}{2} \tag{2.7}$$

The resulting measure is called the relative bid-ask spread $S_{rel.}$:

$$S_{rel.} = \frac{S_{quo.}}{P_{mid}} \tag{2.8}$$

- **Effective spread**

  The quoted spread presented above, however, fails to fully capture the impact of large orders on market prices and the effect that transactions can occur within the quoted bid- and ask-prices. The effective spread addresses this deficiency with actual transaction prices instead of quoted bid- and ask-prices. It is defined as twice the absolute difference between the actual transaction price P_x and the mid-price P_{mid} at the time of the order entry, and it therefore captures the cost of a roundtrip.

$$S_{eff.} = 2 \cdot |P_x - P_{mid}| \tag{2.9}$$

The effective spread is aggregated over a time period (e.g., a month or a year) by calculating the volume-weighted average of all transactions in that time period. Much of the time, only the transaction prices are known, whereas the mid-price is unknown due to limitations in data availability. As a consequence, Roll (1984) developed an implicit estimator of the effective percentage spread $\hat{S_{eff.}}$ based on the serial covariance of the changes in transaction prices that exist due to the bid-ask bounce.[41] The estimator of the effective percentage spread $\hat{S_{eff.}}$is calculated as follows:

$$\hat{S_{eff.}} = 2 \cdot \sqrt{-Cov(r_t, r_{t-1})} \tag{2.10}$$

In this case, $Cov(r_t, r_{t-1})$ is the serial covariance of the returns of the asset. The advantage of the model of Roll (1984) is that it provides a simple method to estimate liquidity costs that solely uses transaction price data.

- **Relation between price change and order flow - Lambda λ**

  In their work, Brennan and Subrahmanyam (1996) distinguish between liquidity costs that are constant for any trading size (which they call fixed costs) and those that vary with the trading size (which they call variable costs). Using the following regression framework that is based on Glosten and Harris (1988)[42]

$$\Delta P_t = \lambda \cdot n_t + \psi \left[D_t - D_{t-1}\right] + \epsilon_t \tag{2.11}$$

  where $\Delta P_t = P_t - P_{t-1}$ is the price change, n_t is trade-size or order flow, and D_t represents the sign of the incoming order ($+1$ for a buy transaction and -1 for a sell transaction), they estimate the variable costs coefficient λ and the fixed cost coefficient ψ. This λ, which is also often called Kyle

41 For extensions of this model see, e.g., Stoll (1989), George et al. (1991) and Huang and Stoll (1997).

42 They further use a regression model that is based on Hasbrouck (1991) and Foster and Viswanathan (1993). However, as this model produces qualitatively similar results, we restrict our discussion to the model based on Glosten and Harris (1988).

(1985)'s λ[43], essentially measures the price impact of a unit of trade size; thus, $\frac{1}{\lambda}$ proxies the depth of the market, as it represents the number of shares required to move the price of the security by one currency unit. A larger absolute value of λ implies a larger price impact and therefore a lower market liquidity. The variable ψ measures the transaction-size-independent fixed liquidity costs. To make this measure more comparable across securities, ψ is often divided by the monthly average of the security price. A larger value of ψ represents a larger fixed liquidity cost.

- **Volume shock related return reversal - Gamma γ**

  Pastor and Stambaugh (2003) suggest a measure of liquidity with conceptual underpinnings that are motivated by an observation of Campbell et al. (1993), who conducted a regression analysis that focused on the impact of the signed lagged trading volume on a stocks daily excess return. In this analysis, they discovered that the negative coefficient for the lagged transaction volume, capturing the price reversal in response to a certain transaction volume, is more pronounced for less liquid stocks. In their study, Pastor and Stambaugh (2003) use this finding of Campbell et al. (1993) and perform the following monthly regressions to estimate their price impact measure called gamma γ.

$$r_{t+1}^{e} = \theta + \phi \cdot r_t + \gamma \cdot sign\left(r_t^e\right) \cdot V_t + \epsilon_t \tag{2.12}$$

  In this equation, r_t is the individual stock's return on day t, r_t^e is the excess return of an individual stock above the market return and V_t is the individual stock's traded volume on day t. The price impact measure gamma

[43] Kyle (1985) argues that λ increases with the extent of information asymmetry.

γ measures the return reversal in response to the previous trading day's order-flow shock. A larger absolute value of γ implies a larger price impact and therefore a lower market liquidity.

- **Price response to turnover - ILLIQ and Amivest**

We have already demonstrated that traded volume alone can be used as a liquidity measure. In recent years, several other liquidity measures have been developed that use the traded volume as a main component. Perhaps the most prominent of these liquidity measures was developed by Amihud (2002) and is called ILLIQ. It is calculated as the daily ratio of the absolute stock return r to its traded volume V and represents the price response that is associated with one currency unit of trading volume. It can be interpreted as a rough measure of the price impact. For longer periods of time, such as months or years, the ratio is averaged over that period.

$$ILLIQ = \frac{|r|}{V} \tag{2.13}$$

Amihud (2002) already states that there are probably better and more precise liquidity measures, such as the (quoted or effective) bid-ask-spread or other, more sophisticated price impact measures. However, these other measures all suffer from the same problem of requiring a large amount of high-frequency microstructure data that are not available in many equity exchanges or over longer time periods, as high-frequency data only recently became available in developed financial markets. This is the main reason for the popularity of the use of the ILLIQ measure in long-term studies that analyze the impact of market liquidity on asset pricing, such as, e.g., Acharya and Pedersen (2005).

One related measure to the ILLIQ is called the Amivest liquidity measure or liquidity ratio[44], which is essentially the reciprocal value of the ILLIQ measure:

$$Amivest = \frac{V}{|r|} \tag{2.14}$$

It compares the traded volume with the absolute price change. Any time interval, like days or months, can be chosen for this measure. However, unlike the ILLIQ measure, the Amivest measure is typically not aggregated by averaging the daily measures; instead, the Amivest measure is calculated using the appropriate overall values (e.g., monthly or yearly) for the traded volume and the absolute percentage change for the chosen time interval. In effect, the Amivest measure or liquidity ratio measures how much volume needs to be traded to induce a price change of one percent. A higher Amivest measure implies a higher market liquidity, as it indicates that a higher trading volume has less influence on price.

- **Volume-weighted spread**

  Volume-weighted spread measures, derive, at any point in time, the ex-ante liquidity costs associated with a transaction of a particular order size by aggregating the state of the limit order book at that particular point of time and for this particular order size. It generalizes the concept of the quoted bid-ask-spread to the rest of the limit order book. Irvine et al. (2000) introduced a volume-weighted spread measure called cost of roundtrip trade (CRT); in addition, Barclay et al. (1999), Coppejans et al. (2002) and Giot and Grammig (2005) used similar liquidity measures. We limit the

[44] This measure has been used by e.g., Amihud et al. (1997) and Berkman and Eleswarapu (1998) to analyze less developed financial markets.

discussion of volume-weighted spread measures in this section, as we will introduce our liquidity measure, which is a volume-weighted spread measure, in great detail in the next section.

Due to the abundance of available liquidity measures, this section could only address the most prominent liquidity measures. For an overview of further liquidity measures, consult, e.g., Sarr and Lybek (2002), Amihud et al. (2005), Goyenko et al. (2009) and Gabrielsen et al. (2011).

2.6 Introduction to the Xetra Liquidity Measure[45]

To measure the liquidity costs, and specifically the roundtrip price impact[46], we use an order-size-dependent volume-weighted spread $WS(q)$ derived from the limit order book. $WS(q)$ represents the cost of immediate order execution of a roundtrip order of a specific Euro volume size q relative to its fair value, which is set at the mid-point of the bid-ask-spread, the mid-price P_{mid}. It is an ex-ante market liquidity measure of the liquidity available in the market at a particular moment in time. The volume-weighted spread is a liquidity measure that combines three aspects of market liquidity in one measure: tightness, depth and immediacy of execution.

Mathematically, $WS(q)$ can be calculated as the average volume-weighted price of all limit orders that are required for transacting a specific Euro volume roundtrip

[45] This section is largely based on Rösch and Kaserer (2010), Rösch and Kaserer (2011) and Rösch and Kaserer (2012).

[46] See section 2.2 for a discussion of the liquidity cost components and price impact. As the Xetra-market for the stocks is a very active market with continuous trading, we can neglect the search and delay costs as a liquidity component. Furthermore, transaction costs are deterministic and rather small (especially for institutional investors) and are also negligible. Thus, an adequate price impact measure captures all relevant aspects of liquidity costs, and we will therefore use this price impact measure as a liquidity measure in line with our definition in equation (2.1).

of size q, divided by the mid-price P_{mid} of the bid-ask-spread and it is measured in basis points:

$$WS_t(q) = \frac{\frac{1}{n}\left(\sum_j a_{j,t}n_{j,t} - \sum_k b_{k,t}n_{k,t}\right)}{P_{mid,t}} \cdot 10,000 \tag{2.15}$$

where $a_{j,t}$ and $n_{j,t}$ are the ask-prices and size (in number of shares) of individual limit orders in the limit order book at time t, sorted according to price priority. In the above equation, n represents the number of shares required to fulfill an order with a volume of size q as measured in terms of the mid-price P_{mid}, and therefore n can be calculated as $n = \frac{q}{P_{mid}}$. The individual limit orders j are added up until the sum of the individual limit order sizes $n_{j,t}$ equals n. The respective measures for the bid-side $b_{k,t}$ and $n_{k,t}$ are defined analogously. Equation (2.15) can thus be simplified to

$$WS_t(q) = \frac{a_t(q) - b_t(q)}{P_{mid,t}} \cdot 10,000 \tag{2.16}$$

where

$$a_t(q) = \frac{1}{n}\sum_j a_{j,t}n_{j,t} \tag{2.17}$$

is the volume-weighted ask-price achieved when buying an order of size q through a market order and $b_t(q)$ is the corresponding volume-weighted bid-price for liquidating the same position.

Graphically, $WS(q)$ is the area between the curves of the price-priority-sorted individual bid and ask orders in the limit order book up to the transaction size n (see Figure 2.4), divided by the order volume q.

A type of volume-weighted spread called the Xetra liquidity measure (XLM) is

[47] Cf. Domowitz et al. (2005) and Stange and Kaserer (2011).

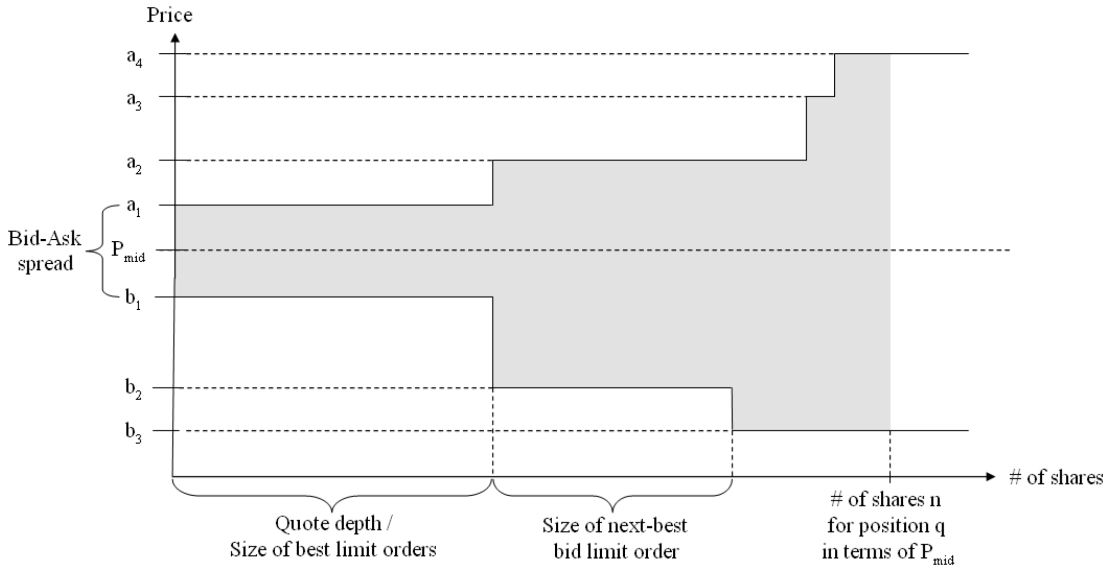

Figure 2.4: The weighted spread as the area between the limit order bid- and ask-curves[47]

automatically calculated by the Xetra system from both the visible and invisible portions of the electronic limit order book, including the hidden part of iceberg orders. Hachmeister (2007) provides theoretical background on this measure, whereas Stange and Kaserer (2008) scrutinize some of its empirical properties for the German stock market. A similar measure called the cost of roundtrip trade (CRT) was introduced by Irvine et al. (2000). Additionally, Barclay et al. (1999), Coppejans et al. (2002) and Giot and Grammig (2005) have used similar liquidity measures.

Deutsche Börse introduced the Xetra liquidity measure in July 2002 to provide Xetra's participants with the ability to diagnose the committed liquidity and implicit transaction costs in the stock market. We obtained daily values of this volume-weighted spread measure for several standardized volume classes for all constituents of the four major German indices (DAX, MDAX, SDAX, and TecDAX) from Deutsche Börse. Daily values of the XLM are aggregated by the Xetra trading system by calculating the equal-weighted average of all individual volume-weighted spread data points calculated at every minute during the trading hours for each standardized volume class q. Daily $WS(q)$ were provided for each stock for 10 out of the following 14 standardized volume classes q of Euro 10, 25, 50, 75, 100, 150, 250, 500, 750, 1000, 2000, 3000, 4000 and 5000 thousand, if sufficient volume was available in the limit order book to calculate the respective volume class for the stock. For DAX stocks, the 10 standardized volume classes comprise all volume classes up to Euro 5000 thsd. with the exception of the following four volume classes: Euro 10, 75, 150 and 750 thsd. By contrast, for the stocks in the other three indices, the XLM was available for all volume classes up to Euro 1 million.

For the purpose of most of our research, we use the XLM data to calculate the liquidity costs L(q) from a transaction perspective, i.e., either a sell or a buy order and not a roundtrip, as a per-transaction figure is much more intuitive than a per-roundtrip figure.[48] For simplicity, we assume that on average, there is a symmetrical limit order book[49], i.e., the liquidity costs for buying and selling are equal. Therefore, we can derive the volume-dependent price impact $PI(q)$ of a hypothetical single (buy or sell) transaction with order size q as

$$L(q) = PI(q) = \frac{WS(q)}{2} \tag{2.18}$$

After having introduced the Xetra liquidity measure, which will be the liquidity measure that we will use in our empirical research, we will now elaborate on the Xetra market, which is the focus of this dissertation.

[48] This approach is consistent with Stange and Kaserer (2008).

[49] This assumption is fair, as Hedvall et al. (1997) found that, in general, the order book is quite symmetrical, and Hachmeister (2007) showed that for the XLM, the liquidity costs do not significantly differ on the buy and the sell side for trading sizes up to Euro 1 million.

2.7 Description of the Xetra market structure[50]

The Xetra system is a fully electronic trading platform for cash market trading in equities and several other financial instruments, including exchange traded funds (ETFs), exchange traded commodities (ETC), bonds, warrants and subscription rights operated by Deutsche Börse. Deutsche Börse is Germany's largest stock exchange, and it is also among the world's top 10 largest stock exchanges in terms of share trading value (see Figure 2.5).[52] The relevance of Xetra for the German equity market is illustrated by the fact that more than 90 percent of the entirety of shares trading at German exchanges are handled through Xetra. One-fifth of these orders are placed by private investors.[53]

Equity trading on Xetra takes place between 9 a.m. and 5.30 p.m. (CET) on all trading days in a trading model based on continuous trading in connection with auctions. Continuous trading and auctions follow the schema illustrated in Figure 2.6. The trading starts with an opening auction followed by continuous trading throughout the day. It is interrupted by an intraday auction approximately 1 p.m. and ends with a closing auction. The exact timing depends on the market segment in question.

The exchange market model for equity trading is order-driven. The Xetra market distinguishes the following three different order types:

- Market order: This is an unlimited order to sell or buy and therefore provides for immediate execution at the best available price.

[50] This section is partly based on Rösch and Kaserer (2010), Rösch and Kaserer (2011) and Rösch and Kaserer (2012).
[51] Cf. World Federation of Exchanges (2011).
[52] As of Dec 2010, according to World Federation of Exchanges (2011).
[53] Cf. Deutsche Boerse (2010).
[54] Cf. Deutsche Boerse (2011).

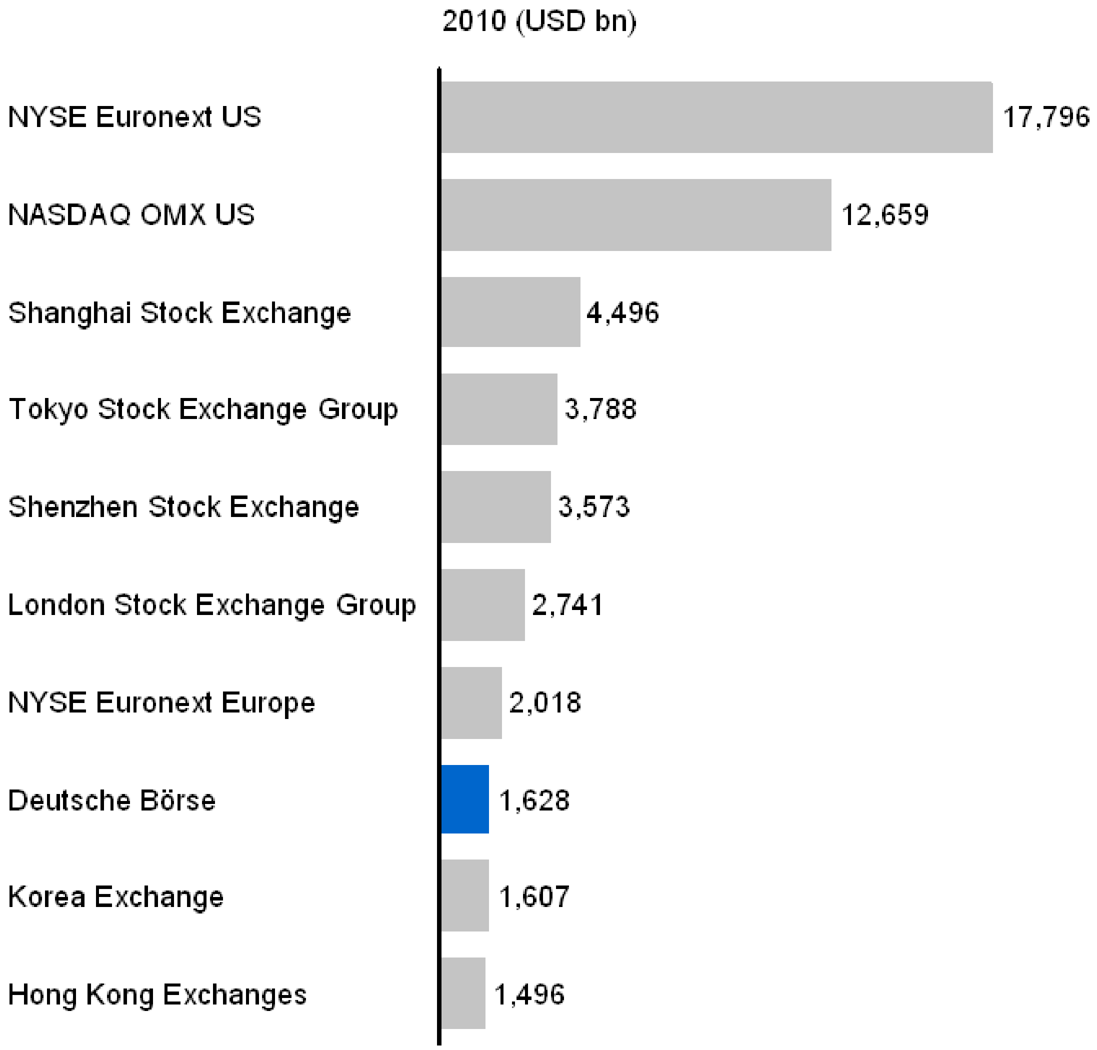

Figure 2.5: Largest exchanges by value of share trading in the electronic order book in 2010[51]

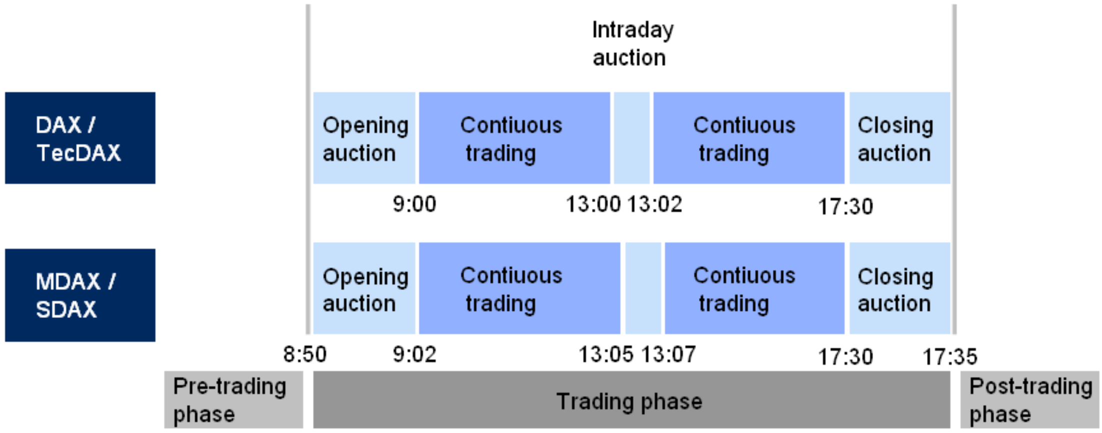

Figure 2.6: Xetra continuous trading and auction plan[54]

- Limit order: This is a bid or ask order, which can only be executed at a price at or better than the specified limit price. The limit order enables traders to achieve better prices than the current prevailing market price. However, the execution at that limit price will not happen immediately and is not guaranteed at all.

- Market-to-limit order: This is an unlimited order to sell or buy which will be executed at the best available limit in the order book. If the order can only be partially fulfilled at that price, then the remaining part of the order will be entered into the limit order book with a limit price and timestamp determined by the price and time of the first executed part of this order.

The choice of the optimal order type for a transaction is highly dependent on the trader's subjective preference between the delay costs and the cost of immediacy. Orders can be further specified by adding execution conditions (which define whether an order has to be executed in full or can be executed in part), validity constraints (which determine how long the respective order is valid) and trading restrictions (which specify the possibilities of assigning orders to auctions).[55]

An electronic order book aggregates all limit and market orders from all Xetra participants. Orders in the order book will be matched based on price and time priority. The limit order book is anonymous but transparent to all Xetra participants. However, market participants have the capability to submit large orders into the electronic limit order book without revealing the entire size of theses orders to other participants. These sort of orders are known as iceberg orders. For an iceberg order, only a specified tranche, or peak, which is the visible volume for other market participants of an iceberg order, is entered in the order book, with the initial timestamp of the iceberg order. As soon as the visible part of the iceberg order has been completely fulfilled, if there is hidden volume remaining, a new tranche is introduced into the limit order book with a current timestamp.[56]

Market makers, also known as designated sponsors, may provide additional liquidity, particularly for less liquid stocks. They support trading on Xetra by committing themselves to the quoting of binding bid and ask prices for securities, up to a prespecified minimum quotation volume.[57] For more detailed information on the Xetra market model for equity trading see Deutsche Boerse (2011).

[55] See Deutsche Boerse (2011) for a full description of these order features.
[56] Cf. Deutsche Boerse (2011).
[57] Cf. Deutsche Boerse (2009).

Chapter 3

Relevant literature on market liquidity and the development of research hypotheses

This chapter gives an overview of the existing literature on market liquidity. After having laid out the foundations of market liquidity, we will now concentrate on the existing literature that relates to our three major research questions (see section 1.2). We begin by addressing literature focusing on market liquidity and the financial crisis. This is followed by an overview of the relevant research that concentrates on the influence of ownership structures, ownership concentration, and blockholder types on market liquidity. The last subsection of this chapter examines one specific type of stock-owner, the insider, and summarizes the literature findings regarding the influence of insider trading behavior on market liquidity.

Furthermore, in each subsection, we will elaborate on our research questions and derive testable research hypotheses that will be the basis for our empirical analysis in Chapter 5.

3.1 Market liquidity and the financial crisis[58]

In this section, we give an overview of the literature that addresses market liquidity in times of crisis, focusing upon considerations of two main liquidity phenomena in the context of the recent financial crisis: liquidity commonality and the flight-to-quality. Furthermore, we present our research hypotheses derived from the discussion of previous works.

3.1.1 Liquidity in times of crisis

In discussions of the current financial crisis, the important role of market liquidity was often highlighted.[59] However, the evolution and drivers of market liquidity in times of crisis have not been widely studied. Certain existing research studying market liquidity has touched on properties of liquidity during times of crisis and, in particular, analyzed the relationship (in both directions) between market liquidity and market returns.[60]

Amihud et al. (1990) were among the first to show that market liquidity can be a driving force for market declines. They propose that the stock market crash of 1987 can be at least partially explained by a comprehensive revision of investors' expectations regarding stock market liquidity. They argue that, as market liquidity is priced into the stock market (see, e.g., Amihud and Mendelson (1986)), a drop in investors' expectations regarding the liquidity of the market will lead to a decline in stock prices.

58 This section is largely based on Rösch and Kaserer (2012).

59 See, e.g., Brunnermeier (2009) for a presentation of the sequence of events of the current financial crisis and the role of liquidity.

60 The main focus of this existing research mostly has not been the analysis of market liquidity during times of crisis. Instead, most of the summarized results can be considered to be a byproduct of research with another primary focus.

Whereas Amihud et al. (1990) show a causal relationship between market liquidity and returns, in more recent research, the theory that market declines are a source for illiquidity is more widely acknowledged. Chordia et al. (2001) detect that market liquidity is affected by market returns in a sample of NYSE stocks from 1988 to 1992. They discover that bid-ask spreads respond asymmetrically to market returns, as they significantly increase in down markets and only marginally decrease in up markets. Liu (2006), with several different liquidity measures, demonstrates that market liquidity in the U.S. stock market is impaired following large economic and financial events such as the 1972–1974 recession, the 1987 crash, the Asian financial crisis in 1997, the 1998 Russian default, the collapse of the Long Term Capital Management hedge fund in 1998, the early 2000 burst of the high-tech bubble and the terrorist attacks on September 11, 2001. Hegde and Paliwal (2005) find that for U.S. companies, both those directly exposed to the Asian crisis[61] and those that were not, liquidity dried-up during this crisis period, resulting in an increase in spreads and a decrease of market depth. Analyzing 23 emerging markets over the period from 1993 to 2000, Lesmond (2005) descriptively demonstrates that bid-ask spreads as well as several other liquidity measures[62] sharply increase during the periods of the Asian and Russian crises. Yeyati et al. (2008), also focusing on emerging markets[63], use a sample of 52 stocks from seven different countries over the period from April 1994 to June 2004 to

[61] They define exposed firms as those U.S. companies that are fundamentally related to the Asian market, i.e., have either operations or significant sales or service offices in the crisis region or have more than 5% of their total sales in this region.

[62] Among the other measures used are the LOT measure, which is an indirect liquidity measure based on the number of zero returns (Lesmond et al. (1999)), Roll's estimator for an implied effective bid-ask spread (Roll (1984)) and Amihud's ILLIQ measure, which is the daily ratio of absolute stock return to its dollar volume (Amihud (2002)). See section 2.5 for a detailed description of these measures.

[63] Yeyati et al. (2008) research the following seven emerging markets: Argentina, Brazil, Indonesia, South Korea, Mexico, Russia, and Thailand.

demonstrate that crisis periods[64] are associated with higher liquidity costs and an initial increase in trading activity, which reverses at a later stage of the crisis. Hameed et al. (2010) also find that there is a negative relationship between market returns and changes in the proportional bid-ask spreads. They provide strong evidence that market declines cause market illiquidity, as on average, the spread increases by 2.8 (6.2) basis points in their sample of NYSE ordinary stocks from January 1988 to December 2003 after a (large)[65] market decline. Additionaly, Næs et al. (2011), by taking a more general view on the relation of business cycles and market liquidity, show that stock market liquidity tends to dry up during economic downturns, using an U.S. sample that considers NYSE common shares from 1947 to 2008 and a Norwegian sample from the Oslo Stock Exchange encompassing the period from 1980 to 2008.

All of these findings lead to our first hypothesis:

> **Hypothesis 1**: Market liquidity varies over time and is especially impaired during times of crisis or periods of market decline. Furthermore, there is a negative relationship between market returns and liquidity costs, i.e., market downturns lead to soaring liquidity costs.

Certain existing research attributes this negative reaction of market liquidity in periods of market downturn to two liquidity phenomena and their underlying causes. We therefore examine these two phenomena in the next two subsections.

[64] They define a crisis as a period that begins when the stock market index starts declining for at least five consecutive weeks and reaches a total loss in market value of more than 25% and ends after the index keeps rising for at least four consecutive weeks.

[65] They define a large market decline as a decrease in the weekly market return to below more than 1.5 standard deviations less than its mean.

3.1.2 Liquidity commonality

The phenomenon of liquidity commonality refers to the synchronicity of an individual asset's liquidity variation with aggregate market-wide liquidity movements and therefore describes the elusive concept of a common liquidity component that influences the secondary market asset liquidity of an individual company.[66] This phenomenon was initially discovered empirically by Chordia et al. (2000), who show that variations in firm-level bid-ask spreads and depths are partially caused by changes in aggregate market-wide spreads and depths. Further research following the initial discovery acknowledges the existence of liquidity commonality. Hasbrouck and Seppi (2001), for instance, use a principal component analysis to provide evidence for a single common liquidity factor influencing the liquidity of the Dow 30 stocks and find a small systematic liquidity component. Huberman and Halka (2001) also find that daily liquidity across NYSE stocks has a systematic and time-varying component. Brockman and Chung (2002) document the existence of liquidity commonality in an order-driven market structure using data from the Hong Kong Stock Exchange. Kamara et al. (2008) study the historic development of liquidity commonality across U.S. stocks for the period from 1963 to 2005. They find a strong time variation in liquidity commonality and an asymmetric development for small and large firms over time, i.e., liquidity commonality has declined for small firms, while it significantly increased for large firms. Kempf and Mayston (2008) focus on the liquidity commonality in an open limit order book market and show that the liquidity commonality becomes stronger with larger transaction sizes in the limit order book and that liquidity commonality exhibits a strong time variation. Additionally, the empirical results of Brockman et al.

[66] See Brockman et al. (2009a).

(2009a) confirm that an individual firm's bid-ask spreads or depths are significantly influenced by changes in the aggregate market's bid-ask spreads or depth, respectively, in 47 stock exchanges throughout the world. Besides the previously acknowledged exchange-level commonality component, they furthermore provide evidence for a global liquidity commonality component. These findings lead to our second research hypothesis:

> **Hypothesis 2**: Liquidity commonality exists and it exhibits a time-varying component.

Although the aforementioned research provides evidence for a strong liquidity co-movement, and research in the area of asset pricing has shown that this systematic and undiversifiable risk factor is also relevant in asset pricing[67], relatively little research has focused on the fundamental drivers affecting liquidity commonality. In fact, liquidity commonality can theoretically have three basic sources: co-variation in liquidity supply, co-movement in liquidity demand, or both. Several theoretical studies trying to explain the causal relationship between market returns and market liquidity that we described above (see 3.1.1), e.g., Bookstaber (2000), Kyle and Xiong (2001), Vayanos (2004), Garleanu and Pedersen (2007) and Brunnermeier and Pedersen (2009), argue that stock market declines either affect the liquidity demand (e.g., panic selling, risk aversion) or the supply for liquidity (e.g., margin or capital constraints, fund withdrawals by financial intermediaries). As these market-wide liquidity demand and supply effects of market declines have a market-wide impact on liquidity through simultaneously occurring transactions, we hypothesize that such declines therefore induce co-movement in

[67] See, e.g., Acharya and Pedersen (2005), Pastor and Stambaugh (2003), Sadka (2006), Korajczyk and Sadka (2008) and Kuan-Hui and Lee (2011) for research that focuses on the pricing of liquidity risk via a systematic liquidity risk component, i.e., liquidity commonality.

liquidity:

> **Hypothesis 3**: Liquidity commonality increases during time of crisis and market downturns.

Indeed, several empirical works provide evidence for such liquidity supply and demand factors influencing liquidity commonality. For instance, support for liquidity supply-side factors such as capital constraints (especially of common market makers and other financial intermediaries) is given by Coughenour and Saad (2004), Hameed et al. (2010) and Comerton-Forde et al. (2010), whereas Karolyi et al. (2011) don't find significantly consistent support for this source of liquidity commonality. Empirical support for demand-side determinants is, to an extent, provided in the works of e.g., Huberman and Halka (2001), Kamara et al. (2008), Karolyi et al. (2011) and Koch et al. (2011), who test demand drivers like common variation in trading activity, concentration of institutional ownership and investor sentiment.

As the theoretical work of Brunnermeier and Pedersen (2009), which focuses on supply-side explanations, has received tremendous academic recognition, we concentrate upon extending and applying this research to our empirical study. Brunnermeier and Pedersen (2009) propose a theoretical model that explains the spiral and dynamic interactions between funding liquidity and market liquidity.[68] See Figure 3.1 for an illustration of this nexus between funding and market liquidity. In their research, they argue that market declines reduce the value of financial intermediaries' assets and thus increase the probability of margin calls

[68] Bookstaber (2000), Kyle and Xiong (2001), Xiong (2001), Bernardo and Welch (2004), Cifuentes et al. (2005) and Garleanu and Pedersen (2007) follow a similar line of argumentation.

[69] Taken from Brunnermeier and Pedersen (2009).

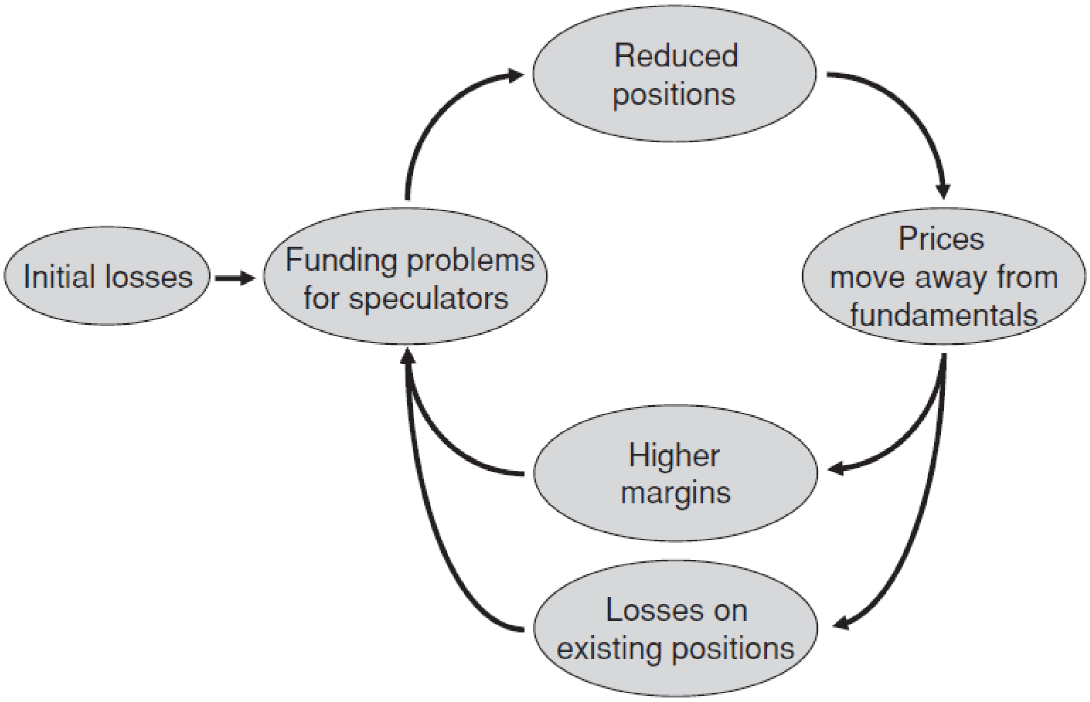

Figure 3.1: Funding and market liquidity spirals[69]

and higher margin requirements[70]. In aggregate, this causes funding liquidity problems for the financial sector, which coerces financial firms to liquidate parts of their portfolios. Those portfolio liquidations put additional pressure on market prices and impair market liquidity. The newly induced price declines due to lack of market liquidity, in combination with marking-to-market of the asset book, in turn induce further margin calls, which require additional portfolio liquidations. Thus, the initially exogenous market shock finally leads to financial contagion by creating a spiral of endogenous funding and market liquidity shocks. As this market-wide liquidity crisis simultaneously affects many securities at a time, their model further proposes that liquidity commonality is at least partially driven by

[70] In practice, one can observe that in addition to margin calls being induced by losses on the portfolio positions, during times of crises and illiquidity margin requirements are often increased.

the funding and market liquidity spiral.

In our research, we seek to empirically test this theory and therefore formulate our fourth hypothesis as follows:

> **Hypothesis 4**: Funding liquidity dry-ups leads to an increase in liquidity commonality.

3.1.3 Flight-to-quality and flight-to-liquidity

Two other liquidity phenomena that prevail in times of crisis and increased market uncertainty are the two interlinked phenomena of flight-to-quality and flight-to-liquidity, which are often used synonymously. These phenomena stem from observations of empirical investment behavior that demonstrate that in times of increased uncertainty in the financial markets, investors move their capital towards less risky (flight-to-quality) and more liquid assets (flight-to-liquidity). One oft-stated explanation of why these two phenomena are intertwined is that risky assets also tend to be less liquid, as noted in, e.g., Ericsson and Renault (2006). This is also our first hypothesis related to the flight-to-quality phenomenon:

> **Hypothesis 5**: An individual stock's asset liquidity is negatively related to its company's default probability, e.g., company rating.

Previous theoretical and empirical research on the impact of credit quality, i.e., the likelihood of default of an asset, on market liquidity typically indicates that there is an inverse relationship between liquidity costs and credit quality, although such studies almost exclusively focus on the bond or CDS markets. Ericsson and Renault (2006) develop a model to demonstrate the impact of market liquidity risk on corporate bond yield spreads. One main qualitative result from their model is that levels of liquidity spreads are positively correlated with credit risk/default probability. Chen et al. (2007a) analyze liquidity costs, using three different measures of liquidity[71], for over 4000 non-callable corporate bonds from 1995 to 2003 and find that liquidity costs decrease with greater creditworthiness, as measured by bond rating. This liquidity trend holds for various bond maturities. Looking at a CDS sample of 32 Fortune 500 companies from January 2004 to August 2006, Dunbar (2008) finds that the average bid–ask spread increases with a deterioration in credit ratings. However, Beber et al. (2009) find a negative relationship between credit quality and market liquidity across the Euro-area government bond market.

The dynamics of this aforementioned relationship in the context of crisis situations leads us directly to the flight-to-quality and flight-to-liquidity. Vayanos (2004) demonstrates theoretically that investors prefer more liquid instruments in times of market uncertainty (i.e., increased market volatility), which is reflected in increasing liquidity premiums. He explains this phenomenon for an increased preference for liquidity as an increase in the investor's risk aversion. Longstaff (2004) finds a flight-to-liquidity premium in U.S. Treasury bond prices, by comparing prices of Treasury bonds with identical bonds of Refcorp[72], which essentially only differ in their liquidity. He shows that there is a movement towards the more liquid Treasury bonds when the concerns about the future economic situation among market participants rise (as approximated by a drop in the consumer confidence index), leading to an increase in the flight-to-liquidity premium. Beber et al. (2009) also demonstrate that in times of financial crisis, investors chase for liquid-

[71] Bid-ask spreads, zero returns and the Lesmond et al. (1999) model's liquidity estimate.

[72] Refcorp is the Resolution Funding Corporation, which is a government agency founded by the Financial Institutions Reform, Recovery, and Enforcement Act of 1989 (FIRREA). Refcorp bonds are fully guaranteed by the U.S. Treasury and therefore necessarily have exactly the same credit risk as T-bonds; however, there is less liquidity for Refcorp bonds.

ity in the bond market. These findings are also consistent with Næs et al. (2011), who use data for Norway to show that in times of increased market uncertainty, some investors exit the stock market, which is perceived to be riskier than other asset classes, whereas others re-balance their equity portfolios towards larger and more liquid stocks.

We expect that the flight-to-quality and flight-to-liquidity also prevail in the stock market and therefore try to test these flight phenomena in the stock market, deriving the following research hypothesis:

> **Hypothesis 6**: Liquidity spreads between high- and low-credit-quality assets widen as a reaction to increased market uncertainty, i.e., assets with a high credit quality become more liquid compared with low-credit-quality assets during times of financial market distress.

As we hypothesize that high-credit-quality stocks are per se more liquid than low-credit-quality assets (see hypothesis 5), this hypothesis implies both a flight-to-liquidity and flight-to-quality in the stock market.

In the next section, we will survey the existing research on the impact of ownership structures on market liquidity.

3.2 Market liquidity and different ownership structures[73]

Blockholders, both internal and external, possess economies of scale in the collection of information or might have access to private, value-relevant information. Thus, there is a strong belief, backed by theoretical models, that market makers

[73] This section is largely based on Rösch and Kaserer (2010).

and other market participants face an adverse selection problem from these informed traders. As a result, market makers and uninformed participants therefore increase the spreads, which leads to poorer market liquidity, as noted in Copeland and Galai (1983), Glosten and Milgrom (1985) and our discussion in section 2.4. Hence, there should be a negative empirical relationship between ownership concentration and market liquidity, and we thus derive our research hypothesis:

> **Hypothesis 7**: Ownership concentration is generally associated with higher liquidity costs.

In fact, there is empirical evidence that supports this hypothesis. Demsetz (1968) was one of the first who showed empirically that ownership dispersion (measured by the number of shareholders) is positively related to liquidity. Becht (1999) demonstrates that voting power concentration through blocks has a negative effect on liquidity, as measured by annual turnover divided by market capitalization, in the Belgian and German stock markets. Heflin and Shaw (2000) find strong evidence in a sample of U.S. stocks that the magnitude of the internal or external blockholder ownership share has a negative impact on the stock liquidity. Sarin et al. (2000) as well as Dennis and Weston (2001) document that both institutions and insiders are better informed than other investors, and therefore, greater insider and institutional ownership is associated with poorer stock liquidity. Brockman et al. (2009b) notice that inside and outside block ownership impairs stock market liquidity (spreads and market depth) by reducing trading activity in an U.S. sample. Ginglinger and Hamon (2007a) find that large insider blockholders exhibit significantly lower liquidity in a French sample. Comerton-Forde and Rydge (2006) provide evidence that there is a negative relationship between stock ownership concentration and liquidity in an Australian sample. The fact that the difference between ultimate ownership and control leads to more severe information asymmetry and poorer stock liquidity was found by Attig et al. (2006) in a Canadian sample. Kothare (1997) find, in the context of rights and public offerings, that higher ownership concentration leads to an increase in liquidity costs. Rights offerings increase bid-ask spreads, whereas public underwritten offerings decrease the spreads. They attribute the difference to a change in the resulting ownership structure, as rights offerings increase the company's ownership concentration but public underwritten offers lead to a more diffuse ownership.

All these findings support our seventh hypothesis that because of information asymmetry, ownership concentration impairs stock market liquidity. Furthermore, these cited examples not only provide evidence for the negative impact of blockholders in general but also present some findings for the same effect for specific types of blockholders, mainly insider blockholders. Therefore, we also expect to provide empirical evidence that market liquidity is impaired by ownership concentration in our sample due to informational effects. In addition, we hypothesize that the shareholdings of specific blockholder types, namely, insiders and financial investors, should decrease market liquidity. These blockholders increase the level of information asymmetry because they are better informed, as they either possess economies of scale in the collection of information or have access to private, value-relevant information and might trade on this information.[74]

However, there is also a hypothesis that shareholder concentration can be positively related to market liquidity, if blockholders do not have access to private information, cannot leverage economies of scale in the acquisition of information,

[74] Existing research that confirms that insiders are able to earn abnormal returns when trading in their own company's securities and therefore fail to provide support for the strong-form market efficiency hypothesis, suggests that these insiders trade using non-public value-relevant information, as noted by, e.g., Jaffe (1974), Finnerty (1976), Demsetz (1986) and Seyhun (1986).

or simply face restrictions upon engaging in information-based trading. These conditions reduce the overall share and probability of information-based trading; consequently, liquidity costs are lower and market liquidity is improved. Thus far, there is little empirical evidence for this hypothesis, which might prove to be conditional on the type of blockholder, as access to private information is not uniformly distributed across all blockholder types. To date, the effects of different blockholder types have not been properly scrutinized.

> **Hypothesis 8**: Certain blockholder types do not have access to value-relevant information and/or face restrictions upon engaging in information-based trading. The presence of such blockholder types improves market liquidity.

Only Ginglinger and Hamon (2007a) and Fehle (2004) provide some evidence for this hypothesis. Ginglinger and Hamon (2007a) find in France that shareholders with double voting right shares (a French means of control enhancement rewarding long-term shareholders, often used by families that want to keep control while increasing free float) lead to increased liquidity for outside investors of small, family firms. They argue that double voting rights prevent informed shareholders from trading on private information, as such trading would lead them to lose their double voting rights. Consequently, information asymmetry is decreased and therefore market liquidity is improved. Fehle (2004) analyzes the effect of institutional blockholders on stock market liquidity. He finds that for his overall sample, there is a negative relationship between the share of institutional owners and bid-ask spreads, but a positive relationship between the number of institutional owners and bid-ask spreads (both effective and posted spreads). In the subsequent analysis of the effect of different institutional blockholder types, Fehle (2004) finds that the positive effect of institutional ownership share on stock market liquidity only holds for mutual funds; whereas for commercial banks and investment managers, the relationship reverses, and for other types, such as insurance companies and pension funds, the relationship is insignificant. Fehle (2004) explains that therefore some types of institutions (like commercial banks and investment managers) increase the adverse selection costs (in line with our first hypothesis), while others (like mutual funds) face restrictions in information based trading (in line with our second hypothesis) or specifically seek out stocks with relatively low liquidity costs.

For our research that scrutinizes the different types of blockholders, we hypothesize that the presence of private blockholders will improve market liquidity. We believe that private investors either do not have access to private information, are not able to leverage economies of scale in information acquisition, or are not willing to trade on any private information. In particular, the unwillingness to trade on private information seems obvious, as private investors mostly have an investment interest in long-term strategic opportunities and therefore follow a buy-and-hold investment strategy, seek a lower security turnover rate and take a long-term perspective regarding their investment.[75]

For the remaining blockholder type, strategic investors, the hypothesis is not so straightforward. As in the case of private blockholders, we would expect that strategic investors are not willing to trade on private information and therefore reduce liquidity costs, as strategic investors also usually take a long-term perspective on their investment if they acquire control of another company. However,

[75] In the context of family firms, several studies, such as, e.g., Casson (1999), Chami (2001) and Bertrand and Schoar (2006), posit that private investors are long-term investors. They argue that those investors even often see their investments as an asset that they want to pass on to their descendants rather than as wealth that they want to consume during their lifetimes (see also Becker (1976) and Becker (1981)).

this intuition might only hold for "real" strategic investors who possess a majority stake ($\geq$ 50%) in the acquired company. Such strategic investors are therefore in control of this company and are usually closely interconnected. For those investors classified as strategic investors with an ownership stake of less than 50%, we expect that they impair stock market liquidity, as their minor stake is usually not driven by a strategic motivation but rather a financial motivation. Therefore, they are more comparable to financial investors and thus we expect a similar deleterious impact on market liquidity for these kinds of strategic blockholders.

In the next section, we will focus on one specific type of shareholder, namely, the insider, and give an overview on the existing research regarding the impact of insider trading behavior on market liquidity.

3.3 Market liquidity and insider trading[76]

Insider trading is a topic that has received a tremendous amount of attention in law, economics and finance in both practice and academia. Considerable resources have been devoted to establishing and enforcing legal restrictions for insider trading, and those researchers in favor of insider trading restrictions at least partially justify these restrictions with the hypothesis that insider trading creates an adverse selection problem that impairs stock market liquidity.[77]

Early empirical research on market liquidity has focused on investigating the determinants of the cross-sectional variation in liquidity across stocks, as seen in, e.g., Benston (1974), Stoll (1978a), Glosten and Harris (1988), Stoll (1989) and George et al. (1991). These researchers conclude that informational effects explain

[76] This section is largely based on Rösch and Kaserer (2011).
[77] See, e.g., Georgakopoulos (1993).

some of the variation in the market liquidity. However, further empirical research is required to better understand the impact of adverse selection on stock market liquidity. In particular, the subject of this work - the impact of insider trading on market liquidity - is an interesting field of research, as insider trading seems to be a prime example of information-based activity in the financial market and, as already mentioned, the few available empirical research results in this field are mixed. To appropriately comprehend the existing research, we summarize it by categorizing these research results in accord with their observed impact of insider trading on market liquidity.

We begin with those studies that indicate that insider trading has no impact on stock market liquidity: Cornell and Sirri (1992) and Chakravarty and McConnell (1997) dedicate their research to two prominent cases of illegal insider trading activity. Cornell and Sirri (1992) identify illegal insider transaction centered around the acquisition of Campbell Taggart by Anheuser-Busch in 1982, by using ex post court records. They report that their spread estimates[78] did not rise during the period of illegal insider trading and therefore market liquidity did not fall.

Chakravarty and McConnell (1997) analyze the illegal insider trading activity of Ivan Boesky surrounding the acquisition of Carnation Company by Nestlé S.A. in 1984. Chakravarty and McConnell (1997) demonstrate that both the bid-ask spreads and depths appear to be unaffected by his trades; however, for certain data depths appear to be improved. Interestingly, both studies that found no impact of insider trading on market liquidity did focus on illegal insider trading.

We now continue with those empirical research studies demonstrating that market liquidity is improved by insider trading: The initial public offering (IPO)

[78] They use the serial covariance measure presented by Roll (1984), which we explained in section 2.5, to estimate spreads, as the bid-ask spread was not directly observable in their data.

lockup expiration constitutes an attractive event in corporate finance for testing the informational effect of insider trading activity on market liquidity, as on the lockup expiration day, insiders are legally allowed to sell their shares for the first time since the IPO. Therefore, lockup expirations presumably marks a pre-announced event during which informed insider traders enter the equity markets via large sale transactions. Both Cao et al. (2004) and Krishnamurti and Thong (2008) concentrate on this event type for their studies. Cao et al. (2004) analyze intraday trades around 1,497 IPO lockup expiration dates. In their overall sample, insider sales have little effect on effective spreads. However, for those lockup expirations where insiders disclose their share sales (23% of the whole sample), spreads actually decline.

Krishnamurti and Thong (2008) focus on the IPO lockup expiration of 399 technology stocks listed on the NASDAQ market for the period covering 1998 to 2000. They found that the market liquidity actually improves immediately after the lockup expiration period. Similarly to Cao et al. (2004), they discover that for the set of firms where insiders actually report their sales during a 10-day post lockup expiration period, bid-ask spreads actually decline more as compared with other firms. They attribute their finding largely to a decline in the adverse selection component of the spread. It is noteworthy that both studies demonstrating a positive relationship between insider trading and market liquidity solely focus on insider sales in the context of lockup expirations.

We conclude our literature overview with the empirical research that discovered that insider trading impairs market liquidity. Bettis et al. (2000) analyze corporate policies and procedures, e.g., blackout periods[79], put in place to regulate insider

[79] According to Bettis et al. (2000), most corporate policies define blackout periods in relation to earnings announcements, in which cases the single most common rule for a blackout period only permits insider trading for the period 3 to 12 trading days after the quarterly

trading in the company's own shares. Bettis et al. (2000) conclude that blackout periods successfully suppress both insider purchases and insider sales, and they found that the bid-ask spread is narrower by approximately two basis points during the blackout period, which implies, in turn, that market liquidity is impaired in periods where insider trading is permitted.

Over a period from May 1996 to April 2000, Cheng et al. (2006) examine the effect of 12,435 insider transactions on the market liquidity of 701 companies listed on the Hong Kong Stock Exchange. For their sample, they concluded that spread widens and depth falls on insider trading days compared with non-insider trading days.

Chung and Charoenwong (1998) analyze 1,101 NYSE and AMEX stocks and 11,522 insider transactions in 1988. Although they did not find any evidence for a spread change on insider trading days in a time-series regression analysis, they found increased spreads for those companies with a greater extent of insider trading in a cross-section analysis. They argue that market participants may not be able to detect insider trading when it occurs; however, in their cross-section analysis they suggest that the uninformed market participants price protect themselves against a cross-sectionally greater extent of insider trading. We conclude that this cross-sectional measure of insider activity can be seen as a proxy for insider ownership. Thus, their findings are in line with several studies analyzing the impact of insider ownership on stock market liquidity, which showed that a concentration of insider holdings impairs market liquidity.

As the existing research on insider trading is very limited, we will further briefly examine an adjacent stream of literature that focuses on the influence of stock repurchases, which are, by definition, large-scale managerial trades, on stock market

earnings announcement and disallows trading at all other times.

liquidity: Barclay and Smith (1988) investigate 244 open-market repurchases by 198 NYSE-listed firms between 1970 and 1978 and find that stock repurchases have a negative impact on market liquidity. Brockman and Chung (2001) study the timing of open market share repurchases and the resultant impact on firm liquidity for firms listed on the Hong Kong Stock Exchange, a market that requires public disclosure of share repurchases. In their sample, market liquidity is impaired by stock repurchases. Ginglinger and Hamon (2007b) use data from Euronext Paris to examine the timing of actual stock repurchases and their impact on market liquidity for the period from 2000 to 2002. They also discover that market liquidity deteriorates during repurchase periods.

Summarizing the literature that indicates a deleterious effect of insider trading, we can conclude that much of this research focuses on either insider purchases (Barclay and Smith (1988), Brockman and Chung (2001) and Ginglinger and Hamon (2007b)) or on a proxy of insider ownership instead of insider trading (Chung and Charoenwong (1998) and Bettis et al. (2000)).

Although the presented previous studies report mixed empirical results and provide no clear indication of how market liquidity is affected by insider trading, we establish a research hypothesis that tries to integrate and explain most of the previously discussed results. The adverse selection theory posits that market liquidity falls, i.e., liquidity costs increase, as the intensity of information asymmetry rises. However, the question then remains of what factors influence the market's assessment of information asymmetry created by insiders. We are confident that market participants proxy the extent of information asymmetry induced by insiders by the share of insider-ownership.[80] Given this, we can derive our research hypothesis that predicts a twofold impact of insider transactions on stock market

[80] See, e.g., Chiang and Venkatesh (1988).

liquidity:

> **Hypothesis 9**: Market liquidity is impaired on and after days of insider purchases.

We expect market participants to price protect by increasing liquidity costs on and after the days of insider purchases. This occurs because insider purchases increase the share of insider ownership and consequently increase the information asymmetry, as insider ownership constitutes a measure of information asymmetry induced by insiders.

This hypothesis is also supported by the findings of Barclay and Smith (1988), Chung and Charoenwong (1998), Bettis et al. (2000), Brockman and Chung (2001) and Ginglinger and Hamon (2007b) presented above that focus on insider purchases or proxy insider ownership in their works.

> **Hypothesis 10**: Market liquidity is improved on and after days of insider sales.

As a corollary to hypothesis 9, insider sales, by decreasing the share of insider holdings, therefore alleviating information asymmetry and improving market liquidity on and after the days of insider sales. Our hypothesis is also consistent with the finding of Lakonishok and Lee (2001), who argue that purchases are the only source of informativeness of insider activities, whereas insider sales appear to have no predictive ability.[81] Therefore, insider sales are driven by liquidity or diversification reasons and thus are bringing additional liquidity into the market.

In addition, the empirical findings of Cao et al. (2004) and Krishnamurti and Thong (2008), who analyzed large-scale insider sales during lockup expirations, seem to support this hypothesis.

[81] Further studies positing the informativeness of purchases compared with sales are Madhavan and Smidt (1991) and Chan and Lakonishok (1993).

Both hypotheses on the effect of insider trading are consistent with empirical literature focusing on the relationship of insider ownership and market liquidity, which showed that insider ownership impairs market liquidity, as seen in, e.g., Heflin and Shaw (2000) and our results in section 5.2. Purchases leading to a higher share of insider ownership should worsen market liquidity, while sales decreasing the insider ownership should improve market liquidity.

In this chapter we provided an overview of the existing literature in our field of research and derived testable hypotheses. This will be followed by an introduction of our empirical data in the next chapter.

Chapter 4

Sample data and descriptive information

This chapter describes in detail the data sets that we will use in the empirical analysis in Chapter 5 to answer our research questions and test our research hypotheses that were derived in Chapter 3. We divide the presentation of the different types of data according to our three main research questions in section 4.1. In particular, the presentation of the average daily liquidity costs $L(q)$ for our sample stocks is quite useful for obtaining a sense of the magnitude and variance of liquidity costs and liquidity risk in the German market. This is followed by an overview of the descriptive statistics of our data sets in section 4.2, which will provide useful first insights into our data sets in the sample period.

4.1 Description of sample data sets[82]

In our research, we focus on the 160 companies listed in one of the four major German stock indices (DAX, MDAX, SDAX, TecDAX), which are all traded on Xetra. The DAX is a blue-chip stock market index consisting of the 30 major publicly

[82] This section is largely based on Rösch and Kaserer (2010), Rösch and Kaserer (2011) and Rösch and Kaserer (2012).

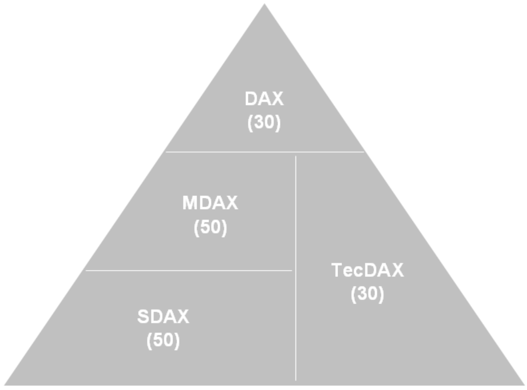

Figure 4.1: Overview of German equity indices

listed companies in Germany (in terms of order book volume and market capitalization). The MDAX comprises the subsequent 50 largest stocks[83], excluding technology stocks. The SDAX consists of the 50 stocks that rank directly below the MDAX. The TecDAX[84] comprises the 30 largest technology stocks listed in Germany. For an overview of the relative ranking of the four indices, see Figure 4.1. With a market capitalization of approximately EUR 800 billion, these four indices represent the largest part of the total domestic market capitalization of EUR 900 billion.[85]

4.1.1 Market liquidity and the financial crisis[86]

The portion of our research dedicated to the effects of the financial crisis on market liquidity focuses on the period from January 2003, as the aftereffects of the previous large crises (the Internet bubble and September 11th, 2001) ceased at the end of 2002, to December 2009.

As described above, our dataset focuses on the four major German indices,

[83] The MDAX consisted of 70 stocks before March 24, 2003 and of 50 stocks thereafter.
[84] TecDax was introduced on March 24, 2003, during our sample period.
[85] As of Dec 2009, according to World Federation of Exchanges (2010).
[86] This section is largely based on Rösch and Kaserer (2012).

and because the composition of the four indices changes over time according to specific rules set by Deutsche Börse, we dynamically adjusted the sample over our sample period from January 2003 to December 2009. We included a company in our sample for the time it has been a constituent of any of the four indices. In line with this procedure, there are 272 companies listed in one of the four indices during our sample period. In the following sections, we will introduce our data for market liquidity, ratings, as well as the control variables, in detail.

4.1.1.1 Market liquidity

In total, our sample contains over 2.3 million observations for the 1,760 trading days in our sample period[87]. Table 4.1 shows an overview of the average daily liquidity costs $L(q)$ for our sample stocks in the four major German stock market indices. Average liquidity costs were 121 bps across all volume classes and indices and range from 6 bps for an order volume of Euro 25,000 in DAX stocks to 500 bps for an order volume of Euro 1 million in SDAX stocks. Table 4.1 also shows that there is a clear ranking of liquidity costs among the stock indices, i.e., stocks in the DAX have the lowest liquidity costs, followed by those in the MDAX, TecDAX and SDAX, and that liquidity costs are order-size-dependent, i.e., the larger the order sizes q, the larger the liquidity costs $L(q)$.

[87] Because for certain stocks, our dataset contains liquidity data for volume classes outside the standardized set of volume classes of the respective index, we excluded these observations (0.02% of the total observations in our sample). We assumed that these observations were due to tests of an extended volume class coverage in the automatic calculation routine of the Xetra system, as the observations were only available for connected periods of less than a trading week. We removed these observations to ensure that our dataset remains representative.

Table 4.1: Liquidity costs $L(q)$ for the impact of the financial crisis

Average of daily liquidity costs $L(q)$ for our sample companies for the portion of the research focusing on the impact of the financial crisis on market liquidity in the four major German indices (DAX, MDAX, SDAX, TecDAX) for the sample period from January 2003 to December 2009. The liquidity costs are calculated for the 14 volume classes q, which are in Euro thousands and are measured in basis points. The total represents the average liquidity costs across all volume classes for the respective index.

Volume class q	DAX	MDAX	SDAX	TecDAX	All
10		20.75	68.36	32.20	41.55
25	6.39	26.55	92.35	43.50	45.99
50	7.42	35.68	136.43	62.40	65.51
75		45.26	177.09	82.27	101.71
100	9.53	54.89	212.52	102.25	99.61
150		74.63	261.52	136.16	151.57
250	15.71	111.83	325.11	191.32	154.49
500	26.25	182.80	393.20	282.29	191.70
750		233.27	448.10	337.80	290.71
1000	49.26	262.38	500.42	371.89	220.58
2000	87.35				87.35
3000	113.64				113.64
4000	138.39				138.39
5000	157.72				157.72
Total	59.29	96.40	195.75	138.78	120.88

4.1.1.2 Ratings

Information on company ratings are obtained from Thomson Financial Datastream. If no rating information was available in Thomson Financial Datastream, we obtained the information from the company's annual or quarterly reports, its website or from the company's investor relations department. We collected the individual company's full history of the long-term issuer ratings from Standard & Poor's (S&P)[88] during the sample period.

Overall, 67 companies[89] possess a rating (at least for some time) during our sample period. For all other companies, we obtained an explicit statement from the respective company that they are not publicly rated.

Figure 4.2 provides an overview of the distribution of our daily liquidity observations by rating category and index. Almost 78% of the observations that are associated with a credit rating are associated with investment grade ratings. However, the distribution is heterogeneous across indices: Almost 93% of the observations in the DAX and only 34% of the rated SDAX observations are associated with investment grade ratings. There appears to be a clear rating ranking among the indices, i.e., companies in larger indices have better ratings than companies in smaller indices.

[88] Five companies, namely Aareal Bank, GEA Group, IKB Deutsche Industriebank, Pfleiderer and ProSiebenSat.1 Media were not rated by S&P but by Fitch; Degussa and Rhoen-Klinikum were only rated by Moody's; and VHB Holding was exclusively rated by Euler Hermes Rating. For these companies we translated the respective ratings into the S&P rating categories. A table matching the different rating categories can be found in the Appendix (see Table A.1).

[89] See Table A.2 in the Appendix for an overview of the rated companies.

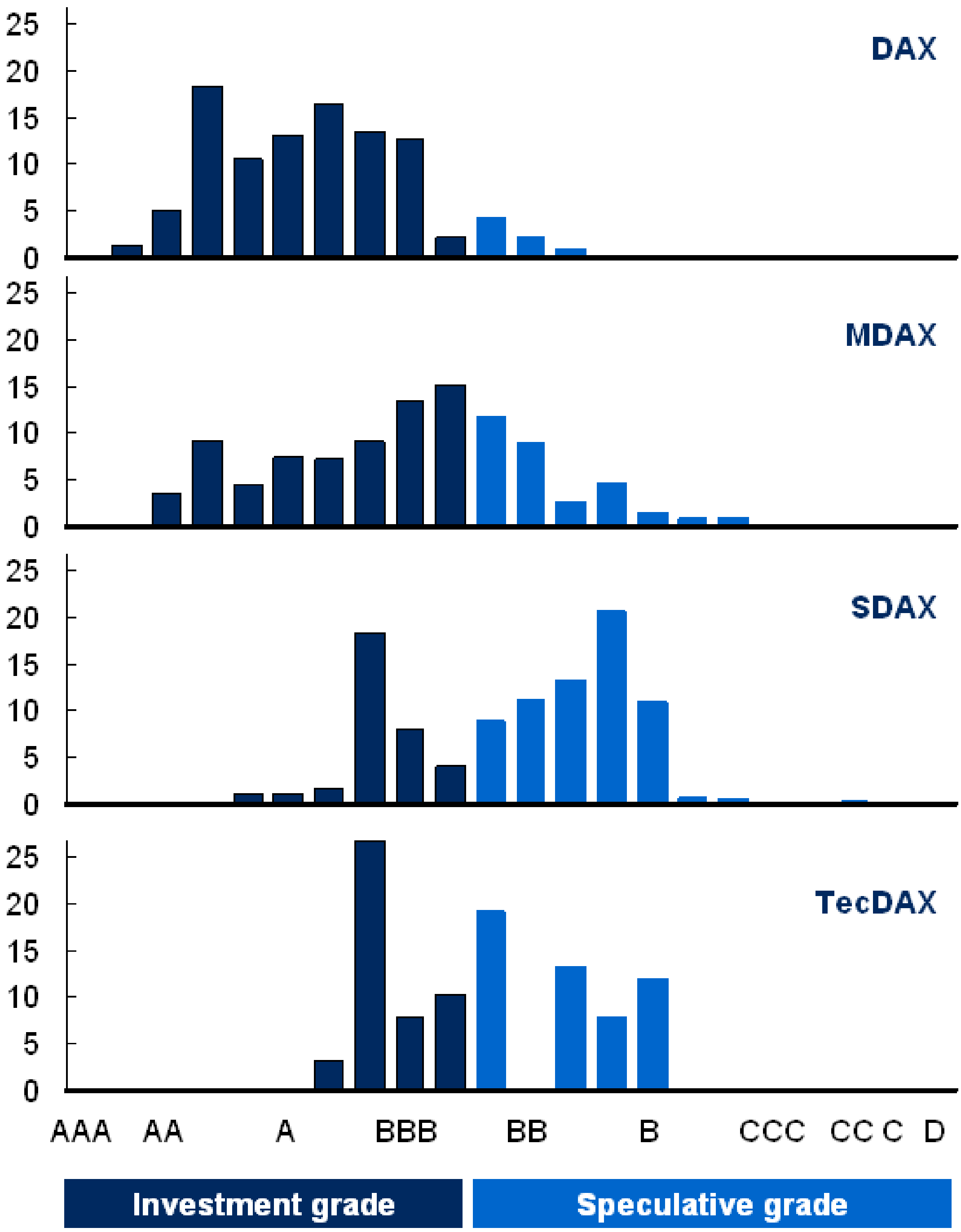

Figure 4.2: Rating distribution of sample observations by index

This figure shows the distribution of our daily sample observations by rating class within one of our four major indices (DAX, MDAX, SDAX, TecDax) over the time period from January 2003 to December 2009. The distribution only includes those observations that are associated with a rating. The figure further distinguishes between investment (dark blue) and speculative (light blue) grade ratings in accord with S&P. The relative frequencies by index are in percent.

4.1.1.3 Index, EONIA and EURIBOR data

For the analysis of liquidity commonality, we further require return data from several indices (DAX, MDAX, SDAX, TecDAX, DAX All Banks) and interest rate data of the EONIA and the EURIBOR. The DAX, MDAX, SDAX and TecDAX are the four major German stock indices, and their index constituents are all traded on Xetra. The DAX All Banks index consists of all major German banks and is therefore a good proxy for the development of the market valuation of the German banking sector. The EONIA (Euro Over Night Index Average) is an interest rate for unsecured, overnight interbank loans. It is computed by the European Central Bank as a weighted average of all such interbank transactions. The same panel of banks is used for the EURIBOR (Euro Interbank Offered Rate). The EURIBOR is the average rate at which the panel banks offer to lend unsecured funds to other panel banks in the interbank market for maturities of one, two and three weeks and all monthly maturities of one to twelve months. For our analyses, we use the 3-month EURIBOR.

The daily index returns of the DAX, MDAX, SDAX, and TecDAX, the monthly index returns of the DAX All Banks and the 3-month EURIBOR are all obtained from Thomson Financial Datastream. The EONIA was provided by the European Central Bank.

4.1.2 Market liquidity and different ownership structures[90]

This portion of our research focuses on the same 7 years, from January 2003 to December 2009, as the research portion above on the impact of the financial crisis. Due to the same dynamic adjustment of the index composition, we end

[90] This section is largely based on Rösch and Kaserer (2010).

up with the same 272 companies as above. However, as it is standard for studies on ownership structures, we exclude all 40 financial firms from our sample. We further remove 20 companies with foreign ISINs, as they have different corporate governance structures, which would distort our analyses. This process leaves us with a total of 212 companies in our sample period. In the following sections we introduce our data for market liquidity as well as for the ownership concentration and structures.

4.1.2.1 Market liquidity

In total, our sample contains over 1.5 million observations in our sample period[91]. For our research we, calculated the yearly average of the liquidity costs $L(q)$ for every single company and every available volume class q. Table 4.2 shows an overview of the average daily liquidity costs $L(q)$ for our sample stocks in the four major German stock market indices. The average liquidity costs were 178 bps across all volume classes and indices and range from 6 bps for an order volume of Euro 25,000 in DAX stocks to nearly 700 bps for an order volume of Euro 1 million in SDAX stocks. Table 4.2 again shows that there is a clear ranking of liquidity costs among the stock indices, i.e., the stocks in the DAX have the lowest liquidity costs followed by those in the MDAX, TecDAX and SDAX, and that liquidity costs are order-size-dependent, i.e., the larger the order sizes q, the larger the liquidity costs $L(q)$.

[91] Because, for certain stocks, our dataset contains liquidity data for volume classes outside the standardized set of volume classes of the respective index, we excluded these 325 observations (0.02% of the total observations in our sample). We assumed that these observations were due to tests of an extended volume class coverage in the automatic calculation routine of the Xetra system, as the observations were only available for connected periods of less than a trading week. We removed these observations to ensure that our dataset remains representative.

Table 4.2: Liquidity costs $L(q)$ for the impact of ownership structures

Average of liquidity costs $L(q)$ for our sample companies for the portion of the research focusing on the impact of ownership structures on market liquidity in the four major German indices (DAX, MDAX, SDAX, TecDAX) for the sample period from 2003 to 2009. The liquidity costs are calculated for the 14 volume classes q, which are in Euro thousands and are measured in basis points. The total represents the average liquidity costs across all volume classes for the respective index.

Volume class q	DAX	MDAX	SDAX	TecDAX	All
10		23.58	95.30	33.33	53.55
25	6.16	30.38	109.54	45.62	53.98
50	7.18	42.86	154.65	65.32	75.28
75		55.53	198.49	86.47	115.45
100	9.24	67.90	239.38	109.43	117.65
150		89.18	301.33	153.28	182.36
250	15.28	125.56	376.74	233.25	203.20
500	25.53	197.96	466.54	382.18	280.44
750		262.84	584.21	480.72	422.46
1000	47.28	308.35	697.01	558.71	388.80
2000	91.63				91.63
3000	127.46				127.46
4000	165.98				165.98
5000	196.55				196.55
Total	70.32	117.30	291.27	210.43	178.19

4.1.2.2 Ownership

Information on stock ownership structures is obtained from Hoppenstedt "Aktienführer". The "Hoppenstedt Aktienführer" is a German annual database that provides certain information on listed German firms (e.g., detailed information on ownership structures, board compositions, and balance sheet data). The ownership structures are those available at the end of each year.

For every company and every year in our sample, we collected the individual blockholders[92] and their respective stockholdings.[93] Furthermore, we collected information on the individual management board and supervisory board members and their respective stockholdings from Hoppenstedt.

From this information, we calculated the following measures that serve as proxies for the ownership concentration: the total share of blockholdings C[94], the number of blockholders CN, the Herfindahl index HHI[95] and the share of the largest $C1$ and the three and five largest blockholders, $C1C3$ and $C1C5$, respectively. Having detailed information on every blockholder, we are able to further break down these proxies into four mutually exclusive and collectively exhaustive categories: insiders, strategic, financial and private investors. For these categories, we calculated the respective percentage of blockholdings. We define as insiders all current and former management board and supervisory board members, employees as well as own shares. The insider category, therefore, includes all shares that are directly or indirectly controlled by the management and supervisory board.

92 We follow prior research to define blockholders as shareholders who hold five percent or more of a company's total shares.

93 We collected a maximum of the 12 largest individual blockholders for our sample companies.

94 Measured as a fraction [0;1].

95 Following prior research we use the sum of the squares of the individual blockholder shareholdings: $HHI = \sum_h p_h^2$ where p_h represents the percentage share of the individual blockholders. The Herfindahl index is a parameter specifying the characteristics of the size distribution of the blockholder shareholdings, see, e.g., Cubbin and Leech (1983).

As private investors, we classify those blockholdings that are held by individuals as part of their personal assets.

4.1.3 Market liquidity and insider trading[96]

As the disclosure requirement of directors' dealings came into effect on July 1st, 2002, we focus on the period from July 2002 to December 2009 in our research on the impact of insider trading activity on market liquidity.

Once again, we dynamically adjust the sample over our sample period from July 2002 to December 2009 to include a company in our sample for the time it has been a constituent of any of the four major indices. In line with this procedure, there are 285 companies listed in one of the four indices during our sample period. In the following sections, we will introduce our data for market liquidity, directors' dealings and insider ownership.

4.1.3.1 Market liquidity

In total, our sample contains over 2.4 million observations for the 1,888 trading days in our sample period[97]. Table 4.3 shows an overview of the average daily liquidity costs $L(q)$ for our sample stocks in the four major German stock market indices. The average liquidity costs were 124 bps across all volume classes and indices and range from 7 bps for an order volume of Euro 25,000 in DAX stocks to 500 bps for an order volume of Euro 1 million in SDAX stocks. Table 4.3 also

96 This section is largely based on Rösch and Kaserer (2011).

97 Because, for certain stocks, our dataset contains liquidity data for volume classes outside the standardized set of volume classes of the respective index, we excluded these 500 observations (0.02% of the total observations in our sample). We assumed that these observations were due to tests of an extended volume class coverage in the automatic calculation routine of the Xetra system, as the observations were only available for connected periods of less than a trading week. We removed these observations to ensure that our dataset remains representative.

Table 4.3: Liquidity costs $L(q)$ for insider trading impact

Average of daily liquidity costs $L(q)$ for our sample companies for the research part focusing on the impact of insider trading on market liquidity in the four major German indices (DAX, MDAX, SDAX, TecDAX) for the sample period from July 2002 to December 2009. The liquidity costs are calculated for the 14 volume classes q, which are in Euro thousands and are measured in basis points. The total represents the average liquidity costs across all volume classes for the respective index.

Volume class q	DAX	MDAX	SDAX	TecDAX	All
10		26.61	78.71	32.20	47.73
25	6.90	34.11	99.43	43.50	50.05
50	8.08	44.17	142.01	62.40	68.80
75		54.50	183.05	82.27	106.05
100	10.50	64.67	218.91	102.25	102.71
150		85.61	267.55	136.16	156.12
250	17.83	122.69	328.48	191.32	156.72
500	30.64	191.20	393.04	282.29	193.05
750		239.14	448.00	337.80	293.35
1000	58.54	266.59	500.37	371.89	221.89
2000	101.73				101.73
3000	126.26				126.26
4000	150.85				150.85
5000	170.52				170.52
Total	65.66	102.64	200.05	138.78	124.48

shows that there is a clear ranking of liquidity costs among the stock indices, i.e., stocks in the DAX have the lowest liquidity costs, followed by those in the MDAX, TecDAX, and SDAX, and that liquidity costs are order-size-dependent, i.e., the larger the order sizes q, the larger the liquidity costs $L(q)$.

4.1.3.2 Directors' dealings

Information on directors' dealings is obtained from the Bundesanstalt für Finanzdienstleistungsaufsicht, which is the financial regulatory authority for Germany and is better known by its abbreviation BaFin. BaFin's security supervision division is, among others duties, responsible for enforcing insider trading and directors' dealings regulations in Germany.

Since July 2002, members of the management or supervisory board and other persons with executive duties, who have access to (value-relevant) insider information are required to notify both the company and BaFin of any dealings in their firm's own shares , in accordance with section 15a of the Securities Trading Act (Wertpapierhandelsgesetz – WpHG). The same requirement "also applies to spouses, registered civil partners, dependent children and other relatives living with them in the same household for at least one year. In certain circumstances, legal persons, such as establishments acting in a fiduciary capacity (e.g., foundations) and partnerships, may also be subject to the notification requirement."[98]

For every company in our sample, we collect every single transaction made by an insider during our sample period. The information on the transaction that was provided by BaFin includes the date, price, size (as the number of shares traded) and type (either a purchase or sale) of the transaction. Combining these data with our detailed information on the insider who initiated the transaction, we are able to further break down the insiders into three mutually exclusive and collectively exhaustive insider categories: the management board, the supervisory board and the other employees. Therefore, we are able to calculate the number of insiders trading on a trading day and the respective total transaction size, and we are able to distinguish this information for both buy and sell transactions and our three insider categories.

4.1.3.3 Insider ownership

Information on insider ownership is also obtained from Hoppenstedt "Aktienführer". The insider ownership data are those that are available at the end of each year.

98 Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin) (2012)

For every company and every year in our sample[99] we collect the 12 largest individual shareholders. We further collect information on the individual management board and supervisory board members and are therefore able to identify their respective stock-holdings from Hoppenstedt. We then calculate the total share owned by insiders[100] at the end of the year. With this information, we are able to relate the nominals transacted by insiders on a day to the total nominals owned by insiders at the end of the year.

4.1.4 General control variables[101]

Prior research suggests that liquidity costs are at least partially explained by the variations in share price, return volatility, trading activity and firm size.[102] Therefore, we use the daily Xetra closing price P, the standard deviation of daily log-returns σ_r, the daily transaction volume VO as a proxy for trading activity and the daily market value MV as a proxy for firm size as control variables in our model specifications. In an order-driven market, the rationale for these control variables is mainly based on considerations about order processing, inventory and information asymmetry.[103]

99 As the insider ownership information is only available at the end of each year, we restrict our sample to the period from January 1st, 2003 to December 31st, 2009 to use only full year periods for the analysis that uses data on insider ownership. Analogously to the portion of our research focusing on the ownership structures, we further excluded all 40 financial firms and all 20 companies with foreign ISINs from our sample, as it is standard for studies that analyze ownership structures, as they might have different corporate governance structures that might distort our analysis.

100 We define as insiders all current and former management board and supervisory board members, employees as well as own shares. The insider category, therefore, includes all shares that are directly or indirectly controlled by the management and supervisory board.

101 This section is largely based on Rösch and Kaserer (2010), Rösch and Kaserer (2011) and Rösch and Kaserer (2012).

102 See, e.g., Benston (1974), Stoll (1978a), Copeland and Galai (1983), Barclay and Smith (1988), Hanley et al. (1993), Corwin (1999), Stoll (2000), Heflin and Shaw (2000), Acharya and Pedersen (2005) and Stange and Kaserer (2008).

103 See, e.g., Stoll (2000) and Corwin (1999).

The price level P controls for the effect of discreteness[104] and is also a further risk proxy, as lower-priced stocks tend to be riskier[105]. Hence, liquidity costs should theoretically be a decreasing function of the price level.[106] On the one hand, return volatility measures the inventory risk of limit order traders, e.g., the risk of non-execution due to adverse price changes of stocks in the inventory, and on the other hand, it serves as a proxy for the general market condition and risk[107]. Therefore, liquidity costs should theoretically increase with a rise in the return volatility.[108] Transaction volume VO proxies inventory risk, as the probability of fulfillment of limit orders tend to increase with high transaction volume. Consequently, there should be an inverse relationship between transaction volume and liquidity costs. Similarly to trading volume, market value MV proxies inventory risk for the same reasons. However, the market value of a company is also a proxy for information asymmetry, as there is usually better analyst and media coverage for larger companies, and therefore, the adverse selection costs resulting from the risk of trading with individuals who possess private information decreases. All in all, smaller stocks tend to be less liquid.[109]

Daily stock returns, daily stock prices, daily trading volume, and daily market capitalization are obtained from Thomson Financial Datastream. We had to adjust the daily price data because Datastream carries forward price data if no transaction took place. We therefore removed all price data from days when no transaction volume was recorded. The data for market value MV and transaction volume VO were used as provided by Datastream. For the portion of our research

[104] Cf. Harris (1994).
[105] See, e.g., Bachrach and Galai (1979).
[106] See, e.g., Stoll (2000).
[107] Stoll (1978b) and Ho and Stoll (1981) theoretically show that return volatility, rather than systematic risk, is a relevant driver for liquidity costs.
[108] See, e.g., Copeland and Galai (1983).
[109] See, e.g., Pastor and Stambaugh (2003).

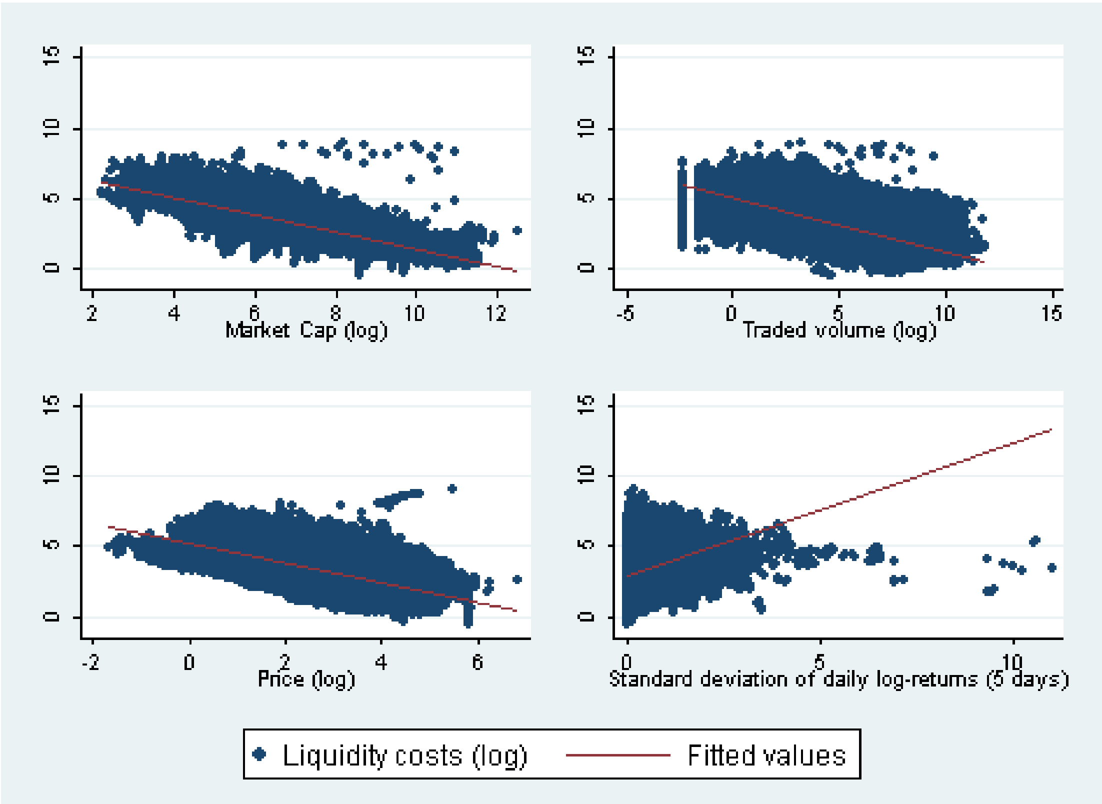

Figure 4.3: Liquidity costs and control variables

These graphs show scatter plots over the time period from January 2003 to December 2009 of log-transformed liquidity costs $L(q)$ (liquidity costs $L(q)$ are represented by the price impact per transaction, calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book) for the volume class of EUR 25 thsd. plotted against the four control variables: log-transformed market value MV, log-transformed transaction volume VO, log-transformed price P and the standard deviation of log-returns σ_r. Closing price is the daily Xetra closing price in Euro. Market cap shows the daily market value at day closing, expressed in Euro millions. Traded volume represents the number of shares traded for a stock on a particular day, expressed in thousands. Stdev. log-returns is the annualized 5-day standard deviation of the daily log-returns. The graphs further show fitted regression lines.

focusing on ownership structures and market liquidity, we calculated yearly averages from these inputs; we also calculated the standard deviations of the stock log-returns for each year. For the portion of our research focusing on the financial crisis and insider trading, we calculated the 5-day standard deviation of daily stock log-returns from the daily price data.

For most of our empirical regression analyses in Chapter 5 we log-transform the liquidity costs in line with Stange and Kaserer (2008) in our regressions to account for the skewness in the liquidity data. We further transform the control variables transaction volume VO, the Xetra closing price P and the market capitalization MV by taking their natural logarithms. The linear relationship between our log-transformed liquidity costs and our log-transformed control variables MV, VO and P and our control variable σ_r can be seen in Figure 4.3. Liquidity costs, therefore, appear to have, as predicted, an inverse relationship with price, market capitalization and trading volume, whereas liquidity costs appear to increase with the return volatility.

4.2 Descriptive information

4.2.1 Market liquidity and the financial crisis[110]

Table 4.4 gives an descriptive overview of all of the variables used in the following empirical analyses of the impact of the financial crisis on market liquidity by the four major indices. As already mentioned above, the average liquidity costs are 121 basis points. The average Xetra closing price is Euro 28.29, the average market capitalization is over Euro 5.1 billion and on average there are 1.1 million

[110] This section is largely based on Rösch and Kaserer (2012).

Table 4.4: Descriptive statistics of variables for the impact of the financial crisis on market liquidity

This table provides an overview of all of the variables (liquidity, indices and control variables) we will use in the following empirical analyses related to the impact of the financial crisis. Liquidity costs $L(q)$ are represented by the price impact per transaction calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Closing price is the daily Xetra closing price in Euro. Market cap shows the daily market value at day closing, expressed in Euro millions. Traded volume represents the number of shares traded for a stock on a particular day. The figure is expressed in thousands. Stdev. log-returns is the annualized 5-day standard deviation of daily log-returns. The DAX, MDAX, SDAX and TecDAX shows the daily log-returns of the respective index. DAX Banks documents the monthly log-return of the DAX All Banks index. The EONIA represents the monthly average of the EONIA stated by the European Central Bank. The EURIBOR is the monthly average of the 3-month EURIBOR. These figures are expressed in percentages. For each variable, we show the first and the third quartile, the median, average and standard deviation as descriptive statistics.

	Q1	Median	Q3	Mean	Stdev.
L(q)	21.96	54.44	131.86	120.88	226.54
Closing price	10.60	19.72	35.16	28.29	29.87
Market cap	341.55	902.03	3499.86	5156.64	11582.96
Traded volume	27.50	128.10	657.90	1082.65	3325.69
Standard deviation of daily log-returns (5 days)	0.17	0.28	0.44	0.35	0.29
DAX	-0.64	0.11	0.76	0.04	1.52
MDAX	-0.55	0.17	0.76	0.05	1.47
SDAX	-0.38	0.14	0.58	0.04	1.12
TecDAX	-0.75	0.12	0.97	0.04	1.77
DAX Banks	-3.64	1.22	5.42	0.16	11.43
EONIA	2.04	2.21	3.57	2.53	1.08
EURIBOR(3M)	2.12	2.27	3.85	2.83	1.22

shares traded per company. The three indices DAX, SDAX and TecDAX have an average daily log-return of 0.04% while the one of the SDAX is 0.05%. The DAX All Banks index has a monthly log-return of 0.16%, the average of the EONIA over our sample period is 2.53% and the average of the 3-month EURIBOR is 2.83% and therefore 30 bps higher than the EONIA.

According to a variance inflation factor (VIF) threshold level of 10, which is proposed in Belsley et al. (1980), none of our following analyses that are related to the portion of our research focusing on the impact of the financial crisis on market liquidity suffer from problematic levels of multi-collinearity; see Table 4.5 that includes the maximum values of the individual variance inflation factors of our regression specifications that are dedicated to the impact of the financial crisis.

Table 4.5: Variance inflation factors (VIFs) for the impact of the financial crisis on market liquidity

This table gives an overview of the maximum variance inflation factors (VIFs) of all independent variables in all our regression related to the impact of the financial crisis on market liquidity. Closing price is the daily Xetra closing price in Euro. Market cap shows the daily market value at day closing, expressed in Euro millions. Traded volume represents the number of shares traded for a stock on a particular day. The figure is expressed in thousands. Stdev. log-returns is the annualized 5-day standard deviation of daily log-returns. Lehman week is a dummy variable, which equals 1 during the week following the collapse of Lehman Brothers (September 15th - September 19th, 2008), Lehman monthis a dummy variable, which equals 1 during the month following the collapse of Lehman Brothers (September 15th - October 14th, 2008) and Financial crisis is a dummy variable, which equals 1 starting with the collapse of Lehman Brothers until the end of the sample period (September 15th, 2008 - December 31st, 2009). Index log-return is the log-return of the index (DAX, MDAX, SDAX, TecDAX) of which the respective stock in the regression is a constituent. Standard deviation of index log-return is the annualized standard deviation of daily index log-returns. Down(dummy) * Index log-return (monthly) is an interaction term of the dummy variable Down, which equals one if the index log-return in month m is at least 1.5 standard deviations below its monthly sample mean, and the variable Index log-return (monthly). Up(dummy) * Index log-return (monthly) is an interaction term of the dummy variable Up, which equals one if the index log-return in month m is at least 1.5 standard deviations above its monthly sample mean, and the variable Index log-return (monthly). DAX Banks log-return (monthly) is the monthly log-return of a bank index that consists of all major German banks. The EURIBOR(3M)-EONIA-spread is the spread between the 3-month EURIBOR and the EONIA. Rating is a dummy variable, which equals 1 if the respective company posses a rating by a rating agency. Investmentgrade rating a dummy variable, which equals 1 if the respective company posses an investment grade rating (rating between AAA and BBB-) and equals 0 if the company has a speculative grade rating (rating between BB+ and D). The reported VIFs are defined as the maximum VIF over all reported regression analyses in the respective part of the dissertation. According to a VIF threshold level of 10, which is proposed in Belsley et al. (1980), none of our analyses suffers from problematic levels of multi-collinearity.

	VIF	1/VIF
Price (log)	2.08	0.481616
Traded volume (log)	3.24	0.309056
Market cap (log)	4.95	0.201969
Standard deviation of daily log-returns (5 days)	1.28	0.779307
Lehman week (dummy)	1.00	0.997548
Lehman month (dummy)	1.04	0.960599
Financial crisis (dummy)	1.10	0.906778
Index log-return	4.15	0.240744
Standard deviation of index log-return (monthly)	1.75	0.572326
Down(dummy) * Index log-return (monthly)	2.37	0.422789
Up(dummy) * Index log-return (monthly)	1.69	0.590157
DAX bank log-return (monthly)	2.59	0.386440
EURIBOR(3M)-EONIA-spread	1.28	0.780061
Rating (dummy)	1.51	0.660363
Investmentgrade rating (dummy)	1.44	0.696276

4.2.2 Market liquidity and different ownership structures[111]

Table 4.6 gives an descriptive overview of all of the variables we use in the following empirical analyses that are related to ownership structures. As already mentioned above, the average liquidity costs are 178 basis points. The average Xetra closing price is Euro 28.98, the average market capitalization is almost Euro 5 billion and on average there are 1.1 million shares traded per company. There are 2.2 blockholders on average per company in Germany. The average Herfindahl index of 0.16 indicates a moderate ownership concentration. The distribution of blockholder ownership in our sample is noteworthy. On average, 42 percent of a company's common shares are in the hand of blockholders, including 15 percent insiders, 13 percent financial investors, 12 percent strategic investors and only 2 percent private investors.

According to a variance inflation factor (VIF) threshold level of 10, which is proposed in Belsley et al. (1980), none of our following analyses that are related to the portion of our research focusing on the impact of ownership structures on market liquidity suffer from problematic levels of multi-collinearity; see Table 4.7 that includes the maximum values of the individual variance inflation factors of our regression specifications that are dedicated to ownership structures and concentration.

[111] This section is largely based on Rösch and Kaserer (2010).

Table 4.6: Descriptive statistics of variables for ownership structures and market liquidity

This table gives an overview of all variables (liquidity, ownership and control variables) we use in the following empirical analyses related to ownership structures. Liquidity costs $L(q)$ are represented by the yearly average of the price impact per transaction calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Closing price is the yearly average of the daily Xetra closing prices in Euro. Market cap shows the yearly average of the daily market value at day closing, expressed in Euro millions. Traded volume represents the yearly average of the number of shares traded for a stock on a particular day. The figure is expressed in thousands. Stdev. log-returns is the annualized yearly standard deviation of daily log-returns. Blockholders is the total share of blockholdings as a fraction. No. of blockholders is the total count of blockholders. Herfindahl represents the sum of the squares of the individual blockholder shareholdings. The largest blockholder is the share of the largest blockholder. $C1C3$ and $C1C5$ represents the combined share of the three or five largest blockholders. We further show the shareholdings of following types of blockholders: insiders, financial, strategic and private investors. For each variable, we show the first and the third quartile, the median, average and standard deviation as descriptive statistics.

	Q1	Median	Q3	Mean	Stdev.
L(q)	31.51	81.50	226.41	178.19	396.88
Closing price	11.52	20.94	36.56	28.98	29.48
Market cap	344.93	904.81	3238.53	4967.44	11488.27
Traded volume	41.37	172.72	716.82	1137.21	3089.66
Stdev. log-returns	0.27	0.36	0.50	0.41	0.20
Blockholders	0.21	0.44	0.61	0.42	0.26
No. of blockholders	1.00	2.00	3.00	2.24	1.44
Herfindahl	0.02	0.09	0.25	0.16	0.19
Largest blockholder	0.10	0.25	0.49	0.30	0.23
C1C3	0.20	0.41	0.59	0.40	0.25
C1C5	0.21	0.43	0.60	0.42	0.26
Insiders	0.00	0.00	0.26	0.15	0.22
Financial investors	0.00	0.05	0.18	0.13	0.19
Stragegic investors	0.00	0.00	0.11	0.12	0.23
Private investors	0.00	0.00	0.00	0.02	0.08

Table 4.7: Variance inflation factors (VIFs) for ownership structures and market liquidity

This table provides an overview of the maximum variance inflation factors (VIFs) of all of the independent variables in all our regression related to the impact of ownership structures on market liquidity. Closing price is the year average of the daily Xetra closing prices in Euro. Market cap shows the yearly average of the daily market value at day closing. Traded volume represents the year average of the number of shares traded for a stock on a particular day. Stdev. log-returns is the annualized yearly standard deviation of daily log-returns. Blockholders is the total share of blockholdings as a fraction. Number of blockholders is the total count of blockholders. Herfindahl represents the sum of the squares of the individual blockholder shareholdings. Largest blockholder is the share of the largest blockholder. $C1C3$ and $C1C5$ represents the combined share of the three or five largest blockholders.We further show the shareholdings of following types of blockholders: insiders, financial, strategic and private investors. The reported VIFs are defined as the maximum VIF over all of the reported regression analyses in the respective parts of the dissertation. On the basis of a VIF threshold level of 10, which is proposed in Belsley et al. (1980), none of our analyses suffers from problematic levels of multi-collinearity.

	VIF	1/VIF
Price (log)	2.86	0.349317
Market cap (log)	9.38	0.106588
Traded volume (log)	7.91	0.126461
Stdev. log-returns	1.52	0.659610
Blockholders	1.69	0.590597
Number of blockholders	1.02	0.982707
Herfindahl	1.37	0.728875
Largest blockholder	1.39	0.720486
C1C3	1.52	0.655777
C1C5	1.51	0.660160
Insiders	1.78	0.562400
Financial investors	1.29	0.774297
Stragegic investors	1.85	0.540683
Private investors	1.06	0.944770

4.2.3 Market liquidity and insider trading[112]

Table 4.8 gives an descriptive overview of all the variables used in the following empirical analyses that are related to the impact of insider trading activities by the four major indices. As already mentioned above, the average liquidity costs are 125 basis points. The average Xetra closing price is Euro 27.76, the average market capitalization is Euro 5 billion and on average there are almost 1.1 million shares traded per company. The annualized average 5-day standard deviation of daily log-returns is 0.36. The pecking order between the DAX, MDAX and SDAX is demonstrated very clearly by the figures in our table, e.g., the companies listed in the DAX have the largest average market capitalization with, over Euro 21 billion; their shares are the most actively traded with 4.6 million shares traded on average per day per company; they possess the smallest average liquidity costs with 66 basis points and they show the smallest volatility.

In total, there were 4,891 buy and 3,112 sell transactions by insiders in our sample. The average size of an insider buy transaction was 81,000 shares, and for a sell transaction initiated by an insider, the average size was 92,000 shares. An interesting point is that the insiders of MDAX companies appear to be the most active insiders, both in terms of the numbers of transactions (1,837 buy and 984 sell transactions) and the average transaction size (148,000 shares bought and 141,000 shares sold in an insider transaction). On average, over 8 percent of the total shares held by insiders are sold in an insider sale, whereas an average insider purchase represents a transaction size of only 2 percent of the total shares held by insiders.

According to a variance inflation factor threshold level of 10, which is proposed

[112] This section is largely based on Rösch and Kaserer (2011).

Table 4.8: Descriptive statistics of variables for insider trading and market liquidity

This table gives an overview of all of the variables (liquidity, insider trading and control variables) that we will use in the following empirical analyses related to insider trading. All of the variables are presented for all of the individual indices and as a total of all indices. Liquidity costs $L(q)$ are represented by the price impact per transaction calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Closing price is the daily Xetra closing price in Euro. Market cap shows the daily market value at day closing, expressed in Euro millions. Traded volume represents the number of shares traded for a stock on a particular day. The figure is expressed in thousands. Stdev. log-returns is the annualized 5-day standard deviation of daily log-returns. For liquidity and control variables, we show the averages. Insider buy and sell transactions are the total number of insider buy and sell transactions respectively. Insider bought and sold nominals represents the average number of shares traded in an insider transaction. These figures are expressed in thousands. Insider transaction as a share of insider ownership (buy) and (sell) are the averages of the ratios that relate the nominals bought or sold by insiders on a day to the total nominals owned by insiders. These figures are expressed in percent.

	DAX	MDAX	SDAX	TecDAX	Total
L(q)	65.66	102.64	200.05	138.78	124.48
Closing price	41.76	31.09	19.90	19.76	27.76
Market cap	21060.80	2373.76	427.56	937.23	5073.44
Traded volume	4551.93	349.58	63.91	374.04	1071.49
Stdev. log-returns	0.31	0.35	0.36	0.41	0.36
Insider buy transactions	909.00	1837.00	1582.00	563.00	4891.00
Insider sell transactions	584.00	984.00	771.00	773.00	3112.00
Insider bought nominals	16.62	148.20	50.39	70.57	81.07
Insider sold nominals	41.07	140.91	81.73	69.36	92.47
Insider transaction as a share of insider ownership (buy)	0.50	1.05	3.27	1.67	2.08
Insider transaction as a share of insider ownership (sell)	1.10	1.86	22.05	2.68	8.27

in Belsley et al. (1980), none of the following analyses that are related to the portion of our research on insider trading suffer from problematic levels of multicollinearity; see Table 4.9 that includes the maximum values of the individual variance inflation factors of our regression specifications that are dedicated to insider trading.

Table 4.9: Variance inflation factors or insider trading and market liquidity

This table gives an overview of the maximum variance inflation factors of all of the independent variables in all our regression related to the impact of insider trading on market liquidity. Closing price is the daily Xetra closing price in Euro. Market cap shows the daily market value at day closing, expressed in Euro millions. Traded volume represents the number of shares traded for a stock on a particular day. The figure is expressed in thousands. Stdev. log-returns is the annualized 5-days standard deviation of daily log-returns. Insider buy and sell transactions are the number of insider buy and sell transactions respectively. Insider bought and sold nominals represents the number of shares traded in an insider transaction. Insider transaction (buy/sell) - Management board/Supervisory board/Other employees are the number of insider buy/sell transactions from the following insider types: management board, supervisory board and other employees. Insider transaction bought/sold nominal lag 1 and lag 2 are the log-transformed nominals bought or sold by insiders on the previous and the penultimate day. Insider transaction as a share of insider ownership (buy) or (sell) represent ratios that relate the nominals bought or sold by insiders on that day to the total nominals owned by insiders. The reported variance inflation factors are defined as the maximum variance inflation factors over all of the reported regression analyses in the respective parts of the dissertation. On the basis of a variance inflation factors threshold level of 10, which is proposed in Belsley et al. (1980), none of our analyses suffers from problematic levels of multi-collinearity.

	VIF	1/VIF
Price (log)	2.37	0.421439
Traded volume (log)	3.41	0.292946
Market cap (log)	5.02	0.199348
Standard deviation of daily log-returns (5 days)	1.22	0.822667
Insider transaction (buy)	1.08	0.926864
Insider transaction (sell)	1.05	0.950803
Insider transaction bought nominal (log)	1.13	0.882914
Insider transaction sold nominal (log)	1.08	0.922459
Insider transaction (buy) - Management board	1.04	0.958590
Insider transaction (buy) - Supervisory board	1.04	0.964010
Insider transaction (buy) - Other employees	1.01	0.989891
Insider transaction (sell) - Management board	1.01	0.992308
Insider transaction (sell) - Supervisory board	1.01	0.987060
Insider transaction (sell) - Other employees	1.03	0.970902
Insider transaction bought nominal (log) - lag 1	1.17	0.855872
Insider transaction bought nominal (log) - lag 2	1.13	0.883445
Insider transaction sold nominal (log) - lag 1	1.12	0.892181
Insider transaction sold nominal (log) - lag 2	1.08	0.922174
Insider transaction as a share of insider ownership (buy)	1.00	0.999499
Insider transaction as a share of insider ownership (sell)	1.00	0.999218

Chapter 5

Empirical analysis

This chapter is dedicated to the empirical analysis of our three main research questions and, more explicitly, to the testing of our more detailed research hypotheses that we derived in Chapter 3. We begin by examining the impact of the financial crisis on market liquidity. This exploration is followed by analyses that concentrate on the influence of ownership structures, ownership concentration, and blockholder types on market liquidity. The last section of this chapter focuses on one specific type of shareholder, the insider, and investigates the influence of its trading behavior on market liquidity.

5.1 Market liquidity and the financial crisis[113]

This section focuses on the empirical analysis of the impact of the financial crisis on market liquidity. For these analyses, we use the dataset that we presented in section 4.1.1. We begin with a more general analysis of the evolution of market liquidity over time and the effect of the financial crisis. To better understand the

[113] This section is largely based on Rösch and Kaserer (2012).

time-series determinants of market liquidity, we will then analyze two main phenomena of market liquidity research in the context of the financial crisis: Liquidity commonality and the flight-to-quality.

5.1.1 Market liquidity over time - the impact of the financial crisis

5.1.1.1 A description of the evolution of market liquidity over time in light of the financial crisis

First, we attempt to discover wether the financial turmoil of the financial crisis had any impact on market liquidity. As a first indication, we therefore graph the development of the liquidity costs measured by the volume-weighted spread measure XLM for all four major German indices (DAX, MDAX, SDAX, and TecDAX) over time. In Figure 5.1, we see that, with the abating of the previous large crisis (the internet bubble and September 11th, 2001), the volume-weighted spreads narrowed in 2003 and 2004 and were relatively stable for the following years, from 2005 to mid-2007. The spreads then started to widen with the first signs of the financial crisis in mid-2007, dramatically increased after the collapse of Lehman Brothers Holdings Inc. in August 2008, and peaked in October and November 2008, after the collapse and bail-out of Hypo Real Estate AG in Germany. At that point of time in the midst of the financial crisis, the average volume-weighted spreads were as high as 1,000 bps for SDAX stocks, 600 bps for TecDAX stocks, 500 bps for MDAX stocks and 400 bps for DAX stocks. In 2009, the spreads began to recover and almost reached pre-crisis levels for the larger indices at the end of 2009.

On the basis of our volume-weighted spread measure XLM, we are also able to

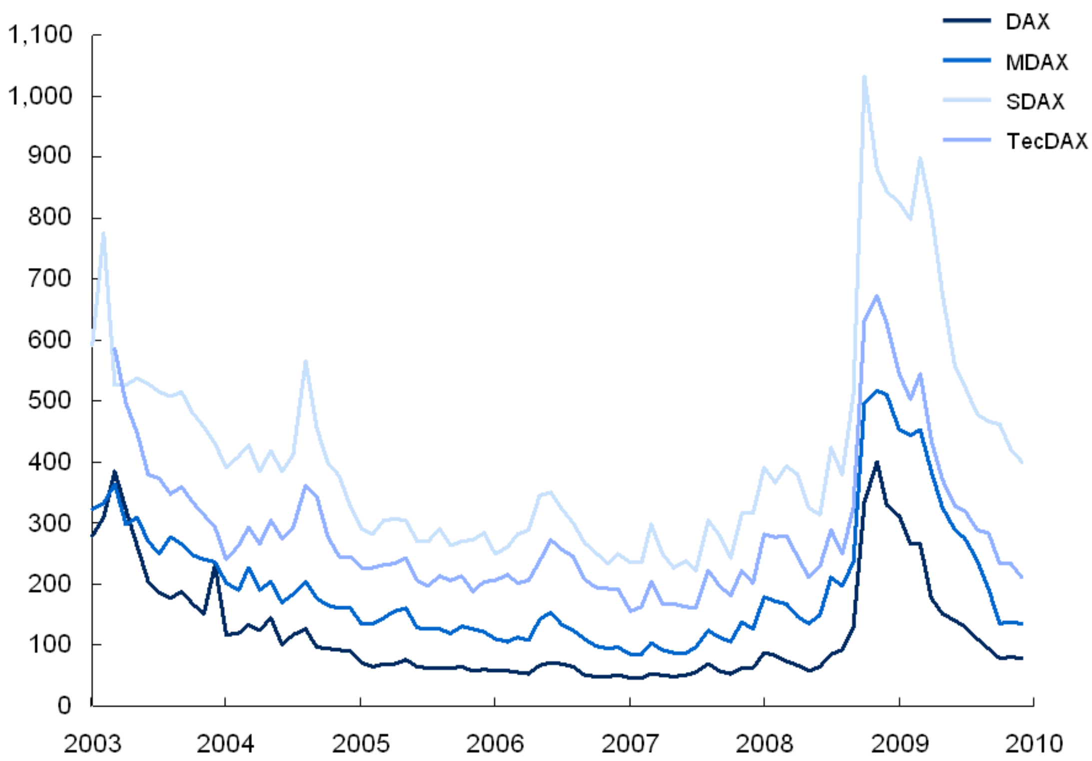

Figure 5.1: Volume-weighted spread (XLM) by index

This figure shows time-series plots of monthly averages of the volume-weighted spread measure XLM for the four major German indices (DAX, MDAX, SDAX, and TecDAX) over the period from January 2003 to December 2009. The XLM is measured in basis points.

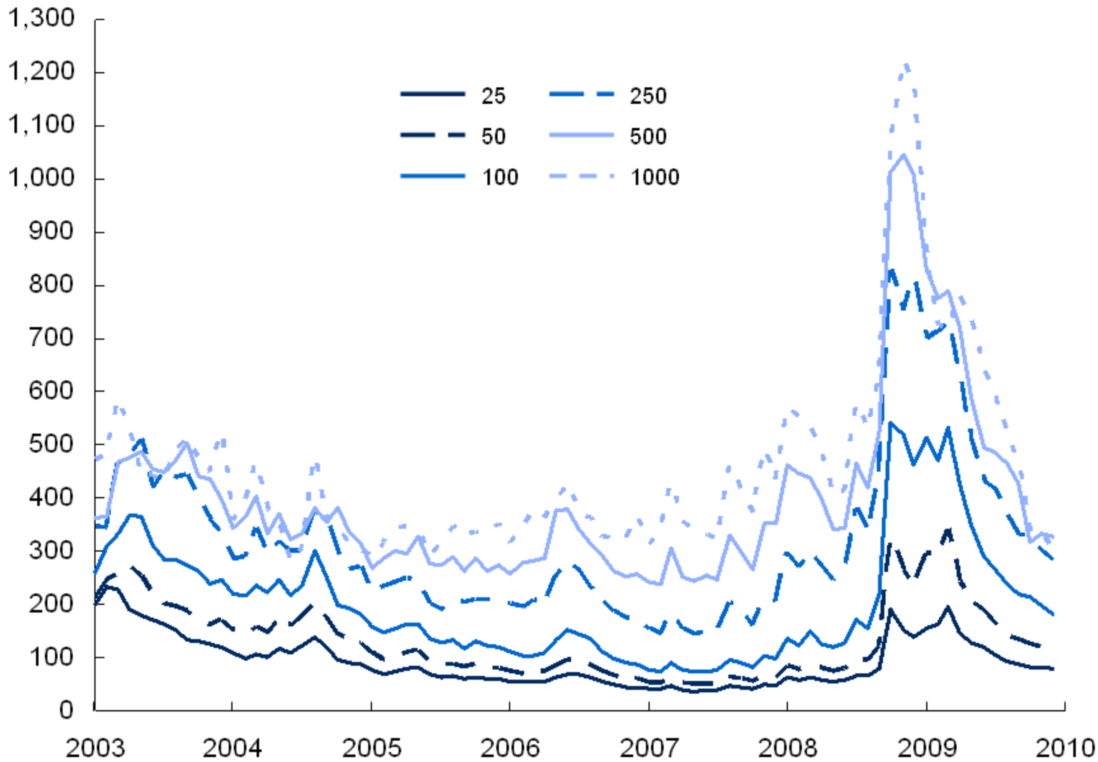

Figure 5.2: Volume-weighted spread (XLM) by volume class
This figure shows time-series plots of monthly averages of the volume-weighted spread measure XLM across the 6 standardized volume classes q that are available for all four major indices (DAX, MDAX, SDAX, and TecDax) over the period from January 2003 to December 2009. The 6 volume classes covered are those with a volume of Euro 25, 50, 100, 250, 500, 1000 thousand. The XLM is measured in basis points.

look into the dynamics inside the limit order book. This ability gives us the unique possibility to uncover previously unexplored market liquidity risk phenomena in the context of the financial crisis for larger order sizes, which might be of special interest to institutional investors who trade larger positions. Figure 5.2 displays the monthly averages of the XLM across the 6 standardized volume classes q that are available for all of the four major indices over the same period of time. These are the volume classes of Euro 25, 50, 100, 250, 500 and 1,000 thousand. We observe a pattern across all 6 volume classes that is similar to the pattern described before. However, the larger volume classes appear to suffer more from the financial crisis than do the smaller order sizes; therefore, the impact of the financial crisis on market liquidity becomes stronger the more deeply we look into the limit order book. In the midst of the financial crisis, the monthly average of the XLM across all four indices rose dramatically to levels above 1,200 basis points for order sizes of Euro 1 million and even transaction sizes of Euro 0.5 million peaked at over 1,000 basis points. These values are almost three times as high as the initial values for these volume classes in our sample. At the same time, the volume-weighted spreads for smaller volume classes also rose significantly but only reached levels of 190 and 320 basis points for order sizes of Euro 25 and 50 thousand, respectively. This unique insight is particularly important for market liquidity risk management, as the impact of order size on liquidity is substantial and therefore cannot be neglected, particularly in times of crisis. Any market liquidity risk management concept needs to account for the peaks in market liquidity risk in times of crisis, which are especially pronounced in larger volume classes. This reasoning leads us to the conclusion that bid-ask-spread data (which are often used to measure market liquidity risk due to their easy availability) might tremendously understate the liquidity risk for large trading positions and therefore can only poorly serve as proxies for the level and especially the variation in liquidity costs for larger volume classes during times of crisis. Therefore, our unique dataset with the order-size-dependent volume-weighted spread measure, which better captures the liquidity dynamics of the whole limit order book, will help us to shed further light on existing market liquidity puzzles in times of crisis.

5.1.1.2 The impact of the financial crisis on our measure of market liquidity

We now have a closer look at the impact of the financial crisis on market liquidity and therefore scrutinize the liquidity data in a panel-data regression analysis. For our panel-data regression analysis, we use a log-log specification. Consistent with Stange and Kaserer (2008), we log-transform the liquidity costs as the dependent variable in our regressions to account for the skewness in the liquidity data. We further transform the control variables transaction volume VO, the Xetra closing prices P and the market capitalization MV by taking their natural logarithms. For our unique panel data set with order-size-dependent liquidity costs, we use a company and volume class[114] fixed effects model[115] for the estimation. In the remainder of this dissertation, all our panel data models[116] include the dependent variable $logL(q)$ and all of the standard control variables in the following form:

$$logL(q) = \alpha_o + \alpha_1 logVO + \alpha_2 logP + \alpha_3 logMV + \alpha_4 \sigma_r + \varepsilon \tag{5.1}$$

We separately add three different dummy variables to capture the impact of the

[114] The volume class q is an inherent characteristic of our order-size-dependent liquidity costs measure.

[115] The Hausman (1978) test statistic supports the usage of a fixed effects model compared with a random effects model.

[116] All variables are time- and company-dependent, but we do not subscript the variables in the representation.

financial crisis: Lehman week, which equals 1 during the 5 trading days immediately following the collapse of Lehman Brothers (September 15th - September 19th, 2008); Lehman month, which equals 1 during the subsequent month of the Lehman collapse (September 15th - October 14th, 2008); and a financial crisis dummy covering the period from the Lehman collapse until the end of 2009 (September 15th, 2008 - December 31st, 2009). On the basis of our more descriptive results in Figures 5.1 and 5.2 and on other studies that discovered liquidity dry-ups during times of crisis, see, e.g., Hegde and Paliwal (2005), we would expect these dummy variables to be positively significant, indicating that liquidity costs are larger and stock market liquidity is impaired during the financial crisis. However, this expectation would only hold if these variables capture market liquidity dynamics that are not already explained by our other four control variables, especially through increased return volatility during the financial turmoil. Therefore, a positive relationship between these dummy variables and the liquidity costs would show that there are unexplained crisis-specific liquidity dynamics.

Table 5.1 presents the results for these regressions. First, we can assert that the estimates of the coefficients for all of our four control variables (price level, market capitalization, volume and return volatility) are significant and have the predicted signs. Liquidity costs are therefore, as predicted, a decreasing function of price level, market capitalization and trading volume, whereas these costs increase with the return volatility, which is a proxy for the general market risk. These results are, as expected, consistent with results reported in previous studies.

Furthermore, Table 5.1 gives ample evidence that the financial crisis had a major impact on the market liquidity, as all of our three dummy variables are positive significant at the 1 percent significance level, with the Lehman week dummy having the largest impact on liquidity costs. This observation clearly shows that market liquidity is impaired during times of crisis and that this increase in liquidity costs cannot be fully explained by the standard control variables. These positive relationships between liquidity costs and our dummy variables for the financial crisis justify a further exploration of the liquidity dynamics during times of crisis, as there are, thus far, unexplained crisis-specific liquidity dynamics.

Thus far, our results are in line with several empirical studies that showed that market crises lead to market liquidity dry-ups, see, e.g., Yeyati et al. (2008) and Næs et al. (2011), and several theoretical works, see, e.g., Bookstaber (2000), Kyle and Xiong (2001), Xiong (2001), Bernardo and Welch (2004), Garleanu and Pedersen (2007) and Brunnermeier and Pedersen (2009), that argue that market declines cause asset illiquidity. As a first step towards a better understanding of the dynamics of market liquidity during the financial crisis, we now want to analyze the relationship between individual stock liquidity and aggregate index returns. This analysis provides further empirical insights whether there is a negative relationship, as postulated by the theoretical works.

5.1.1.3 The impact of market returns on our measure of market liquidity

Therefore, we add the variable index log-return, which is the daily log-return of the index (DAX, MDAX, SDAX, and TecDAX) in which the respective stock is a constituent to our reference specification (see equation 5.1).[117] We analyze this relationship for three different subsamples to assess whether there are variations in the relationship in times of crises and non-crises: (5.2.1) covers the pre-crisis period from January 2003 to September 14th, 2008, (5.2.2) covers the period of financial crisis from September 15th, 2008 (collapse of Lehman Brothers) to

[117] We also analyzed the same regressions for the CDAX, which is a broad German market index, instead of the four individual indices. However, the results were very similar to the ones reported for the indices and can be found in Table A.3 in the Appendix.

Table 5.1: The effect of the financial crisis on market liquidity

This table reports company and volume-class fixed effects regressions that analyze the effects of the financial crisis on liquidity costs during the sample period of January 2003 to December 2009. The dependent variable of liquidity costs is represented by the daily price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the annualized 5 day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of the financial crisis using three different dummy variables: Lehman week (5.1.1), which equals 1 during the week following the collapse of Lehman Brothers (September 15th - September 19th, 2008), Lehman month (5.1.2), which equals 1 during the month following the collapse of Lehman Brothers (September 15th - October 14th, 2008) and Financial crisis (5.1.3), which equals 1 starting with the collapse of Lehman Brothers until the end of the sample period (September 15th, 2008 - December 31st, 2009). This table shows the estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients and the adjusted R^2 values are presented below the corresponding model.

	(5.1.1)	(5.1.2)	(5.1.3)
Price (log)	-0.507***	-0.505***	-0.341***
	(-225.52)	(-225.24)	(-148.07)
Traded volume (log)	-0.223***	-0.224***	-0.223***
	(-617.26)	(-621.05)	(-624.88)
Market cap (log)	-0.291***	-0.294***	-0.409***
	(-130.44)	(-132.23)	(-182.16)
Standard deviation of daily log-returns (5 days)	0.677***	0.651***	0.609***
	(581.62)	(552.70)	(518.02)
Lehman week (dummy)	0.404***		
	(74.93)		
Lehman month (dummy)		0.360***	
		(138.39)	
Financial crisis (dummy)			0.242***
			(270.82)
Constant	8.565***	8.591***	8.898***
	(881.56)	(886.52)	(920.92)
Observations	2373418	2373418	2373418
Adjusted R^2	0.524	0.527	0.537
F	522742.2	528420.6	551153.8

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

December 2009, while (5.2.3) covers the whole data for our sample period January 2003 to December 2009. A better understanding of the relationship between aggregate market returns and individual stock liquidity is an important building block for tackling the liquidity dynamics during the financial market crisis.

Table 5.2 shows the results for our three different subsamples. Across all subsamples, we observe a significant negative relationship between aggregate index returns and individual stock liquidity, indicating that, in all types of general market conditions, market declines (negative index returns) impair individual stock liquidity as measured by an increase in liquidity costs, whereas rising markets improve individual stock liquidity. This analysis provides support for former theoretical works and is consistent with findings of Chen and Poon (2008), which demonstrate local stock market returns to be one of the greatest causes of illiquidity. Furthermore, this analysis worryingly implies that market liquidity evaporates when it is most needed, as investors might need to cover their losses in market downturns, and further demonstrates that there is clearly a positive relationship between market risk and liquidity risk.

Hence, Figure 5.1 and our empirical results in Tables 5.1 and 5.2 clearly show that market liquidity was heavily affected during the financial crisis, and therefore, a more thorough analysis is required to understand the dynamics behind it. We begin with an analysis of a widely stated phenomenon in market liquidity: liquidity commonality.

5.1.2 Liquidity commonality

In brief, liquidity commonality describes the phenomenon of the synchronicity of an individual asset's liquidity variation with aggregate market-wide liquidity

Table 5.2: The impact of market returns on market liquidity: crisis vs. non-crisis

This table reports company and volume-class fixed effects regressions that analyze the effects of index returns on the liquidity costs during the sample period of January 2003 to December 2009. The dependent variable of liquidity costs is represented by the daily price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the annualized 5 day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of the variable index log-returns, which are the daily log-return of the index (DAX, MDAX, SDAX, or TecDAX) of which the respective stock is a constituent. The results are reported for three different subsamples: (5.2.1) covers the pre-crisis period from January 2003 to September 14th, 2008, (5.2.2) covers the period of financial crisis from September 15th, 2008 (collapse of Lehman Brothers) to December 2009, whereas (5.2.3) covers the whole data for our sample period January 2003 to December 2009. This table shows the estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.2.1)	(5.2.2)	(5.2.3)
Price (log)	-0.440***	-0.199***	-0.507***
	(-155.98)	(-20.58)	(-225.76)
Traded volume (log)	-0.221***	-0.106***	-0.223***
	(-593.76)	(-96.24)	(-617.46)
Market cap (log)	-0.323***	-0.960***	-0.290***
	(-123.15)	(-103.42)	(-130.08)
Standard deviation of daily log-returns (5 days)	0.644***	0.433***	0.679***
	(434.77)	(221.20)	(583.00)
Index log-return	-1.707***	-1.181***	-1.663***
	(-67.70)	(-39.17)	(-82.93)
Constant	8.560***	12.09***	8.561***
	(779.05)	(297.19)	(881.42)
Observations	1940124	433294	2373418
Adjusted R^2	0.485	0.394	0.524
F	366188.5	56651.6	523272.1

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

movements and was initially discovered by Chordia et al. (2000). Extending the stream of research presented in 3.1.2, we first seek to explore two characteristics of liquidity commonality using our unique volume-dependent liquidity measure: Is liquidity commonality a phenomenon that holds for the whole limit order book, and is it sensitive to shocks, such as the financial crises? We will then pursue a line of possible further research suggested by the aforementioned discussion and examine factors determining the observed liquidity commonality.

5.1.2.1 Liquidity commonality and the financial crisis

Following the work of Chordia et al. (2000), we adapt the return market model used in asset pricing and apply it in the context of liquidity to estimate the sensitivity of an individual firm's liquidity to changes in the aggregate market liquidity. We extend the original specification of Chordia et al. (2000) to account for our volume-dependent liquidity measure to derive our extended liquidity market model. For each individual firm i, we therefore estimate the following time-series regression:

$$\Delta WS\left(q\right)_{i,t} = \alpha_i + \beta_i \cdot \Delta WS\left(q\right)_{M,i,t} + X \cdot A + \varepsilon_{i,t} \tag{5.2}$$

where $\Delta WS\left(q\right)_{i,t}$ measures the proportional change (Δ) in the volume-weighted spread $WS(q)$ across successive trading days:

$$\Delta WS(q)_{i,t} = \frac{WS(q)_{i,t} - WS(q)_{i,t-1}}{WS(q)_{i,t-1}} \tag{5.3}$$

The market volume-weighted spread $WS(q)_{M,i}$ is an equal weighted average of all individual stocks' volume-weighted spreads in the market, excluding, as in prior research, e.g., Chordia et al. (2000) and Coughenour and Saad (2004), the volume-weighted spread of firm i, i.e., the dependent variable. The proportional change in the market volume-weighted spread $\Delta WS(q)_{M,i}$ is derived as in equation (5.3). Following Chordia et al. (2000) we include further variables (vector (A)): lead and lag variables[118] of the proportional change in market volume-weighted spread $\Delta WS(q)_{M,i,t-1}$ and $\Delta WS(q)_{M,i,t+1}$; the contemporaneous, lead, and lag market return, which is an equal weighted average of all individual stocks' daily returns[119]; and the proportional change in the individual squared return of stock i. The lead and lag liquidity variables capture any non-synchronous liquidity co-movement, whereas the return and volatility variables in our regression control for general market conditions and changes in stock-specific volatility.

Our main interest lies in the analysis of the co-movement of an individual stock's liquidity with the aggregate market liquidity and, therefore, in the coefficient estimates of β_i. Following the linguistic usage in the context of asset pricing, the coefficient estimate β_i is called liquidity beta in most of the literature and, henceforth, in our research. As in asset pricing, the liquidity beta can be viewed as a measure for systematic liquidity risk. We use individual liquidity beta estimates to calculate an equal-weighted cross-sectional average for the liquidity beta, which is reported in Tables 5.3 to 5.5. However, we also provide information on the cross-sectional distribution of the individual liquidity betas, as we further report the percentage of positive slope coefficients and the percentage of significantly[120] positive slope coefficients, as estimated from the individual regressions. On the basis of the finding of Kamara et al. (2008), who found a strong time variation

118 Lead and lag variables refer to the previous and next trading day observations of the variable.

119 As in the market volume-weighted spread, we exclude the dependent variable stock from the calculation of the market averages.

120 At the 5% significance level.

in commonality, we want to analyze whether the sudden liquidity dry-up in the market induced by the financial crisis, which we discovered earlier in this work, can at least to a certain extent be explained by an increase in the liquidity commonality during times of crisis. To scrutinize the impact of the financial crisis on the liquidity commonality, we therefore estimate the liquidity betas for our three sub-periods defined above, to reveal the impact of the financial crisis on liquidity co-movements.

Tables 5.3 to 5.5 provide strong support for the existence of liquidity commonality. As the averages of the contemporaneous liquidity beta estimates are significantly different from zero across all sub-periods, we find a co-movement of individual stocks' liquidity with the aggregate market liquidity. We further observe in Table 5.3, which covers all of the data of our sample period, that almost 80% of the individual liquidity beta estimates are significantly positive, which shows that liquidity co-movement is a pervasive phenomenon across all stocks and that almost all stocks are influenced by changes in the aggregate market liquidity. Our results reported for the non-crisis subsample in Table 5.4 are very much in the range of liquidity betas reported in earlier research that did not focus on crises in their samples, see, e.g., Chordia et al. (2000), Brockman and Chung (2002) and Kempf and Mayston (2008). As we use a volume-dependent liquidity measure, we are able to show that liquidity commonality is a phenomenon that holds for the whole limit order book. Consistent with previous research, the coefficient estimates for leading and lagged aggregate market liquidity are mostly positive and often significant; however, they are very small in magnitude.

As Kamara et al. (2008) have shown that liquidity betas vary over time, we now want to focus on the inter-sample differences and, therefore, on the impact of the financial crisis: Most notably, the average liquidity beta is more than 5

Table 5.3: Market-wide commonality in liquidity: overall sample

This table reports firm-by-firm volume-class fixed effects regressions that relate daily proportional changes in an individual stock's volume-weighted spread (the stock's liquidity) to the equal-weighted average liquidity for all stocks in the sample (liquidity of the market), for a sample that covers all of the data for our sample period of January 2003 to December 2009. The dependent variable, daily change of liquidity costs of an individual stock, is represented by the daily change of the order-size-dependent volume-weighted spread $WS(q)$ derived from the limit order book of this stock; therefore, the delta symbol (Δ) preceding the liquidity variables denotes a proportional change in the variable across successive trading days, i.e., $\Delta WS\left(q\right)_{i,t} = \frac{WS(q)_{i,t} - WS(q)_{i,t-1}}{WS(q)_{i,t-1}}$. The main regressors $\Delta WS\left(q\right)_{M,i,t,}$, $\Delta WS\left(q\right)_{M,i,t-1}$,and $\Delta WS\left(q\right)_{M,i,t,+1}$ are the contemporaneous, lag, and lead daily changes in the market average liquidity costs. We do not report the following additional regressors of the regression: the contemporaneous, lead and lag values of the equal-weighted market return and the proportional daily change in individual squared returns (which captures the change in return volatility). For the calculation of the market averages in each individual regression, the dependent-variable stock is excluded. Contemporaneous, lag, and lead refer, respectively, to the same, previous, and next trading day observations of the variable.
We do report the cross-sectional averages of time-series slope coefficients, the corresponing t-statistics, the % positive, which reports the percentage of positive slope coefficients, and the % positive significant, which shows the percentage of positive slope coefficients with p-values smaller than 5%.

	Coefficient	t-statistic	% positive	% positive significant
$\Delta WS(q)_{M,t}$	1.66670332***	4.4975121	93.26	79.40
$\Delta WS(q)_{M,t-1}$	0.25432800***	2.9452898	48.69	21.35
$\Delta WS(q)_{M,t+1}$	0.07578768***	2.7775431	35.96	11.99
Adjusted R^2	0.06159368			

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

times higher ($\beta = 2.51$) during the financial crisis in Table 5.5 compared with the non-crisis period ($\beta = 0.45$) in Table 5.4. Therefore, the relationship between individual stock liquidity and aggregate market liquidity becomes much stronger in times of crisis, and liquidity commonality increases strongly in crises. This increased systematic market liquidity risk leads to illiquidity spill-overs across the market and illustrates that liquidity commonality can be a source of financial contagion.

Table 5.4: Market-wide commonality in liquidity: non-financial crisis (Jan 1, 2003 - Sep 14, 2008)

This table reports firm-by-firm volume-class fixed effects regressions that relate daily proportional changes in an individual stock's volume-weighted spread (the stock's liquidity) to the equal-weighted average liquidity for all of the stocks in the sample (liquidity of the market), for a sample that covers the pre-crisis period from January 2003 to September 14th, 2008. The dependent variable, daily change of liquidity costs of an individual stock, is represented by the daily change of the order-size-dependent volume-weighted spread $WS(q)$ derived from the limit order book of this stock; therefore, the delta symbol (Δ) preceding the liquidity variables denotes a proportional change in the variable across successive trading days, i.e., $\Delta WS\left(q\right)_{i,t} = \frac{WS(q)_{i,t}-WS(q)_{i,t-1}}{WS(q)_{i,t-1}}$. The main regressors $\Delta WS\left(q\right)_{M,i,t,}$, $\Delta WS\left(q\right)_{M,i,t-1}$,and $\Delta WS\left(q\right)_{M,i,t,+1}$ are the contemporaneous, lag, and lead daily changes in the market average liquidity costs. We do not report the following additional regressors of the regression: the contemporaneous, lead and lag values of the equal-weighted market return and the proportional daily change in individual squared returns (which captures the change in return volatility). For the calculation of the market averages in each individual regression, the dependent-variable stock is excluded. Contemporaneous, lag, and lead refer, respectively, to the same, previous, and next trading day observations of the variable.
We do report the cross-sectional averages of the time-series slope coefficients, the corresponding t-statistics, the % positive, which reports the percentage of positive slope coefficients, and the % positive significant, which shows the percentage of positive slope coefficients with p-values smaller than 5%.

	Coefficient	t-statistic	% positive	% positive significant
$\Delta WS(q)_{M,t}$	0.45257737***	13.280457	95.33	84.82
$\Delta WS(q)_{M,t-1}$	0.05046204*	1.6565841	74.32	38.91
$\Delta WS(q)_{M,t+1}$	0.06758632***	3.200769	66.15	33.46
Adjusted R^2	0.01493528			

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.5: Market-wide commonality in liquidity: financial crisis (Sep 15, 2008 - Dec 31, 2009)

This table reports firm-by-firm volume-class fixed effects regressions that relate daily proportional changes in an individual stock's volume-weighted spread (the stock's liquidity) to the equal-weighted average liquidity for all stocks in the sample (liquidity of the market), for a sample that covers the period of the financial crisis from September 15th, 2008 (the collapse of Lehman Brothers) to December 2009. The dependent variable, daily change of liquidity costs of an individual stock, is represented by the daily change of the order-size-dependent volume-weighted spread $WS(q)$ derived from the limit order book of this stock; therefore, the delta symbol (Δ) preceding the liquidity variables denotes a proportional change in the variable across successive trading days, i.e., $\Delta WS\left(q\right)_{i,t} = \frac{WS(q)_{i,t} - WS(q)_{i,t-1}}{WS(q)_{i,t-1}}$. The main regressors $\Delta WS\left(q\right)_{M,i,t,}$, $\Delta WS\left(q\right)_{M,i,t-1}$,and $\Delta WS\left(q\right)_{M,i,t,+1}$ are the contemporaneous, lag, and lead daily changes in the market average liquidity costs. We do not report the following additional regressors of the regression: the contemporaneous, lead and lag values of the equal-weighted market return and the proportional daily change in individual squared returns (which captures the change in return volatility). For the calculation of the market averages in each individual regression, the dependent-variable stock is excluded. Contemporaneous, lag, and lead refer, respectively, to the same, previous, and next trading day observations of the variable.
We do report the cross-sectional averages of the time-series slope coefficients, the corresponding t-statistics, the % positive, which reports the percentage of positive slope coefficients and the % positive significant, which shows the percentage of positive slope coefficients with p-values smaller than 5%.

	Coefficient	t-statistic	% positive	% positive significant
$\Delta WS(q)_{M,t}$	2.50867074***	3.8664311	90.06	64.09
$\Delta WS(q)_{M,t-1}$	0.25782698***	3.6416402	48.62	18.78
$\Delta WS(q)_{M,t+1}$	-0.09077858	-1.5535007	43.65	11.60
Adjusted R^2	0.07971010			

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.1.2.2 Liquidity commonality over time

Given this strong liquidity commonality variation in times of crises, we now want to further explore the dynamics of the liquidity commonality over time, as, despite the strong evidence for the existence of commonality in liquidity, few studies have focused on the drivers of liquidity co-movement. We particularly want to understand the source of and dynamics behind liquidity commonality, especially in times of crises. As a first step towards a better understanding of liquidity commonality dynamics, we use a measure for the degree of liquidity commonality called the R^2 statistic, which has proven its relevance in the measurement of individual stock return synchronicity, to further analyze the liquidity commonality behavior over time and for different order sizes.

The usage of the R^2 statistic in the context of stock price co-movement with the market was first proposed by Roll (1988) and later further developed and used, among others, by Morck et al. (2000) and Chen et al. (2007b). The idea of market model return R^2s was recently adapted to measure the degree of individual stock liquidity synchronicity by Hameed et al. (2010) and was also used by Karolyi et al. (2011). This measure for the degree of liquidity commonality is simply the coefficient of determination R^2 resulting from a regression of the following single-factor liquidity market model, which is a simplification of specification (5.2):

$$\Delta WS\left(q\right)_{i,t} = \alpha_i + \beta_i \cdot \Delta WS\left(q\right)_{M,i,t} + \varepsilon_{i,t} \tag{5.4}$$

For every stock and each month in our sample, we estimate the R^2 statistic if there are at least 15 observations[121] available for the respective company in

[121] The requirement of at least 15 observations is in line with Hameed et al. (2010) and Karolyi et al. (2011).

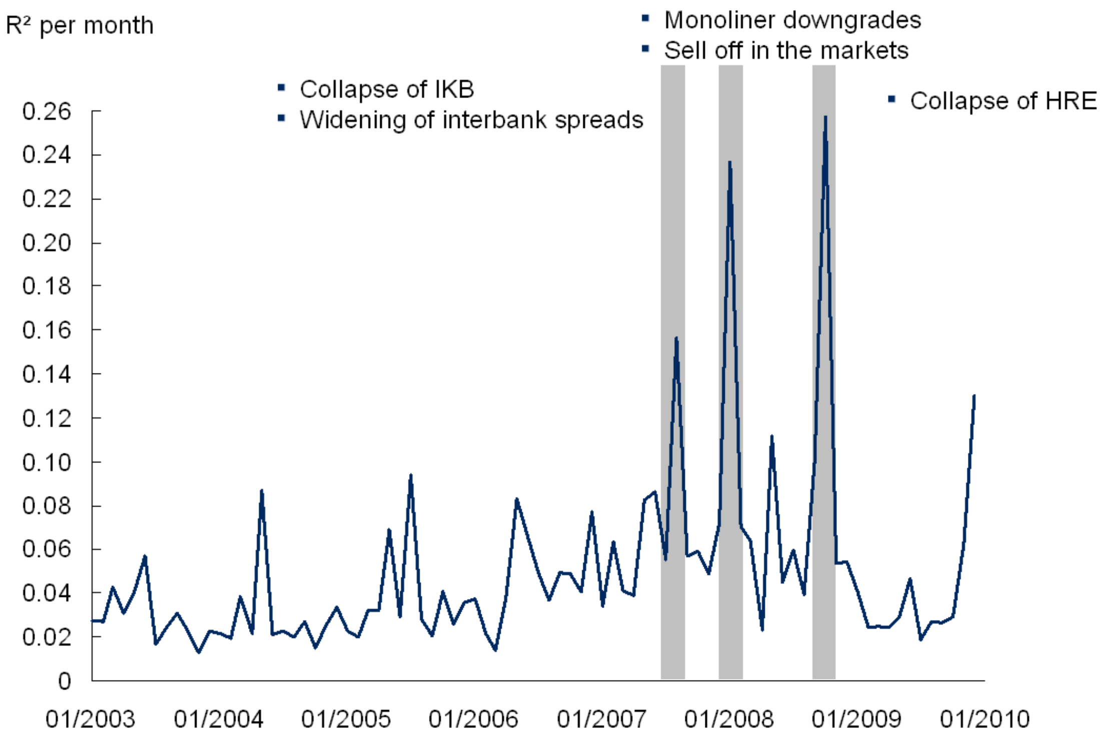

Figure 5.3: Liquidity commonality over time

This figure shows a time-series plot of monthly cross-sectional averages of the R^2 statistic, which serves as a proxy for the degree of liquidity commonality over the time period from January 2003 to December 2009. The R^2 statistic is derived by an equal-weighted average of individual stock's R^2 statistic estimated by a single-factor liquidity market regression model.

the respective month. Using this monthly individual estimates we are able to calculate monthly equal-weighted average R^2 statistics. This gives us a measure for the degree of liquidity commonality in the market for a given month. A high R^2 statistic indicates a high degree of liquidity commonality, as a large portion of the variation in the change of individual stock's liquidity can be explained by aggregate market liquidity movements, and conversely, a low R^2 statistic indicates a low degree of liquidity commonality.

Figure 5.3 shows several interesting facts about the development of our measure for the degree of liquidity commonality over time. First, this figure provides additional support for the existence of liquidity commonality and, therefore, for a systematic liquidity risk component, as the R^2 statistic indicates that a certain portion of the individual stock's innovations in daily liquidity can be explained by the innovations in daily market liquidity. Furthermore, we can observe that liquidity commonality varies markedly over time during our sample period from 2003 to 2009. Moreover, the level of liquidity commonality appears to be higher, on average, during the financial crisis compared with the non-crisis period before. However, most interestingly, there are large peaks of liquidity commonality at major events of the financial crisis: e.g., the highest level of liquidity commonality in our sample coincides with the probably most important event of the financial crisis in Germany, which is the collapse and bail out of Hypo Real Estate (HRE), a German bank specialized in commercial real estate and public finance, right after the collapse of Lehman Brothers. However, other large spikes also coincide with the major crisis events, e.g., the collapse of IKB Deutsche Industriebank, a German bank that was the first European victim of the sub-prime crisis, the dramatic widening of interbank spreads in the mid of 2007, the mono-liner downgrades and the subsequent sell-off in the market in January 2008. This result is in line with the earlier insights of Hameed et al. (2010), who also found that high levels of liquidity commonality are associated with periods of liquidity crisis. The large peaks and the high level of liquidity commonality during the financial crisis confirm our earlier finding that liquidity betas are higher during times of crisis.

Due to the usage of our volume-dependent liquidity measure our results in Figure 5.3 are able to show that liquidity commonality exists for the whole limit order book. However, we are further interested in the more detailed dynamics inside the limit order book.

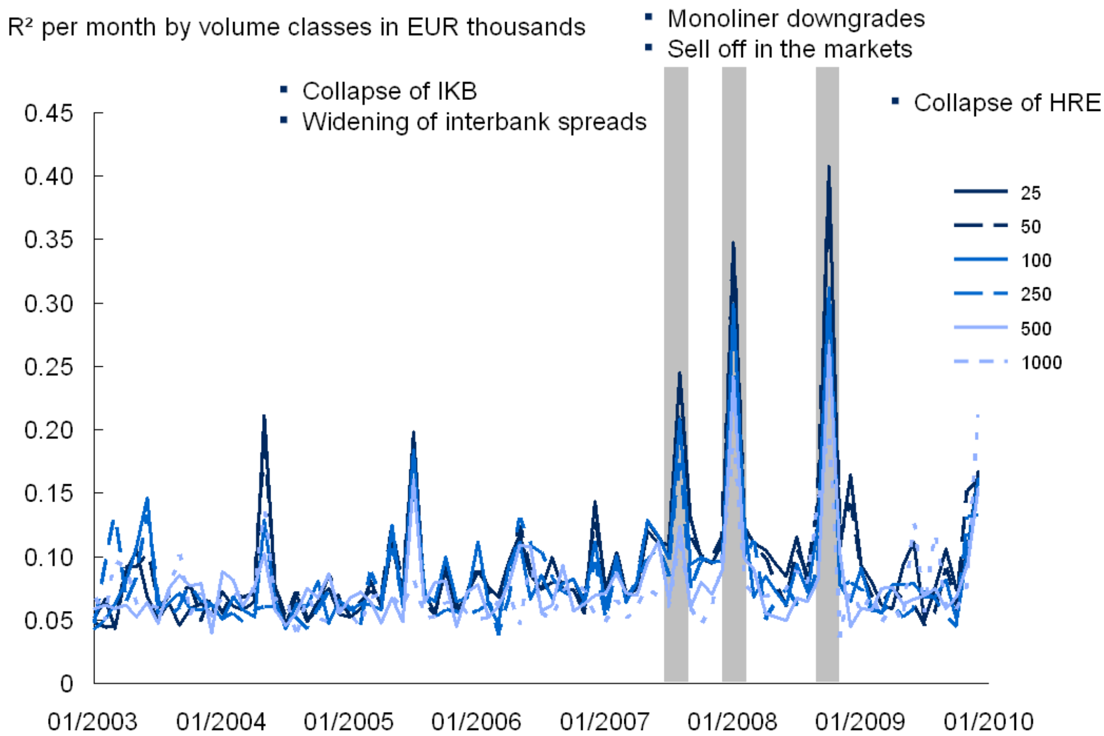

Figure 5.4: Liquidity commonality over time by different volume classes

This figure shows time-series plots of the monthly averages of the volume-weighted spread measure XLM across the 6 standardized volume classes q which are available for all four major indices (DAX, MDAX, SDAX, and TecDax) over the time period from January 2003 to December 2009.

5.1.2.3 Liquidity commonality and the impact of different order sizes

Therefore, we redo the same analysis using specification (5.4); however, this time, we estimate the R^2 statistic for every volume class of every individual stock independently in each month of our sample. Using these monthly individual estimates, we are able to calculate monthly equal-weighted average R^2 statistics for every standardized volume class q across all companies.

Figure 5.4 shows the same liquidity commonality development over time as Figure 5.3. Hence, the liquidity commonality dynamics over time do not differ significantly for different order-sizes. Liquidity commonality is, therefore, a phenomenon that is relevant for all order-sizes, prevails throughout the whole limit order book and is heavily influenced by crises. However, Figure 5.4 gives a first indication that the absolute level of liquidity commonality might differ across volume classes. One can easily see that larger volume classes, e.g., order sizes of EUR 1 million, feature lower levels of liquidity commonality than smaller volume classes. As a further proof, we calculate the average monthly R^2 statistics for all 6 standardized volume classes q that are available for all four major German indices (DAX, MDAX, SDAX, and TecDAX).

Figure 5.5 shows a clear liquidity commonality ranking across the volume classes from small to large volume classes, i.e., the larger the order size, the smaller the average liquidity commonality, and therefore, the systematic liquidity risk. Whereas, for example, the average monthly R^2 statistic for order sizes of EUR 25,000 is 9.51%, it is only 8.70% for order sizes of EUR 100,000 and 7.27% for order sizes of EUR 1 million. Hence, the liquidity commonality becomes weaker as we look more deeply into the limit order book.[122] These findings, however,

[122] The decreasing liquidity commonality with order size cannot be explained by a change in the composition of the sample stocks that went into the calculation between times of low

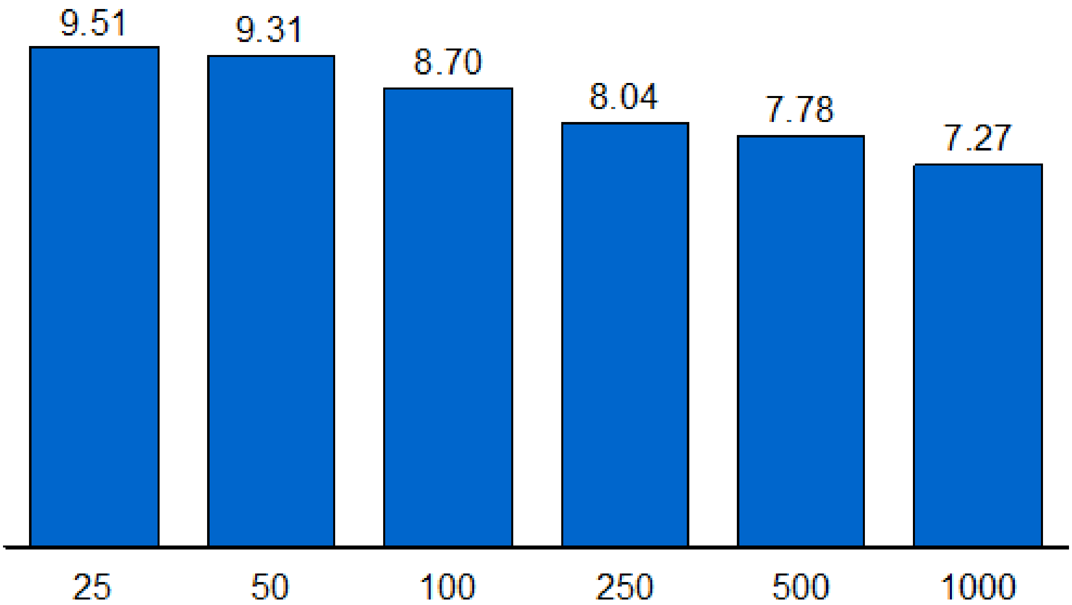

Figure 5.5: Average liquidity commonality by different volume classes
This figure shows averages of the monthly R^2 measure, a measure for the degree of liquidity commonality, for 6 standardized volume classes q (in EUR thousand) that are available for all four major indices (DAX, MDAX, SDAX, and TecDax) over the time period from January 2003 to December 2009. The figures are in percent.

contradict those of Kempf and Mayston (2008), who showed in their analysis that commonality in liquidity becomes stronger the more deeply they look into the limit order book.

Thus far, we can record four interesting facts about liquidity commonality: liquidity commonality exists (in the whole limit order book), it varies over time, it is particularly pronounced in times of crisis, and it becomes weaker the more deeply we look into the limit order book.

5.1.2.4 Liquidity commonality and market declines

After having analyzed the dynamics of liquidity commonality, we now want to focus on the drivers behind liquidity commonality, as few studies to date have focused on the factors influencing liquidity commonality. By and large, liquidity commonality can have three basic sources: co-variation in liquidity supply, co-movement in liquidity demand, or both.

Earlier, we observed that individual stock liquidity is influenced by index returns (see Table 5.2), i.e., aggregate stock market declines reduce individual stock liquidity. Further research on return co-movement, see, e.g., Ang and Chen (2002), showed that co-variation in stock returns increases after large market declines. We now want to determine wether there is a similar pattern in liquidity commonality as in return co-movement after market declines. We want to test the hypothesis that aggregate stock market return is a major driver of liquidity commonality. We base this hypothesis on a broad range of theoretical research, see, e.g., Bookstaber (2000), Kyle and Xiong (2001), Vayanos (2004), Garleanu and Pedersen (2007)

liquidity commonality (pre-crisis period) and high liquidity commonality (crisis period). See Figure A.1 in the Appendix, which shows that the distribution of the stocks by index that are used to calculate our (average) liquidity commonality measure R^2 is virtually constant in a comparison of a pre-crisis and a crisis period for every volume class.

and Brunnermeier and Pedersen (2009), that argues that stock market declines either affect the liquidity demand (e.g., panic selling, risk aversion), the supply for liquidity (e.g., margin constraints, fund withdrawals by financial intermediaries), or both. We thus argue that these market-wide liquidity demand and supply effects of market declines therefore induce co-movement in liquidity.

Before we begin with the regression analysis, we must perform certain mathematical transformations, as our measure for the degree of liquidity commonality, namely the R^2 statistic, is mathematically restricted to the interval $[0;1]$ and therefore of limited suitability as a dependent variable in a regression. We thus follow the approach of Morck et al. (2000), Hameed et al. (2010) and Karolyi et al. (2011) by applying a logistic transformation to our R^2 statistic to calculate $LiqCom$, a regression-suitable measure of liquidity commonality, and use it as a dependent variable in the following regressions:

$$LiqCom = ln\left[\frac{R^2}{1-R^2}\right] \tag{5.5}$$

First, we want to analyze the impact of market returns on our measure for liquidity commonality. Therefore, we use the respective index return (DAX, MDAX, SDAX, or TecDAX) and the standard deviation of the index log-returns as independent variables in specification (5.6.1). We observe that there is a clear negative relationship between index returns and liquidity commonality. This finding shows that liquidity commonality is increased in market declines and supports our hypothesis 3 that we developed in section 3.1.2. Even the significantly positive relationship between the standard deviation of index log-returns, as a proxy for market risk, and liquidity commonality, shows that liquidity commonality increases in times of crises. On the basis of the theoretical work of Vayanos (2004),

Table 5.6: The effect of index returns on liquidity commonality

This table reports OLS regressions that analyze the effect of market returns on liquidity commonality during the sample period of January 2003 to December 2009. The dependent variable, liquidity commonality, is generated as follows: For each stock, the daily changes in the order-size-dependent volume-weighted spread $WS(q)$, derived daily from the limit order book, are regressed on changes in the market average volume-weighted spreads, which are the daily equally weighted volume-weighted spreads of all stock excluding the dependent variable stock, within each month m. The degree of liquidity commonality in each month is measured by taking an equally weighted average of the R^2 statistics by index i. Our dependent variable, liquidity commonality, for each month m is then derived by the logit transformation of these cross-sectional R^2 averages by index i: $LiqCom_{m,i} = ln\left[R^2_{m,i}/\left(1 - R^2_{m,i}\right)\right]$. Index log-return (monthly) is the monthly log-return of the respective major German index i (DAX, MDAX, SDAX, or TecDAX). The standard deviation of the index log-return (monthly) is the annualized standard deviation of the daily index log-returns in month m. Down (dummy) * Index log-return (monthly) is an interaction term of the dummy variable Down, which equals one if the index log-return in month m is at least 1.5 standard deviations below its monthly sample mean, and the variable Index log-return (monthly). Up (dummy) * Index log-return (monthly) is an interaction term of the dummy variable Up, which equals one if the index log-return in month m is at least 1.5 standard deviations above its monthly sample mean, and the variable Index log-return (monthly). This table shows the estimated coefficients: the t-statistics are reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.6.1)	(5.6.2)	(5.6.3)	(5.6.4)
Index log-return (monthly)	-2.913***	-1.644***	-2.626***	-0.660
	(-5.12)	(-2.59)	(-3.30)	(-0.71)
Standard deviation of index log-return (monthly)	1.254***	0.956***	1.354***	1.162***
	(3.98)	(3.11)	(3.73)	(3.46)
Down(dummy) * Index log-return (monthly)		-3.740***		-4.429***
		(-2.88)		(-3.26)
Up(dummy) * Index log-return (monthly)			-0.956	-2.494**
			(-0.86)	(-2.13)
Constant	-3.412***	-3.404***	-3.429***	-3.447***
	(-47.49)	(-49.62)	(-44.16)	(-47.54)
Observations	334	334	334	334
Adjusted R^2	0.161	0.179	0.160	0.183
F	26.32	25.39	20.92	23.62

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

this phenomenon can be at least partially attributed to liquidity demand effects, as in times of volatile markets, institutional investors, mainly due to a higher probability of fund withdrawals that are subject to performance thresholds, become more risk-avers and have an increased liquidity preference. Therefore, an increase in market volatility is associated with an increase in liquidity demand and hence leads to higher levels of liquidity commonality.

We further separately add a variable that captures abnormally large negative one-day returns and a variable that captures abnormally large positive returns in specifications (5.6.2) and (5.6.3), respectively. Technically, these two variables are interaction terms of a dummy variable that equals one if the one-day index return is at least 1.5 standard deviations[123] above or below its sample mean, respectively, and the respective index log-return. These two variables should shed light on the liquidity dynamics on days with strong market reactions. We hypothesize that stronger market reactions will even magnify the impact of the relationship between liquidity commonality and aggregate index returns, as most theoretical explanations, e.g., panic selling or higher margin requirements, are even more relevant for large market reactions. Finally, we use all of the aforementioned control variables together in the specification (5.6.4).

The results in model (5.6.2) show that large negative market shocks significantly magnify even the liquidity co-movement induced by index returns. This finding provides further support to the theoretical liquidity demand and supply explanations, as most of these explanations should only loom large for large market drops. This interesting observation for unusual large market downturns also confirms other empirical results of Chordia et al. (2001), Chordia et al. (2002) and

[123] Consistent with Hameed et al. (2010), we use a threshold of 1.5 standard deviations; however, also other threshold levels, e.g., 1 and 2 standard deviations, also lead to similar results.

Hameed et al. (2010), who found a highly significant bid-ask spread widening at the days of or days following negative market returns, which can be attributed to an increase in liquidity commonality on days of strong negative market reactions. This relationship has an important consequence for liquidity risk management, as diversifying liquidity risk in times of market downturns, when diversification is most needed, becomes more difficult due to the strong liquidity commonality.

The specification (5.6.3), which only includes abnormally large positive returns in addition to index returns and volatility, does not yield any significant results for the impact of large positive market reactions. However, in specification (5.6.4), we see that only large, either negative or positive, market reactions significantly impact liquidity commonality and that the index return variable is not significant. However, large negative market returns have, by far a greater impact on liquidity commonality than abnormal positive returns. This result is important because it demonstrates the asymmetry in liquidity commonality and again highlights the soaring liquidity risk induced by liquidity commonality in market downturns.

Our findings, therefore, give support for our hypothesis that stock market declines by affecting liquidity demand (e.g., panic selling, risk aversion) or liquidity supply (e.g., margin constraints, fund withdrawals by financial intermediaries) lead to liquidity commonality.

5.1.2.5 Liquidity commonality and funding liquidity

The theoretical concept that market-wide supply effects in liquidity during market declines impair market liquidity by inducing market commonality, which is also known as the funding and market liquidity spiral, see, e.g., Brunnermeier and Pedersen (2009), has recently received huge attention. In their theoretical work (see section 3.1.2), they argue that a large market-wide price decline could initiate a spiral of funding and market liquidity dry-ups that induces liquidity commonality. This effect should even have intensified with an increasing financial integration in the last decade.

We therefore want to empirically test this liquidity supply side effect on liquidity commonality and investigate the dynamic interactions between financial liquidity and market liquidity. We separately use two proxies for funding liquidity tightness: the banking sector returns and the EURIBOR-EONIA-spreads.

Banking sector returns measure the change in the aggregate market value of the banking sector and therefore serve as proxies for their performance. As the tendency of investors to withdraw funds from intermediary financial institutions, such as banks, is linked to the intermediaries' performance, a drop in the market valuation of the banking sector is therefore a good proxy for a weak aggregate funding liquidity situation.

Hence, we start off with specification (5.7.1) that adds the DAX Banks log-returns, a bank index that consists of all major German banks, to specification (5.6.1), that consists of index returns and the standard deviation of the index log-returns. The significant negative relationship between the DAX Banks log-returns and our liquidity commonality measure supports our liquidity supply hypothesis. If we further add the two variables that capture abnormally large negative and positive one-day returns in the specification (5.7.2), we see that the index return becomes insignificant, whereas the impact of abnormally large negative and large positive one-day returns remains significant; however, become less significant, and the impact of the DAX Banks log-returns remains robust. Thus, we see that under-performance of the banking sector, which proxies a tight aggregate funding liquidity situation, leads to an increase in liquidity commonality.

To test the robustness of this result we use a second proxy for funding liquidity

Table 5.7: The effect of index and banking sector returns on liquidity commonality

This table reports OLS regressions that analyze the effect of market and banking sector returns on liquidity commonality during the sample period of January 2003 to December 2009. The dependent variable, liquidity commonality, is generated as follows: For each stock, daily changes in the order-size-dependent volume-weighted spread $WS(q)$, derived daily from the limit order book, are regressed on changes in market average volume-weighted spreads, which are the daily equally weighted volume-weighted spreads of all stocks excluding the dependent-variable stock, within each month m. The degree of liquidity commonality in each month is measured by taking an equally weighted average of the R^2 statistics for each index d. Our dependent variable, liquidity commonality, for each month m is then derived by the logit transformation of these cross-sectional R^2 averages by index d: $LiqCom_{m,d} = ln\left[R^2_{m,d}/\left(1 - R^2_{m,d}\right)\right]$. Index log-return (monthly), is the monthly log-return of the respective major German index d (DAX, MDAX, SDAX, or TecDAX). DAX Banks log-return (monthly) is the monthly log-return of a bank index that consists of all major German banks. Standard deviation of index log-return (monthly) is the annualized standard deviation of the daily index log-returns in month m. Down (dummy) * Index log-return (monthly) is an interaction term of the dummy variable Down, which equals one if the index log-return in month m is at least 1.5 standard deviations below its monthly sample mean, and the variable Index log-return (monthly). Up (dummy) * Index log-return (monthly) is an interaction term of the dummy variable Up, which equals one if the index log-return in month m is at least 1.5 standard deviations above its monthly sample mean, and the variable Index log-return (monthly). This table shows the estimated coefficients: the t-statistics are reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.7.1)	(5.7.2)
Index log-return (monthly)	-0.0206	1.414
	(-0.02)	(1.35)
Standard deviation of index log-return (monthly)	1.221***	1.187***
	(4.40)	(3.87)
DAX bank log-return (monthly)	-2.201***	-1.949***
	(-4.32)	(-3.77)
Down(dummy) * Index log-return (monthly)		-3.303**
		(-2.33)
Up(dummy) * Index log-return (monthly)		-2.148*
		(-1.84)
Constant	-3.429***	-3.458***
	(-51.72)	(-51.09)
Observations	334	334
Adjusted R^2	0.207	0.217
F	26.49	22.80

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

tightness: the EURIBOR-EONIA-spread. To finance themselves, banks, among other possibilities, participate in the interbank market, in which banks make unsecured, short-term loans to each other. The Euro Over Night Index Average (EONIA) is the interest rate, computed as a weighted average of all transactions by the European Central Bank, for such unsecured, overnight interbank loans. The EURIBOR is the average rate at which the same panel of banks, used for the EONIA calculation, offer to lend unsecured funds to other banks in the interbank market for maturities of one, two and three weeks and all monthly maturities of one to twelve months. For our calculation, we use the 3-month EURIBOR. Therefore, the level of the EURIBOR-EONIA-spread can be viewed as the proxy for ease of funding liquidity available to banks, i.e., the spread will widen in tight liquidity conditions and in situations where the banks' liquidity uncertainty increases.

Analogous to specification (5.7.1) we add the EURIBOR-EONIA-spread to the index returns and the standard deviation of the index log-returns. In specification (5.8.1) in Table 5.8, we see that there is a significant positive relationship between the EURIBOR-EONIA-spread and our measure for liquidity commonality. An increase in the EURIBOR-EONIA-spread, a sign of tight funding liquidity, is associated with soaring liquidity commonality. This relationship is also robust to the inclusion of abnormally large negative and positive one-day index returns in specification (5.8.2).

Overall, we observe that our results for the two different proxies for funding liquidity tightness (bank returns and EURIBOR-EONIA-spread) are relatively consistent. These findings show that market-wide liquidity dry-ups (induced by liquidity commonality) are related to funding liquidity tightness and therefore strongly support the theoretical concept of funding and market liquidity spirals by Brunnermeier and Pedersen (2009). We are therefore able to empirically demon-

Table 5.8: The effect of funding liquidity (measured by the EURIBOR-EONIA-spread) on liquidity commonality

This table reports OLS regressions that analyze the effect of market and banking sector returns on liquidity commonality during the sample period of January 2003 to December 2009. The dependent variable, liquidity commonality, is generated as follows: For each stock, daily changes in the order-size-dependent volume-weighted spread $WS(q)$, derived daily from the limit order book, are regressed on changes in market average volume-weighted spreads, which are the daily equally weighted volume-weighted spreads of all stocks excluding the dependent-variable stock, within each month m. The degree of liquidity commonality in each month is measured by taking an equally weighted average of the R^2 statistics by index i. Our dependent variable, liquidity commonality, for each month m is then derived by the logit transformation of these cross-sectional R^2 averages by index d: $LiqCom_{m,i} = ln\left[R^2_{m,d}/\left(1 - R^2_{m,d}\right)\right]$. Index log-return (monthly) is the monthly log-return of the respective major German index d (DAX, MDAX, SDAX, or TecDAX). The EURIBOR(3M)-EONIA-spread is the spread between the 3-month EURIBOR and the EONIA. The standard deviation of index log-return (monthly) is the annualized standard deviation of the daily index log-returns in month m. Down (dummy) * Index log-return (monthly) is an interaction term of the dummy variable Down, which equals one if the index log-return in month m is at least 1.5 standard deviations below its monthly sample mean, and the variable Index log-return (monthly). Up (dummy) * Index log-return (monthly) is an interaction term of the dummy variable Up, which equals one if the index log-return in month m is at least 1.5 standard deviations above its monthly sample mean, and the variable Index log-return (monthly). This table shows the estimated coefficients: the t-statistics are reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.8.1)	(5.8.2)
Index log-return (monthly)	-2.556***	-0.899
	(-4.21)	(-0.96)
Standard deviation of index log-return (monthly)	0.731**	0.717**
	(2.18)	(1.99)
EURIBOR(3M)-EONIA-spread	0.643***	0.571***
	(4.57)	(3.87)
Down(dummy) * Index log-return (monthly)		-3.353**
		(-2.27)
Up(dummy) * Index log-return (monthly)		-1.859
		(-1.52)
Constant	-3.501***	-3.516***
	(-49.37)	(-47.85)
Observations	334	334
Adjusted R^2	0.209	0.219
F	26.60	20.43

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

strate that the rather elusive theoretical concept, that the lack of market liquidity is both a symptom of the financial crisis and, at the same time, responsible for exacerbating its consequences, holds.

Having analyzed the liquidity commonality dynamics during the financial crisis, we now want to turn our focus to another phenomenon in the market liquidity context: the flight-to-quality.

5.1.3 Flight-to-quality or flight-to-liquidity in the stock market

Previous theoretical and empirical research on the impact of credit quality, i.e., the likelihood of default of an asset, on market liquidity almost exclusively focuses on the bond or CDS market (see, e.g., Longstaff et al. (2005), Ericsson and Renault (2006) and Chen et al. (2007a)), which indicates that there is an inverse relationship between liquidity costs and credit quality. In the context of crisis, there further has been a stream of literature that focuses on the liquidity spread widening between high- and low-credit-quality assets as a reaction to increased market uncertainty, i.e., a tendency of assets with a high credit quality to become more liquid compared with low-credit-quality assets during times of financial market distress. This phenomenon is argued to be the result of the investor's tendency to shift their portfolios toward less risky and more liquid assets in times of crisis. This is known as the flight-to-quality or flight-to-liquidity phenomenon, see, e.g., Vayanos (2004), Longstaff (2004), Acharya and Pedersen (2005) and Beber et al. (2009).

To the best of our knowledge, however no research relating the effect of the likelihood of default, as measured by the company's rating, on market liquidity

Table 5.9: Descriptive statistics on the effect of ratings on stock market liquidity

This table gives an overview of average order-size-dependent volume-weighted spreads $WS(q)$ for different rating categories during the sample period of January 2003 to December 2009. The average weighted spreads, which are derived from the limit order book, are reported for 6 standardized volume classes q, which are available for all four major German indices. The volume classes q are reported in Euro thousand. The weighted spreads are measured in basis points. The average order-size-dependent volume-weighted spreads $WS(q)$ are reported for different rating categories: Investment grade includes all observations of companies that have a rating between AAA and BBB-. Speculative grade includes all observations of companies with a rating between BB+ and D. Non-rated includes all observations of companies that do not possess a rating from an external rating agency. Furthermore, this table includes inter-category differences and respective t-test results: Difference Investment - Speculative provides the difference of the weighted spreads between the observations of companies that possess an investment grade rating and companies that have a speculative grade rating. Difference Rated - Non-rated gives the difference of the weighted spreads between the observations of companies that possess any rating (either an investment or speculative grade rating) and companies that are not rated by external rating agencies.

The results are reported for two different subsamples: Panel A covers the pre-crisis period from January 2003 to September 14th, 2008, while Panel B covers the period of the financial crisis from September 15th, 2008 (collapse of Lehman Brothers) to December 2009.

Volume class q	Investment grade	Speculatvie grade	Non-rated	Difference Investment - Speculative	Difference Rated - Non-rated
Sample A: Non financial crisis (Jan 1, 2003 - Sep 14, 2008)					
25	22.76	81.82	103.91	-59.06***	-67.29***
50	28.70	112.38	140.42	-83.69***	-92.18***
100	40.65	160.69	205.83	-120.04***	-137.67***
250	76.35	265.59	331.92	-189.24***	-214.49***
500	115.14	387.48	433.34	-272.34***	-264.47***
1000	171.96	477.91	541.45	-305.95***	-320.83***
Total	74.03	221.95	253.48	-147.93***	-147.85***
Sample B: Financial crisis (Sep 15, 2008 - Dec 31, 2009)					
25	59.68	134.93	150.74	-75.25***	-71.16***
50	83.75	221.71	252.59	-137.96***	-132.46***
100	124.51	378.26	431.31	-253.75***	-240.83***
250	156.28	602.43	668.76	-446.14***	-402.20***
500	234.22	619.43	820.51	-385.21***	-500.30***
1000	321.19	789.03	899.81	-467.84***	-486.49***
Total	158.18	418.84	457.87	-260.66***	-235.89***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

has focused on the stock market. This part of our research will therefore look into this area of market liquidity.

5.1.3.1 Descriptive statistics uncovering the flight-to-quality

To analyze the flight-to-quality effect, we will first explore several univariate statistics. This process is followed by a panel-data regression analysis that examines the effect of different company ratings on liquidity costs in great detail, while controlling for variables that have proven to at least partially explain liquidity costs (e.g., share price, return volatility, trading activity and firm size).

First, we want to obtain an impression of how liquidity costs differ across rating categories and what influence the financial crisis has on these differences. Table 5.9 shows average volume-weighted spreads $WS(q)$[124] for three different rating categories (investment grade, speculative grade and non-rated) and for two different periods (pre-crisis vs. crisis). We can observe that there is a clear liquidity ranking across rating categories during both pre-crisis and crisis period. Liquidity costs for investment grade stocks are the lowest, followed by speculative grade stocks and companies that do not possess external ratings. This liquidity ranking can be best seen in the differences between the rating categories on the right side of the table. The difference between rated (both investment and speculative grades) and non-rated companies is 148 bps during the pre-crisis period and 254 bps during the crisis. This difference between rated and non-rated companies gives support for the adverse selection component of liquidity costs, which was theoretically introduced by Copeland and Galai (1983) and Glosten and Milgrom (1985). Rating agencies are a means of private information production and therefore alleviate

[124] For a better comparison and to avoid an index bias in the volume-weighted spreads, we only focus on the 6 standardized volume classes q, which are available for all four major indices. These are the volume classes of EUR 25, 50, 100, 250, 500 thousand and 1 million.

the adverse selection component of liquidity costs by decreasing the information asymmetry problem.[125] The reduced information asymmetry therefore explains the comparatively lower liquidity costs of rated stocks.

The pre-crisis difference of 148 bps and the crisis difference of 261 bps for the spread between investment and speculative grade ratings clearly show that stocks associated with a higher credit quality of the company possess lower liquidity costs. These results are in line with our hypothesis that there is a positive relationship between credit risk/default probability and liquidity risk and the findings in the bond and CDS market (see, e.g., Ericsson and Renault (2006) and Chen et al. (2007a)). All of those differences across rating categories hold across all volume classes for both sub-periods and are significant at a 1 percent significance level.

However, in the context of the impact of credit risk on market liquidity, the analysis of the flight-to-quality or flight-to-liquidity phenomenon appears to be most interesting, as this phenomenon has been widely discussed in market liquidity research, see, e.g., Vayanos (2004), Longstaff (2004), and Acharya and Pedersen (2005). In brief, the flight-to-quality phenomenon in market liquidity states that in times of increased market uncertainty, e.g., during the financial crisis, the impact of credit risk on liquidity risk is expected to intensify, mostly due to an increase in the investor's risk aversion and preference for liquidity. Therefore, we should see an increase in liquidity cost deltas between investment and speculative grade ratings. Indeed, if we look at Table 5.9, we clearly see an increase in the liquidity spread between stocks with a high and low probability of default, as the pre-crisis difference of 148 bps between investment- and speculative-grade rated stocks increases to 261 bps during the crisis. These findings give support to the flight-

[125] For an overview on the impact of rating agencies on information asymmetry see Healy and Palepu (2001).

Table 5.10: Effect of rating information on stock market liquidity

This table reports company and volume-class fixed effects regressions that analyze the effect of rating information on market liquidity during the sample period January of 2003 to December 2009. The dependent variable, liquidity costs, is represented by the daily price impact per transaction $L(q)$ calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. The standard deviation of daily log-returns is the annualized 5 day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of a dummy variable, which equals 1 if the respective company posses a rating by a rating agency. This table shows the estimated coefficients: the t-statistics are reported in parentheses below their corresponding estimated coefficients and the adjusted R^2 values are presented below their corresponding models.

	(5.10.1)
Price (log)	-0.514***
	(-228.04)
Market cap (log)	-0.282***
	(-125.79)
Traded volume (log)	-0.222***
	(-613.08)
Standard deviation of daily log-returns (5 days)	0.678***
	(582.00)
Rating (dummy)	-0.101***
	(-47.61)
Constant	8.546***
	(878.71)
Observations	2373418
Adjusted R^2	0.523
F	521337.7

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

to-quality phenomenon in the stock market. Furthermore, the increase in the liquidity deltas between investment- and speculative-grade rated stocks is robust for all volume classes.

5.1.3.2 The impact of rating information on market liquidity

To show that these findings based on univariate test statistics are not due to biases in the composition of the rating categories (e.g., a greater extent of companies with large market cap, see Figure 4.2, which are usually associated with lower liquidity costs among the investment-grade companies), we proceed with a multivariate analysis of this issue. In detail, we will extend the panel data regression specification (5.1), which accounts for well-known variables, that have proven to at least partially explain the variation in liquidity costs (e.g., share price, return volatility, trading activity and firm size), to analyze the impact of ratings on market liquidity. We start off with an analysis of the impact of rating information in general. Therefore, we introduce a dummy variable that indicates if a company possesses a rating by an external rating agency. This setting should analyze whether a rating produced by an external rating agency conveys additional private information to reduce the information asymmetry, leading to a reduction in the adverse selection component of the weighted spread and finally leading to lower liquidity costs.

The negative impact of the rating dummy in our specification provides further empirical support for the adverse selection component of liquidity costs and shows that rating agencies, by providing company credit ratings, are able to reduce the information asymmetry; see Table 5.10. To quantify the impact of external ratings, we can observe that an external rating reduces the liquidity costs by roughly 10%. The result is also significant at the 1% significance level.

5.1.3.3 The flight-to-quality - the impact of credit quality/default probability on market liquidity during the financial crisis

We now want to turn our focus to the multivariate analysis of the flight-to-quality or flight-to-liquidity phenomenon. We particularly seek to answer two fundamental questions in this analysis: Is there a liquidity cost spread between companies with a high and companies with a low credit quality, and does this spread intensify in times of increased market uncertainty, supporting the flight-to-quality theory?

Table 5.11: Effect of credit quality/default probability on stock market liquidity

This table reports company and volume-class fixed effects regressions that analyze the effect of credit quality as measured by credit ratings on market liquidity during the sample period of January 2003 to December 2009. The dependent variable, liquidity costs, is represented by the daily price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. The standard deviation of daily log-returns is the annualized 5 day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of a dummy variable that equals 1 if the respective company possess an investment-grade rating (rating between AAA and BBB-) and equals 0 if the company has a speculative-grade rating (rating between BB+ and D). The sample consists only of those companies that possess a rating from an external rating agency, and therefore, non-rated companies are excluded. The results are reported for three different subsamples: (5.11.1) covers the pre-crisis period from January 2003 to September 14th, 2008, (5.11.2) covers the period of financial crisis from September 15th, 2008 (collapse of Lehman Brothers) to December 2009, and (5.11.3) covers all of the data for our sample period of January 2003 to December 2009. This table shows the estimated coefficients: the t-statistics are reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.11.1)	(5.11.2)	(5.11.3)
Price (log)	-0.461***	-0.364***	-0.454***
	(-421.75)	(-112.73)	(-420.94)
Market cap (log)	-0.228***	-0.283***	-0.237***
	(-265.55)	(-109.07)	(-278.23)
Traded volume (log)	-0.338***	-0.318***	-0.334***
	(-633.72)	(-202.26)	(-634.16)
Standard deviation of daily log-returns (5 days)	1.036***	0.631***	0.964***
	(321.74)	(167.31)	(439.35)
Investmentgrade rating (dummy)	-0.0473***	-0.0567***	-0.0479***
	(-25.54)	(-11.20)	(-26.28)
Constant	10.76***	11.33***	10.88***
	(1892.38)	(768.18)	(1980.42)
Observations	649778	141798	791576
Adjusted R^2	0.880	0.834	0.865
F	164398.1	24534.8	174581.4

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Therefore, we add a dummy variable to our panel data regression specification (5.1) that captures the difference between investment- and speculative-grade-rated companies and which we call investment grade rating (dummy). To test our flight-to-quality hypothesis that during time of crisis the spread between the liquidity costs of high- and low-credit-quality stocks widens, we separately estimate the impact of this dummy for three different subsamples: (5.11.1) covers the pre-crisis period, (5.11.2) covers the period of the financial crisis, and (5.11.3) covers our entire sample period. A comparison of the two first subsamples in particular will yield insight into the flight-to-quality phenomenon.

Table 5.11 shows that the coefficient of our dummy variable is significantly negative across all subsamples and that, therefore, investment grade stocks have liquidity costs that are roughly 5% less than those of speculative grade stocks. This finding clearly indicates that, in the stock market, liquidity costs increase with credit risk. By comparing the coefficient for the investment grade rating dummy for the pre-crisis period (5.11.1) with the coefficient during the financial crisis (5.11.2), we clearly see that the impact of credit risk, as expected, intensifies during the financial crisis. This effect shows that the flight-to-quality or flight-to-liquidity phenomenon also holds for the stock market which demonstrates that, in times of crisis investors become increasingly risk-averse and exhibit a preference for more liquid instruments. As we are using a volume-weighted spread measure derived from the limit order book, our results, which are all significant at the 1% significance level, prove that the flight-to-quality phenomenon holds for the whole depth of the limit order book in the stock market.

5.2 Market liquidity and ownership structures[126]

In this section, we focus on the empirical analysis of the impact of different ownership structures on market liquidity. For our analyses, we use the dataset presented in section 4.1.2. We begin with an analysis of the impact of different measures of ownership concentration on market liquidity in subsection 5.2.1. The subsequent analyses in subsection 5.2.2 should then help us to better understand the liquidity effect that different types of blockholders have. To finalize this section, we will provide several robustness tests for our empirical findings in subsection 5.2.3.

As a basis for our empirical analysis on the impact of ownership concentration and blockholder types on market liquidity, we use the log-log specification (5.1) that we introduced in section 5.1.1.2 and a company and volume class[127] fixed effects model[128] for the estimation.[129]

5.2.1 Market liquidity and ownership concentration

To test our initial hypothesis that information asymmetry problems impair stock market liquidity for companies with a concentrated ownership structure, we add several ownership concentration measures, one after the other, to the reference specification above. In turn, we add the following measures, all of serve as proxies for the ownership concentration: the total percentage of blockholdings, the number of blockholders, the Herfindahl index and the percentage share of the largest

[126] This section is largely based on Rösch and Kaserer (2010).

[127] The volume class q is an inherent characteristic of our order-size-dependent liquidity costs measure.

[128] The Hausman (1978) test statistic supports the usage of a fixed effects model compared with a random effects model.

[129] In addition, we also test the same models with company, volume and time fixed effects. The results are consistent with those reported in Tables 5.12 to 5.14 and can be found in the Appendix in Tables B.1 and B.2.

Table 5.12: Different measures of ownership concentration

This table reports company and volume-class fixed effects regressions that relate liquidity costs to various measures of ownership concentration for the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. The price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the year average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. In addition to the aforementioned control variables, we test the impact of the following measures of ownership concentration: share of blockholders is the total share of blockholdings as a fraction. Number of blockholders is the total count of blockholders. Herfindahl represents the sum of the squares of the individual blockholder shareholdings. Largest blockholder is the share of the largest blockholder. $C1C3$ and $C1C5$ represent the combined share of the three and five largest blockholders, respectively. This table shows the estimated coefficients: the t-statistics are reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.12.1)	(5.12.2)	(5.12.3)	(5.12.4)	(5.12.5)	(5.12.6)	(5.12.7)
Price (log)	-0.437***	-0.430***	-0.432***	-0.437***	-0.438***	-0.432***	-0.431***
	(-16.37)	(-16.14)	(-16.18)	(-16.39)	(-16.41)	(-16.20)	(-16.16)
Market cap (log)	-0.195***	-0.206***	-0.201***	-0.197***	-0.197***	-0.204***	-0.205***
	(-7.50)	(-7.90)	(-7.72)	(-7.56)	(-7.56)	(-7.82)	(-7.86)
Traded volume (log)	-0.378***	-0.365***	-0.376***	-0.374***	-0.373***	-0.366***	-0.366***
	(-49.89)	(-45.96)	(-49.38)	(-48.09)	(-47.93)	(-46.12)	(-46.09)
Stdev. log-returns	1.637***	1.613***	1.632***	1.631***	1.627***	1.615***	1.615***
	(66.15)	(64.33)	(65.92)	(65.57)	(65.31)	(64.46)	(64.40)
Share of blockholders		0.142***					
		(5.44)					
Number of blockholders			0.0127***				
			(3.28)				
Herfindahl				0.0786**			
				(2.42)			
Largest Blockholder					0.0963***		
					(3.26)		
C1C3						0.138***	
						(5.10)	
C1C5							0.135***
							(5.12)
Constant	8.371***	8.306***	8.360***	8.350***	8.329***	8.304***	8.308***
	(81.95)	(80.93)	(81.85)	(81.50)	(80.97)	(80.77)	(80.91)
Observations	9060	9060	9060	9060	9060	9060	9060
Adjusted R^2	0.608	0.609	0.608	0.608	0.608	0.609	0.609
F	3985.1	3206.8	3194.6	3191.4	3194.5	3204.5	3204.6

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and the three and five largest blockholders, $C1C3$ and $C1C5$, respectively.

Table 5.12 presents the results for the first set of regressions. The reference model (5.12.1) that only includes the control variables shows that the estimates of the coefficients of price level, market capitalization, volume and return volatility are, as expected, consistent with the results reported in previous studies and our results reported in subsection 5.1.1.2. Liquidity costs are, therefore, once again a decreasing function of price level, market capitalization and trading volume. In contrast, the return volatility, which is a proxy for the general market condition and risk, increases liquidity costs.

Adding the proxy variables for ownership concentration consecutively to the reference specification in the specifications (5.12.2) to (5.12.7), we see that the results support our information asymmetry hypothesis. Models (5.12.2) to (5.12.7) show that liquidity costs, represented by our order-size-dependent volume-weighted spread measure, increase with ownership concentration. Therefore, stock market liquidity is impaired by blockholder ownership, as overall blockholders possess economies of scale in the collection of information or might have access to private, value-relevant information. These results are significant at the 1% significance level and robust for all our measures of ownership concentration, i.e., total share of blockholdings, total number of blockholders and share of the largest and three and five largest shareholders, except for the Herfindahl index, which is only significant at the 5% significance level. The total share held by blockholders (see specification 5.12.2) displays the highest level of significance, with a t-statistic of 5.44.

These findings contribute to the existing literature the fact that our liquidity price impact measure $L(q)$, derived from the limit order book shows a positive linkage to ownership concentration and therefore confirms research, see, for example Heflin and Shaw (2000), on other direct and indirect measures of liquidity.

5.2.2 Market liquidity and blockholder types

In the previous subsection, we found evidence that ownership concentration significantly matters for stock market liquidity. However, we further hypothesized that access to private or value-relevant information or the willingness to exploit this information is not uniformly distributed across all types of blockholders and that, therefore, different blockholder types have different impacts on the stock market liquidity.

To test this hypothesis, we scrutinize the impact of different types of blockholders on the stock market liquidity. Table 5.13 shows that separate analyses of different blockholder types yield interesting results. In model (5.13.1), we begin with the same specification as in model (5.12.2), which includes all control variables and the total share of blockholdings, which showed the highest significance among all measures of ownership concentration. In succession, we then add the following four mutually exclusive and collectively exhaustive blockholder types: insiders and financial, strategic and private investors.

We find that firms with insider blockholders exhibit a significantly lower market liquidity or higher liquidity costs, even after controlling for total blockholder ownership (see model 5.13.2).[130] This effect can be explained by the fact that inside blockholders are more likely to possess private information than any other outside blockholder[131] and therefore to exacerbate the information asymmetry problem compared with other blockholder types. Therefore, it is not surprising that intro-

[130] This result is consistent with the findings of Ginglinger and Hamon (2007a).
[131] Consistent with this argument, Lakonishok and Lee (2001) find that managerial trades are more informative than large shareholder trades.

Table 5.13: Liquidity costs, ownership concentration and several blockholder types

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the share of various blockholder types for the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. The price (log) is the logarithm of the year average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the year average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. We further include the share of blockholders which is the total share of blockholdings as a control variable in all models. In addition to the aforementioned control variables, we test the impact of the shareholdings of following types of blockholders: insiders, financial, strategic and private investors. This table shows the estimated coefficients: the t-statistics are reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.13.1)	(5.13.2)	(5.13.3)	(5.13.4)	(5.13.5)	(5.13.6)
Price (log)	-0.430***	-0.446***	-0.432***	-0.430***	-0.443***	-0.453***
	(-16.14)	(-16.60)	(-16.14)	(-16.14)	(-16.59)	(-16.85)
Market cap (log)	-0.206***	-0.192***	-0.205***	-0.206***	-0.192***	-0.184***
	(-7.90)	(-7.30)	(-7.88)	(-7.90)	(-7.35)	(-6.99)
Traded volume (log)	-0.365***	-0.362***	-0.364***	-0.365***	-0.364***	-0.362***
	(-45.96)	(-45.33)	(-44.55)	(-45.30)	(-45.92)	(-45.40)
Stdev. log-returns	1.613***	1.608***	1.610***	1.613***	1.615***	1.611***
	(64.33)	(64.12)	(63.47)	(63.93)	(64.53)	(64.31)
Share of blockholders	0.142***	0.123***	0.155***	0.141***	0.176***	0.157***
	(5.44)	(4.67)	(4.90)	(4.96)	(6.58)	(5.74)
Insider		0.195***				0.141***
		(4.26)				(3.00)
Financial investors			-0.0261			
			(-0.73)			
Strategic investors				0.00232		
				(0.06)		
Private investors					-0.388***	-0.331***
					(-5.38)	(-4.44)
Constant	8.306***	8.216***	8.300***	8.306***	8.236***	8.181***
	(80.93)	(78.52)	(80.61)	(80.91)	(79.77)	(78.07)
Observations	9060	9060	9060	9060	9060	9060
Adjusted R^2	0.609	0.610	0.609	0.609	0.611	0.611
F	3206.8	2681.8	2672.2	2672.0	2687.6	2307.5

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ducing financial and strategic investors to the regression, while controlling for the total blockholder share (see models 5.13.3 and 5.13.4), does not yield any significant result. These variables do not seem to convey any further information that is not already included in the total blockholder share.

However, if we add the share of private blockholders to our initial model of control variables and total blockholder share (see model 5.13.5), we see that private blockholders have a positive effect on stock market liquidity and decrease liquidity costs.

One explanation for this result is that private blockholders might not have access to private information (in contrast to insiders or likely strategic investors) or cannot leverage economies of scale in the information acquisition and exploration (in contrast to financial and strategic investors). Another highly probable explanation might be that private investors simply face a (self-imposed) restriction on engaging in information-based trading, as they are usually more long-term oriented investors. Hence, private blockholders allay the information asymmetry problem and decrease the liquidity costs.

If we combine both significant variables, insider and private blockholders, with the total blockholder share in one regression (see model 5.13.6), the results remain stable: insider blockholders increase liquidity costs, whereas private blockholders have a beneficial impact on liquidity costs.

To further explore the impact of different blockholder types on stock market liquidity, we set up another model that includes the share of all four mutually exclusive and collectively exhaustive blockholder types (insiders and financial, strategic and private investors), together with the control variables, omitting the total share of blockholders that we included in the previous regressions. Table 5.14 shows the results of this model. Not surprisingly, insiders have the largest

Table 5.14: Liquidity costs and several blockholder types

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the share of various blockholder types for the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book.The price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. In addition to the aforementioned control variables, we test the impact of the shareholdings of the following types of blockholders: insiders and financial, strategic and private investors. This table shows the estimated coefficients: the t-statistics are reported in parentheses next to their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.14.1)	
Insider	0.299***	(6.11)
Financial investors	0.154***	(4.86)
Strategic investors	0.162***	(4.51)
Private investors	-0.172**	(-2.40)
Price (log)	-0.453***	(-16.83)
Market cap (log)	-0.184***	(-6.99)
Traded volume (log)	-0.361***	(-44.30)
Stdev. log-returns (annualized)	1.610***	(63.63)
Constant	8.181***	(78.03)
Observations	9060	
Adjusted R^2	0.611	
F	2018.8	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

impact on liquidity costs, but this time financial and strategic investors have a significant impact on stock market liquidity. These three blockholder types impair stock market liquidity and therefore increase the liquidity costs, as presented by our volume-weighted spread measure. These results are consistent with the hypothesis that certain blockholder types possess economies of scale in the collection of information or have access to private, value-relevant information and may trade on this information to extract the private benefits of control. Thus, market makers and other market participants face an adverse selection problem from these informed traders and therefore increase the spreads, which leads to poorer market liquidity. In contrast, private blockholders reduce the liquidity costs, as they are not able to extract value-relevant information or willing to trade on this information, due to their often more long-term oriented investment style.

As in the case of private blockholders, we would have expected that strategic investors are also not willing to trade on private information and therefore reduce liquidity costs, as strategic investors typically assume a long-term perspective on their investment if they acquire the control of another company. However, this intuition might only hold for "real" strategic investors who possess a majority stake ($\geq 50\%$) in the acquired company, are therefore in control of this company and are usually closely interconnected. To test this hypothesis, we take a closer look at the impact of different strategic blockholder sizes and therefore split the total strategic blockholder share into two parts: one representing the share of majority blockholders, i.e., the share of individual blockholders holding more than or equal to 50%, and the other representing the share of minority blockholders, i.e., the share of individual blockholders holding less than 50%. Table 5.15 shows the results of a model that adds these two variables to our initial model of control variables and total blockholder share. This model supports our hypothesis that only "real" strategic blockholders with a majority share are not willing to trade on their private information and therefore reduce the liquidity costs compared with other blockholders, whereas those strategic blockholders with a minority share are willing to trade on the information, which they acquire through economies of scale in the collection of information or access to private, value-relevant information, and therefore increase liquidity costs.

Overall, our results prove that the often-claimed tradeoff between the liquidity benefits obtained through dispersed corporate ownership and the benefits from efficient management control achieved by a certain degree of ownership concentra-

Table 5.15: The blockholder size effect for strategic blockholders

This table reports company and volume-class fixed effects regressions that analyze the shareholding size effect of strategic blockholders on stock market liquidity during the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. The price (log) is the logarithm of the yearly average of the the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. In addition to the aforementioned control variables, we test the impact of the share of blockholders (as a measure of ownership concentration) together with two variables that split the total share in the hands of strategic blockholders: one representing the share of individual blockholders holding more than or equal to 50% and the other representing the share of individual blockholders holding less than 50%. This table shows the estimated coefficients: the t-statistics are reported in parentheses next to their corresponding estimated coefficients, and the adjusted R^2 value is presented below the model.

	(5.15.1)	
Share of blockholders	0.147***	(5.19)
Strategic investors (5-50%)	0.321***	(5.45)
Strategic investors (>50%)	-0.0836**	(-2.19)
Price (log)	-0.415***	(-15.57)
Market cap (log)	-0.224***	(-8.57)
Traded volume (log)	-0.361***	(-44.76)
Stdev. log-returns	1.588***	(62.51)
Constant	8.361***	(81.46)
Observations	9060	
Adjusted R^2	0.612	
F	2311.7	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

tion does not hold for private blockholders and to some extent strategic investors, as they improve stock market liquidity. The results for all of the blockholder types are highly significant at either the 1 percent or the 5 percent significance level.

Table 5.16: The effect of a change in the ownership structure towards a private blockholder

This table reports company and volume-class fixed effects regressions that analyze the effect of private blockholders on stock market liquidity. The sample consists of companies that experienced a change in the ownership structure towards a private blockholder as the largest single blockholder during the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. In addition to the aforementioned control variables, we test the impact of the dummy variable private largest blockholder, which equals 1 in those years in which the single largest blockholder is a private blockholder, and the interaction term between the dummy variable private largest blockholder and the total share of private blockholders. This table shows the estimated coefficients with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.16.1)	(5.16.2)
Price (log)	-0.388***	-0.382***
	(-9.38)	(-9.25)
Market cap (log)	-0.297***	-0.299***
	(-7.86)	(-7.90)
Traded volume (log)	-0.351***	-0.356***
	(-22.26)	(-22.46)
Stdev. log-returns	1.359***	1.350***
	(25.22)	(25.23)
Private largest blockholder(dummy)	-0.0822***	
	(-3.25)	
Private share × Private largest blockholder		-0.239***
		(-2.99)
Constant	8.801***	8.825***
	(61.96)	(62.55)
Observations	1782	1782
Adjusted R^2	0.652	0.651
F	740.8	739.6

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.3 Robustness tests

5.2.3.1 Endogeneity

To test the robustness of our results for the impact of ownership concentration and different blockholder types, we first analyze the endogeneity that might potentially prevail in the ownership structure determination, especially private blockholder ownership, and market liquidity. We want to ensure that it is unlikely that the negative relationship between the share of private blockholders and stock market liquidity is due to an alternative explanation, i.e., private investors tend to invest in companies with more liquid stocks. Therefore, we use a subsample of our dataset that consists only of companies that experienced a change in the ownership structure towards a private blockholder as the largest single blockholder during our sample period of 2003 to 2009, to analyze whether there are significant differences in the stock market liquidity after the private blockholder becomes the largest single blockholder.

Together with our reference specification (equation 5.1), we test the impact of a dummy variable 'private largest blockholder' (see model 5.16.1), which equals 1 in those years in which the single largest blockholder is a private blockholder. This variable captures the effect on the stock market liquidity of the change in the ownership structure towards a private blockholder as the largest blockholder. We further test an interaction term between the above dummy variable 'private largest blockholder' and the total share of private blockholders of the respective company (see model 5.16.2). The results of both models can be found in Table 5.16.

If the negative relationship that we found in our analyses thus far is only due to differences in the stock selection between private investors and other investors, then we should not find any significant results for the two variables as the stock market liquidity should not be affected by the change in the ownership structure. However, as our results indicate a significant negative relation for both variables, we are confident that endogeneity is not a problem in our analyses and private investors, therefore, do not specifically seek out stocks with relatively small liquidity costs. Instead, these results support our previous findings that private blockholders reduce the liquidity costs.

5.2.3.2 Disclosure thresholds

If our hypothesis holds that the positive effect of private investors and majority strategic blockholders on stock market liquidity can be explained by the fact that they face a (self-imposed) restriction on engaging in information-based trading because they are typically more long-term oriented investors, then other blockholders should also decrease liquidity costs if they are in situations where they are not willing to trade on private information.

One of these situations could be if the blockholder is holding a position that is close to an official disclosure threshold, at which a shareholder must publicly disclose an additional purchase or sale of shares, if the total shareholding owned by this particular shareholder reaches, exceeds or falls below this disclosure threshold[132]. This disclosure requirement might therefore also lead to an unwillingness to engage in information-based trading. Therefore, we analyze the effects of different types of blockholder ownership around important disclosure thresholds on stock market liquidity. Table 5.17 shows the impact on market liquidity of the

[132] According to §21 WpHG, a shareholder must publicly disclose an additional purchase or sale of shares of a company listed in Germany, if the total shareholding owned by this particular shareholder reaches, exceeds or falls below the official disclosure thresholds of 3%, 5%, 10%, 15%, 20%, 25%, 30%, 50% and 75%.

shareholdings of our four types of blockholders - insiders, financial, strategic and private investors - when they are in the range of ± 1.5% of the following major disclosure thresholds: 25%, 50% and 75%.

Not surprisingly, private investors at major disclosure thresholds decrease liquidity costs.[133] However, strategic blockholders and insiders at major disclosure thresholds also have a positive effect on the market liquidity. Insiders, strategic and private investors appear to be unwilling to trade on private information because doing so would result in a public disclosure requirement. These results support our hypothesis that a (self-imposed) restriction of blockholders on engaging in information-based trading lowers liquidity costs.

Only financial blockholders do not appear to care about the disclosure requirement and do appear to be willing on engaging information-based trading at major disclosure thresholds. This finding is not very surprising, as their business model is based on, amongst others, the trading of stocks; therefore, a disclosure threshold should not hinder them from exploiting private information. Therefore, financial blockholders also lead to increased liquidity costs at disclosure thresholds.

5.2.3.3 Further robustness tests

We further conduct a series of robustness tests[134] and therefore re-estimate the regressions in Table 5.12, Table 5.13 and Table 5.14 for different subsamples.

First, we create two subsamples using the volume classes q of our order-size-dependent volume-weighted liquidity cost measure $L(q)$ as a split criterion. The

[133] Because less than 13% of the private investor ownership observations in our sample are at disclosure thresholds, our results presented in the subsection 5.2.3.2 cannot be used as an explanation for our results in subsection 5.2.2.

[134] For the remaining robustness tests, we focus on the volume classes smaller than Euro 1 million, as the volume classes larger than Euro 1 million are only represented in the DAX index.

first subsample contains all of the volume classes q smaller than or equal to Euro 100,000, whereas the second subsample consists of the five volume classes q that are larger than Euro 100,000. Our results for ownership concentration and blockholder types remain robust for both the large and the small volume-class subsamples. Only the influence of the private blockholders in the regression together with the three other blockholder types is insignificant for the small volume classes (see model 5.21.5). Detailed results can be found in Tables 5.18 to Tables 5.21.

Second, we re-estimate the same regressions considering subsamples by index affiliation. The first subsample contains the two indices with the larger companies, namely the DAX and MDAX, whereas the second subsample consists of all of the companies listed in the SDAX or the TecDAX, which are, by definition, smaller companies. For our DAX and MDAX subsample, all our model specifications remain highly significant. For the smaller companies in the second subsample, most of the regressions using ownership concentration proxies are also significant, indicating that a concentrated ownership structure impairs stock market liquidity. Only the regression including the Herfindahl index and the largest blockholder are insignificant, although even these still have the right sign. If we consider the impact of different blockholders, only the impact of three out of the four blockholder types (namely, insiders, financial and strategic investors) is significant. Tables 5.22 to Tables 5.25 report more detailed results.

Third, we re-estimate the same regressions for daily liquidity data and daily values for the control variables. This time, our results are also robust and highly significant for all our specifications.

Thus, overall, we can conclude that our findings for ownership concentration and blockholder types discussed in sections 5.2.1 and 5.2.2 are robust. However, the liquidity benefit from private blockholders appear to be more pronounced for larger companies and when trading larger volumes. Therefore, it is not surprising that, by now, this effect was undiscovered, as only our order-size-dependent liquidity measure is able to scrutinize the liquidity cost effects for the whole limit order book.

Table 5.17: Impact of disclosure thresholds

This table reports company and volume-class fixed effects regressions that analyze the effect of different types of blockholder ownership around important disclosure thresholds on stock market liquidity during the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the year average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. In addition to the aforementioned control variables, we test the impact of the share of blockholders (which is our preferred measure of ownership concentration) together with the shareholdings of four types of blockholders - insiders and financial, strategic and private investors - when they are in the range of ± 1.5% of the following major disclosure thresholds: 25%, 50% and 75%. This table shows the estimated coefficients, with the t-statistics reported in parentheses next to their corresponding estimated coefficients, and the adjusted R^2 value is presented below the model.

	(5.17.1)	
Share of blockholders	0.156***	(5.93)
Insiders at disclosure threshold	-0.251***	(-4.07)
Financial investors at disclosure threshold	0.173**	(2.42)
Strategic investors at disclosure threshold	-0.229***	(-4.62)
Private investors at disclosure threshold	-0.739***	(-5.40)
Price (log)	-0.413***	(-15.49)
Market cap (log)	-0.215***	(-8.27)
Traded volume (log)	-0.372***	(-46.11)
Stdev. log-returns	1.637***	(64.79)
Constant	8.346***	(81.44)
Observations	9060	
Adjusted R^2	0.613	
F	1808.1	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.18: Different measures of ownership concentration - Large volume classes

This table reports company and volume-class fixed effects regressions that relate liquidity costs to various measures of ownership concentration for the subsample that contains all volume classes larger than Euro 100,000 for the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. In addition to the aforementioned control variables, we test the impact of the following measures of ownership concentration: share of blockholders is the total share of blockholdings as a fraction. Number of blockholders is the total count of blockholders. Herfindahl represents the sum of the squares of the individual blockholder shareholdings. Largest blockholder is the share of the largest blockholder. $C1C3$ and $C1C5$ represent the combined share of the three and five largest blockholders, respectively. This table shows the estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.18.1)	(5.18.2)	(5.18.3)	(5.18.4)	(5.18.5)	(5.18.6)	(5.18.7)
Price (log)	-0.376***	-0.371***	-0.371***	-0.377***	-0.377***	-0.372***	-0.371***
	(-8.94)	(-8.82)	(-8.82)	(-8.96)	(-8.96)	(-8.84)	(-8.83)
Market cap (log)	-0.293***	-0.302***	-0.301***	-0.294***	-0.294***	-0.300***	-0.301***
	(-7.20)	(-7.43)	(-7.40)	(-7.22)	(-7.21)	(-7.37)	(-7.41)
Traded volume (log)	-0.365***	-0.349***	-0.360***	-0.360***	-0.360***	-0.351***	-0.350***
	(-29.68)	(-27.09)	(-29.20)	(-28.58)	(-28.63)	(-27.29)	(-27.19)
Stdev. log-returns	1.729***	1.699***	1.721***	1.721***	1.720***	1.703***	1.701***
	(41.89)	(40.62)	(41.72)	(41.50)	(41.41)	(40.73)	(40.67)
Share of blockholders		0.176***					
		(4.08)					
Number of blockholders			0.0216***				
			(3.37)				
Herfindahl				0.0998*			
				(1.89)			
Largest Blockholder					0.0846*		
					(1.76)		
C1C3						0.161***	
						(3.60)	
C1C5							0.168***
							(3.86)
Constant	9.394***	9.295***	9.366***	9.362***	9.353***	9.301***	9.299***
	(59.14)	(57.99)	(58.99)	(58.65)	(58.30)	(57.91)	(57.97)
Observations	3993	3993	3993	3993	3993	3993	3993
Adjusted R^2	0.557	0.560	0.559	0.558	0.558	0.559	0.559
F	1471.3	1186.3	1183.2	1178.7	1178.5	1184.2	1185.3

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.19: Liquidity costs, ownership concentration and several blockholder types - Large volume classes

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the share of various blockholder types for the subsample that contains all volume classes larger than Euro 100,000 for the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. We further include the share of blockholders which is the total share of blockholdings as a control variable in all but the last model. In addition to the aforementioned control variables, we test the impact of the shareholdings of following types of blockholders: insiders and financial, strategic and private investors. This table shows the estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.19.1)	(5.19.2)	(5.19.3)	(5.19.4)	(5.19.5)
Price (log)	-0.371***	-0.389***	-0.398***	-0.407***	-0.410***
	(-8.82)	(-9.26)	(-9.39)	(-9.60)	(-9.65)
Market cap (log)	-0.302***	-0.281***	-0.278***	-0.266***	-0.265***
	(-7.43)	(-6.89)	(-6.79)	(-6.50)	(-6.47)
Traded volume (log)	-0.349***	-0.349***	-0.344***	-0.346***	-0.343***
	(-27.09)	(-27.22)	(-26.70)	(-26.87)	(-26.17)
Stdev. log-returns	1.699***	1.706***	1.694***	1.701***	1.696***
	(40.62)	(40.92)	(40.60)	(40.83)	(40.43)
Share of blockholders	0.176***	0.218***	0.145***	0.188***	
	(4.08)	(4.97)	(3.33)	(4.18)	
Private investors		-0.577***		-0.481***	-0.288**
		(-4.95)		(-3.99)	(-2.43)
Insider			0.313***	0.234***	0.425***
			(4.23)	(3.06)	(5.33)
Financial investors					0.160***
					(3.08)
Strategic investors					0.229***
					(3.86)
Constant	9.295***	9.195***	9.153***	9.105***	9.095***
	(57.99)	(57.13)	(56.04)	(55.73)	(55.57)
Observations	3993	3993	3993	3993	3993
Adjusted R^2	0.560	0.563	0.562	0.564	0.564
F	1186.3	1000.1	996.9	860.8	753.4

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.20: Different measures of ownership concentration - Small volume classes

This table reports company and volume-class fixed effects regressions that relate liquidity costs to various measures of ownership concentration for the subsample that contains all volume classes smaller than or equal to Euro 100,000 for the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. In addition to the aforementioned control variables, we test the impact of the following measures of ownership concentration: share of blockholders is the total share of blockholdings as a fraction. Number of blockholders is the total count of blockholders. Herfindahl represents the sum of the squares of the individual blockholder shareholdings. Largest blockholder is the share of the largest blockholder. $C1C3$ and $C1C5$ represent the combined share of the three and five largest blockholders, respectively. This table shows the estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.20.1)	(5.20.2)	(5.20.3)	(5.20.4)	(5.20.5)	(5.20.6)	(5.20.7)
Price (log)	-0.475***	-0.464***	-0.467***	-0.474***	-0.475***	-0.467***	-0.465***
	(-15.76)	(-15.46)	(-15.52)	(-15.77)	(-15.80)	(-15.55)	(-15.48)
Market cap (log)	-0.0879***	-0.107***	-0.0972***	-0.0912***	-0.0915***	-0.102***	-0.105***
	(-2.96)	(-3.59)	(-3.27)	(-3.07)	(-3.09)	(-3.44)	(-3.53)
Traded volume (log)	-0.381***	-0.363***	-0.378***	-0.376***	-0.374***	-0.366***	-0.364***
	(-44.38)	(-39.94)	(-43.80)	(-42.38)	(-42.23)	(-40.26)	(-40.09)
Stdev. log-returns	1.445***	1.410***	1.438***	1.437***	1.432***	1.416***	1.413***
	(50.52)	(48.57)	(50.26)	(49.91)	(49.68)	(48.80)	(48.64)
Share of blockholders		0.181***					
		(6.00)					
Number of blockholders			0.0169***				
			(3.87)				
Herfindahl				0.0908**			
				(2.49)			
Largest Blockholder					0.113***		
					(3.39)		
C1C3						0.163***	
						(5.18)	
C1C5							0.169***
							(5.55)
Constant	6.952***	6.895***	6.942***	6.937***	6.913***	6.896***	6.898***
	(63.67)	(63.23)	(63.68)	(63.47)	(63.05)	(63.07)	(63.19)
Observations	4383	4383	4383	4383	4383	4383	4383
Adjusted R^2	0.707	0.710	0.708	0.707	0.707	0.709	0.709
F	2875.0	2330.6	2312.3	2304.7	2309.3	2322.7	2326.1

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.21: Liquidity costs, ownership concentration and several blockholder types - Small volume classes

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the share of various blockholder types for the subsample that contains all volume classes smaller than or equal to Euro 100,000 for the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. We further include the share of blockholders which is the total share of blockholdings as a control variable in all but the last model. In addition to the aforementioned control variables, we test the impact of the shareholdings of following types of blockholders: insiders and financial, strategic and private investors. This table shows the estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.21.1)	(5.21.2)	(5.21.3)	(5.21.4)	(5.21.5)
Price (log)	-0.464***	-0.470***	-0.476***	-0.479***	-0.478***
	(-15.46)	(-15.61)	(-15.74)	(-15.80)	(-15.77)
Market cap (log)	-0.107***	-0.100***	-0.0960***	-0.0928***	-0.0921***
	(-3.59)	(-3.36)	(-3.21)	(-3.10)	(-3.08)
Traded volume (log)	-0.363***	-0.362***	-0.359***	-0.360***	-0.361***
	(-39.94)	(-39.92)	(-39.30)	(-39.33)	(-38.36)
Stdev. log-returns	1.410***	1.412***	1.404***	1.406***	1.409***
	(48.57)	(48.64)	(48.27)	(48.31)	(47.86)
Share of blockholders	0.181***	0.195***	0.166***	0.178***	
	(6.00)	(6.35)	(5.42)	(5.67)	
Private investors		-0.194**		-0.142*	0.0338
		(-2.38)		(-1.69)	(0.41)
Insider			0.148***	0.127**	0.304***
			(2.97)	(2.45)	(5.58)
Financial investors					0.189***
					(5.20)
Strategic investors					0.164***
					(4.01)
Constant	6.895***	6.865***	6.829***	6.816***	6.816***
	(63.23)	(62.57)	(61.41)	(61.18)	(61.16)
Observations	4383	4383	4383	4383	4383
Adjusted R^2	0.710	0.710	0.710	0.710	0.710
F	2330.6	1945.8	1948.1	1671.1	1461.9

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.22: Different measures of ownership concentration - DAX and MDAX

This table reports company and volume-class fixed effects regressions that relate liquidity costs to various measures of ownership concentration for the subsample that contains companies listed in the DAX or MDAX index for the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. In addition to the aforementioned control variables, we test the impact of the following measures of ownership concentration: share of blockholders is the total share of blockholdings as a fraction. Number of blockholders is the total count of blockholders. Herfindahl represents the sum of the squares of the individual blockholder shareholdings. Largest blockholder is the share of the largest blockholder. $C1C3$ and $C1C5$ represent the combined share of the three and five largest blockholders, respectively. This table shows the estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.22.1)	(5.22.2)	(5.22.3)	(5.22.4)	(5.22.5)	(5.22.6)	(5.22.7)
Price (log)	-0.606***	-0.602***	-0.606***	-0.611***	-0.604***	-0.601***	-0.602***
	(-13.25)	(-13.22)	(-13.28)	(-13.41)	(-13.24)	(-13.20)	(-13.21)
Market cap (log)	-0.0158	-0.0272	-0.0172	-0.0175	-0.0237	-0.0253	-0.0261
	(-0.35)	(-0.60)	(-0.38)	(-0.39)	(-0.52)	(-0.56)	(-0.58)
Traded volume (log)	-0.381***	-0.362***	-0.380***	-0.365***	-0.368***	-0.364***	-0.363***
	(-36.57)	(-32.40)	(-36.41)	(-33.47)	(-33.48)	(-32.57)	(-32.53)
Stdev. log-returns	1.801***	1.764***	1.800***	1.772***	1.772***	1.766***	1.766***
	(50.95)	(48.90)	(50.98)	(49.63)	(49.15)	(48.77)	(48.93)
Share of blockholders		0.158***					
		(4.69)					
Number of blockholders			0.0116**				
			(2.16)				
Herfindahl				0.212***			
				(4.81)			
Largest Blockholder					0.147***		
					(3.73)		
C1C3						0.145***	
						(4.18)	
C1C5							0.150***
							(4.42)
Constant	7.357***	7.269***	7.338***	7.271***	7.303***	7.273***	7.272***
	(38.07)	(37.57)	(37.95)	(37.60)	(37.76)	(37.53)	(37.55)
Observations	3876	3876	3876	3876	3876	3876	3876
Adjusted R^2	0.686	0.688	0.686	0.688	0.687	0.688	0.688
F	2330.0	1881.4	1867.2	1882.3	1874.8	1877.7	1879.4

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.23: Liquidity costs, ownership concentration and several blockholder types - DAX and MDAX

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the share of various blockholder types for the subsample that contains companies listed in the DAX or MDAX index for the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which iscalculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. We further include the share of blockholders, which is the total share of blockholdings as a control variable in all but the last model. In addition to the aforementioned control variables, we test the impact of the shareholdings of following types of blockholders: insiders and financial, strategic and private investors. This table shows the estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.23.1)	(5.23.2)	(5.23.3)	(5.23.4)	(5.23.5)
Price (log)	-0.602***	-0.615***	-0.625***	-0.628***	-0.628***
	(-13.22)	(-13.54)	(-13.75)	(-13.85)	(-13.84)
Market cap (log)	-0.0272	-0.00755	-0.00857	0.000661	-0.000352
	(-0.60)	(-0.17)	(-0.19)	(0.01)	(-0.01)
Traded volume (log)	-0.362***	-0.363***	-0.360***	-0.361***	-0.360***
	(-32.40)	(-32.65)	(-32.37)	(-32.53)	(-31.24)
Stdev. log-returns	1.764***	1.766***	1.763***	1.764***	1.762***
	(48.90)	(49.18)	(49.17)	(49.29)	(48.41)
Share of blockholders	0.158***	0.193***	0.114***	0.148***	
	(4.69)	(5.66)	(3.35)	(4.18)	
Private investors		-0.425***		-0.291***	-0.141*
		(-5.46)		(-3.49)	(-1.74)
Insider			0.364***	0.281***	0.432***
			(6.07)	(4.38)	(6.74)
Financial investors					0.141***
					(3.51)
Strategic investors					0.164***
					(3.18)
Constant	7.269***	7.158***	7.156***	7.106***	7.105***
	(37.57)	(36.96)	(37.03)	(36.73)	(36.72)
Observations	3876	3876	3876	3876	3876
Adjusted R^2	0.688	0.691	0.692	0.693	0.693
F	1881.4	1587.8	1592.6	1371.9	1200.1

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.24: Different measures of ownership concentration - SDAX and TecDAX

This table reports company and volume-class fixed effects regressions that relate liquidity costs to various measures of ownership concentration for the subsample that contains companies listed in the SDAX or TecDAX index for the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which iscalculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. In addition to the aforementioned control variables, we test the impact of the following measures of ownership concentration: share of blockholders is the total share of blockholdings as a fraction. Number of blockholders is the total count of blockholders. Herfindahl represents the sum of the squares of the individual blockholder shareholdings. Largest blockholder is the share of the largest blockholder. $C1C3$ and $C1C5$ represent the combined share of the three and five largest blockholders, respectively. This table shows the estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.24.1)	(5.24.2)	(5.24.3)	(5.24.4)	(5.24.5)	(5.24.6)	(5.24.7)
Price (log)	-0.348***	-0.336***	-0.333***	-0.348***	-0.348***	-0.340***	-0.337***
	(-10.62)	(-10.29)	(-10.19)	(-10.62)	(-10.64)	(-10.42)	(-10.33)
Market cap (log)	-0.266***	-0.284***	-0.284***	-0.266***	-0.266***	-0.279***	-0.282***
	(-8.39)	(-8.97)	(-8.96)	(-8.39)	(-8.39)	(-8.80)	(-8.91)
Traded volume (log)	-0.348***	-0.329***	-0.337***	-0.347***	-0.346***	-0.333***	-0.331***
	(-30.44)	(-28.04)	(-29.23)	(-30.19)	(-30.10)	(-28.41)	(-28.16)
Stdev. log-returns	1.359***	1.318***	1.334***	1.358***	1.355***	1.330***	1.322***
	(37.91)	(36.34)	(37.15)	(37.78)	(37.74)	(36.80)	(36.44)
Share of blockholders		0.270***					
		(6.09)					
Number of blockholders			0.0335***				
			(5.80)				
Herfindahl				0.0138			
				(0.28)			
Largest Blockholder					0.0623		
					(1.37)		
C1C3						0.229***	
						(4.96)	
C1C5							0.253***
							(5.63)
Constant	8.334***	8.230***	8.292***	8.332***	8.310***	8.245***	8.237***
	(77.20)	(75.70)	(77.00)	(77.00)	(75.99)	(75.58)	(75.66)
Observations	4500	4500	4500	4500	4500	4500	4500
Adjusted R^2	0.508	0.514	0.513	0.508	0.509	0.512	0.513
F	1469.1	1195.6	1193.7	1174.9	1176.0	1188.7	1192.6

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.25: Liquidity costs, ownership concentration and several blockholder types - SDAX and TecDAX

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the share of various blockholder types for the subsample that contains companies listed in the SDAX or TecDAX index for the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. We further include the share of blockholders, which is the total share of blockholdings as a control variable in all but the last model. In addition to the aforementioned control variables, we test the impact of the shareholdings of following types of blockholders: insiders and financial, strategic and private investors. This table shows the estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.25.1)	(5.25.2)	(5.25.3)	(5.25.4)	(5.25.5)
Price (log)	-0.336***	-0.339***	-0.342***	-0.345***	-0.346***
	(-10.29)	(-10.25)	(-10.30)	(-10.26)	(-10.26)
Market cap (log)	-0.284***	-0.281***	-0.278***	-0.276***	-0.276***
	(-8.97)	(-8.77)	(-8.66)	(-8.52)	(-8.51)
Traded volume (log)	-0.329***	-0.329***	-0.327***	-0.327***	-0.326***
	(-28.04)	(-28.03)	(-27.40)	(-27.40)	(-26.91)
Stdev. log-returns	1.318***	1.319***	1.315***	1.316***	1.314***
	(36.34)	(36.30)	(36.13)	(36.06)	(35.73)
Share of blockholders	0.270***	0.277***	0.264***	0.269***	
	(6.09)	(6.09)	(5.88)	(5.84)	
Private investors		-0.0965		-0.0789	0.194
		(-0.65)		(-0.53)	(1.32)
Insider			0.0674	0.0629	0.330***
			(1.01)	(0.94)	(4.42)
Financial investors					0.256***
					(4.72)
Strategic investors					0.283***
					(5.21)
Constant	8.230***	8.220***	8.197***	8.191***	8.191***
	(75.70)	(74.78)	(72.19)	(71.72)	(71.71)
Observations	4500	4500	4500	4500	4500
Adjusted R^2	0.514	0.514	0.514	0.514	0.514
F	1195.6	996.3	996.5	854.0	747.1

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Market liquidity and insider trading[135]

This section focuses on the empirical analysis of the impact of insider trading on market liquidity. For our empirical analyses, we use our dataset presented in section 4.1.3. We begin with an application of the standard event study methodology to analyze the behavior of market liquidity around insider trading days. The event study is followed by a panel-data regression analysis that examines the effect of insider trading activity on liquidity costs in great detail, while controlling for variables that have proven to at least partially explain liquidity costs (e.g., share price, return volatility, trading activity and firm size).

5.3.1 Event study

5.3.1.1 Theoretical framework for a market liquidity event study

As a first indicator of the magnitude and direction of the impact of insider trading on market liquidity, we conduct an event study. This statistical method has been widely used to measure the impact of a specific event (e.g., mergers and acquisitions, earnings announcements, issues of new debt or equity) on the value of a firm; see, e.g., Campbell et al. (1996) and MacKinlay (1997). These studies typically scrutinize the abnormal equity return to appraise the event's impact on the firm value. However, this method can be easily adapted to use abnormal liquidity costs around specific events instead, see, e.g., Chung and Charoenwong (1998), to analyze the event's impact on the market liquidity. The rationale for this procedure is that the effects of an event are reflected immediately in the bid and ask prices.

[135] This section is largely based on Rösch and Kaserer (2011).

As a starting point, we assume, as in the constant expected return model, that the volume-weighted spread for firm i and time t follows the following stochastic process:

$$WS(q)_{i,t} = \mu\left(q\right)_i + \epsilon\left(q\right)_{i,t} \tag{5.6}$$

where

$$\epsilon\left(q\right)_{i,t} \sim GWN\left(0, \sigma\left(q\right)_i^2\right) \tag{5.7}$$

$$cov\left(\epsilon\left(q\right)_{i,t}, \epsilon\left(q\right)_{l,s}\right) = \begin{cases} \sigma\left(q\right)_{l,i} & t = s \\ 0 & t \neq s \end{cases} \tag{5.8}$$

which defines the stochastic disturbance term $\epsilon\left(q\right)_{i,t}$ as a Gaussian white noise (GWN) process with $E\left[\epsilon\left(q\right)_{i,t}\right] = 0$ and $var\left(\epsilon\left(q\right)_{i,t}\right) = \sigma\left(q\right)_i^2$. In addition, the stochastic disturbance term $\epsilon\left(q\right)_{i,t}$ is independent of $\epsilon\left(q\right)_{l,s}$ for all time periods $t \neq s$.

In other words, the volume-weighted spread is equal to a volume- and firm-dependent constant $\mu\left(q\right)_i$ plus a normally distributed random variable $\epsilon\left(q\right)_{i,t}$ with mean zero and constant variance.

In our event study, the constant term $\mu\left(q\right)_i$ is the ex-ante expected volume-weighted spread for firm i and an estimate for the expected volume-weighted spread is calculated as the average volume-weighted spread for firm i and volume class q during the reference period. We define the reference period as the 30 trading days surrounding the insider transaction, i.e., 15 trading days before and after the insider transaction (see Figure 5.6). The disturbance term $\epsilon\left(q\right)_{i,t}$

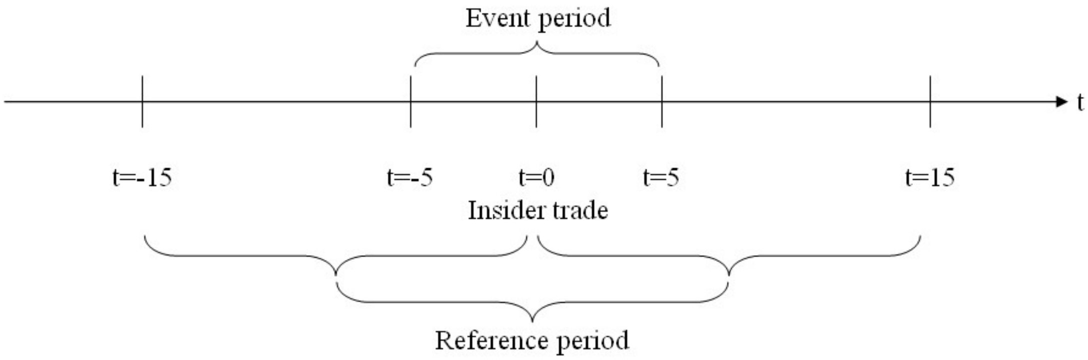

Figure 5.6: Illustration of event and reference period in the event study

represents the abnormal component of the spread as it captures the change in the volume-weighted spread for firm i attributable to the insider trading activity. The calculation of the abnormal component is straightforward, as it is simply the difference between the actual volume-weighted spread for firm i at time t and an estimate of $\mu(q)_i$. We calculate the abnormal component for all of the trading days in our event period, which comprises the insider trading ($t = 0$) itself and the five preceding and consecutive days.

For the purpose of our analysis, we calculate a standardized abnormal volume-weighted spread for firm i and time t during the event window:

$$SAWS(q)_{i,t} = \frac{WS(q)_{i,t} - \hat{\mu}(q)_i}{\hat{\sigma}(q)_i} \tag{5.9}$$

where $\hat{\mu}(q)_i$ and $\hat{\sigma}(q)_i$ are defined as the sample mean and standard deviation of the volume-weighted spread during the reference period. We calculate this standardized abnormal volume-weighted spread for all different event periods e for firm i (i.e., for all the different insider transactions of firm i during the sample period) $SAWS(q)_{i,t,e}$. We then average these standardized abnormal volume-weighted spreads across all volume classes and across all other firms in the sample to derive an average abnormal volume-weighted spread on day t:

$$AAWS_t = \frac{\sum_{i,q,e} SAWS(q)_{i,t,e}}{IQE} \tag{5.10}$$

where IQE is the total number of insider transactions across all firms i and volume classes q. We further compute a cumulative abnormal volume-weighted spread $CAWS_\tau$ as the sum of the average abnormal volume-weighted spread for a period $\tau \subseteq [-5; 5]$ during the event period:

$$CAWS_\tau = \sum_\tau AAWS_t \tag{5.11}$$

In our event study, we use three different periods: one period covers the five days preceding the insider transaction ($\tau = [1; 5]$), one period consists of the five days following the insider transaction ($\tau = [-5; -1]$) and the last period covers the whole event window ($\tau = [-5; 5]$).

5.3.1.2 Univariate results from the event study

Tables 5.26 and 5.27 show the results for three different subsamples: one consists of all insider transactions in the sample period, one only comprises exclusive insider buy transactions (i.e., on the event date $t = 0$, insiders only initiated buy transactions) and another only consists of exclusive sell transactions. These results are insightful in several ways.

First, on the day of the insider transaction ($t = 0$), the abnormal volume-weighted spreads are significantly negative for all three subsamples, which shows that the stocks are more liquid on the day of the insider transactions compared with the reference period, which is consistent with our expectation for the insider

Table 5.26: Event study - abnormal liquidity costs around insider transactions

This table reports $AAWS_t$, which are the average abnormal volume-weighted spreads derived from the limit order book for the sample period of July 2002 to December 2009. The average abnormal volume-weighted spread on day t $AAWS_t$ is derived by averaging the standardized abnormal weighted spreads $SAWS(q)_{i,t,e}$ across all firms i and volume classes q, i.e., $AAWS_t=\sum_{i,q,e} SAWS(q)_{i,t,e}/IQE$, where $SAWS(q)_{i,t,e}=[WS(q)_{i,t,e}-\hat{\mu}(q)_i]/\hat{\sigma}_i$, $\hat{\mu}(q)_i$ and $\hat{\sigma_i}$, are the sample mean and standard deviation of the order-size-dependent volume-weighted spread of stock i during the reference period, IQE is the total number of insider transactions across all firms i and volume classes q. $AAWS_t$ are reported for three different subsamples: one consisting of all insider transactions in the sample period, one only consisting of exclusive insider buy transactions and one only consisting of exclusive insider sell transactions. The t-statistics are reported in parentheses below their corresponding average abnormal order-size-dependent volume-weighted spread.

Day(s) relative to insider transaction	All	Buy-only	Sell-only
Average abnormal order-size dependent volume-weighted spread			
-5	-0.03971059***	-0.03215462***	-0.05713176***
	(-8.7843748)	(-5.3862063)	(-7.7404589)
-4	-0.01387776***	0.00109799	-0.03763815***
	(-3.0587499)	(.18328491)	(-5.0710223)
-3	-0.02798849***	0.01002136*	-0.07509007***
	(-6.1908195)	(1.674977)	(-10.185585)
-2	-0.06207095***	-0.03025518***	-0.09552372***
	(-13.545365)	(-5.0112013)	(-12.621778)
-1	-0.09361492***	-0.04306183***	-0.17178925***
	(-20.322134)	(-6.9864755)	(-23.178374)
0	-0.11050997***	-0.01744638**	-0.25109369***
	(-18.443065)	(-2.0047439)	(-32.242082)
1	-0.04962112***	0.02367176***	-0.14938278***
	(-10.694084)	(3.8106071)	(-19.97106)
2	-0.03560743***	0.00641142	-0.09752313***
	(-7.9060846)	(1.0775259)	(-13.162669)
3	-0.01863610***	0.01595656***	-0.06089954***
	(-4.0509186)	(2.5931707)	(-8.1747328)
4	-0.02641736***	0.00751798	-0.08304752***
	(-5.7200628)	(1.2354468)	(-10.918369)
5	-0.00548511	0.01588330***	-0.03159374***
	(-1.2006274)	(2.6064943)	(-4.2314352)

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.27: Event study - abnormal liquidity costs around insider transactions

This table reports$CAWS_\tau$, which are the cumulative abnormal volume-weighted spreads derived from the limit order book for the sample period of July 2002 to December 2009. An average abnormal volume-weighted spread on day t $AAWS_t$ is derived by averaging the standardized abnormal weighted spreads $SAWS(q)_{i,t,e}$ across all firms i and volume classes q, i.e., $AAWS_t = \sum_{i,q,e} SAWS(q)_{i,t,e}/IQE$, where $SAWS(q)_{i,t,e} = [WS(q)_{i,t,e} - \hat{\mu}(q)_i]/\hat{\sigma_i}$, $\hat{\mu}(q)_i$ and $\hat{\sigma_i}$ are the sample mean and standard deviation of the order-size-dependent volume-weighted spread of stock i during the reference period, IQE is the total number of insider transactions across all firms i and volume classes q. The cumulative abnormal volume-weighted spread $CAWS_\tau$ is obtained by the summation of the average abnormal volume-weighted spread over a given period, i.e., $CAWS_\tau = \sum_\tau AAWS_t$, where $\tau \subseteq [-5;5]$ represents a period during the event period. $CAWS_\tau$ are reported for three different subsamples: one consisting of all insider transactions in the sample period, one only consisting of exclusive insider buy transactions and one only consisting of exclusive insider sell transactions. The t-statistics are reported in parentheses below their corresponding cumulative abnormal order-size-dependent volume-weighted spread.

Day(s) relative to insider transaction	All	Buy-only	Sell-only
Cumulative abnormal order-size dependent volume-weighted spread			
-5 to +5	-0.47494375***	-0.04192808	-1.09000000***
	(-23.393358)	(-1.5193394)	(-34.815505)
-5 to -1	-0.23181997***	-0.09214990***	-0.42770861***
	(-17.488366)	(-5.2304756)	(-20.042014)
+1 to +5	-0.13261380***	0.06766821***	-0.41282505***
	(-9.7897511)	(3.7034044)	(-19.04054)

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

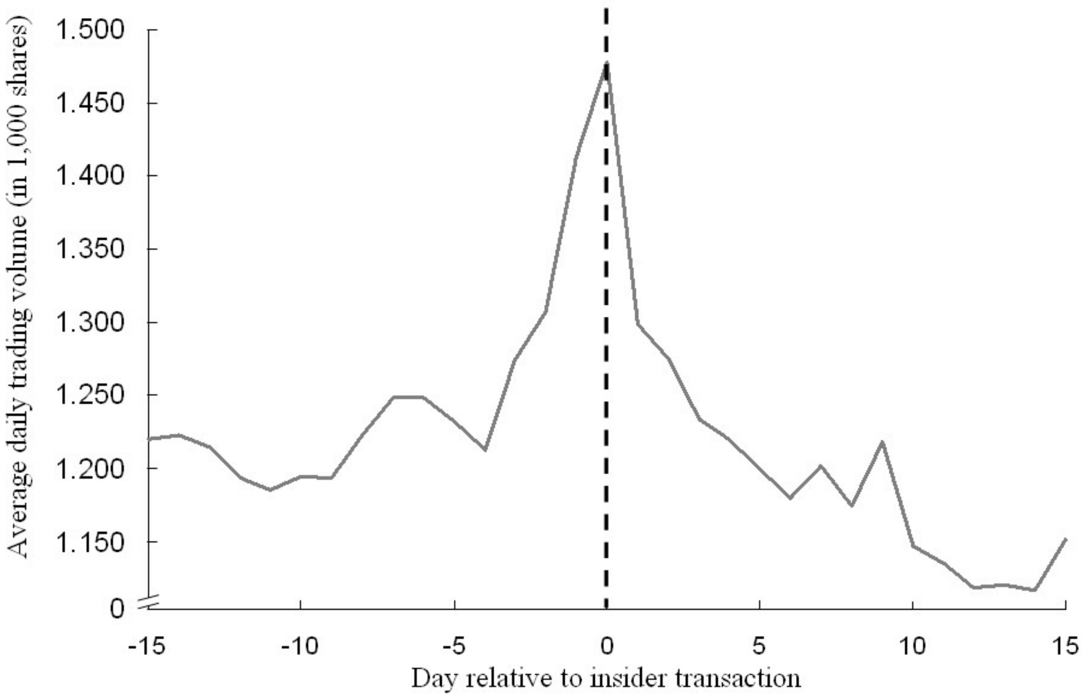

Figure 5.7: Trading volumes on and around the insider transaction day

sell transaction. However, at first glance it appears to be counter-intuitive for the subsample focusing on exclusive insider buy transactions, as we were expecting that insiders buying a certain stock will distort the liquidity of that stock because other market participants will widen the spreads to protect themselves from the adverse selection problem caused by these informed traders. However, as the event study does not control for any other factor affecting market liquidity, the improved market liquidity can also be driven by another factor that has a positive effect on market liquidity (e.g., trading volume) and that coincides with the insider transaction; therefore, an increase in liquidity costs that is due to information asymmetry, might be concealed by the liquidity benefits from increased trading volume.

In fact, the trading volumes are much higher on the day of the insider transactions[136]: Figure 5.7 shows that trading volumes peak for the whole sample on the day of the insider transaction, with almost 1.5 million shares traded, which is more than 20% higher than in the reference period and almost 40% higher compared with the average of the whole sample.[137] This finding supports the hypothesis that insiders trade at times of unusually high trading volumes to conceal their information-based trading activity. We can therefore conclude that insider appear to trade on days that are very active, most likely to hide their information-based trading in higher trading volumes. The fact that the abnormal volume-weighted spread is less pronounced for insider-initiated buy transactions may indicate that buy transactions have a negative counter-effect on the market liquidity compared with the high market liquidity resulting from insider sell transactions that are amplified by high trading volumes.

The effect of an improved market liquidity already emerges in the five days preceding the insider transaction. This effect is be best observed in Table 5.27 on the cumulative abnormal volume-weighted spread covering the period before the insider transaction but also on the individual abnormal volume-weighted spreads in Table 5.26 in the days before the insider transactions, which are almost all significantly negative. This observation also supports our finding that insiders try to time their transaction to trade on days of high liquidity.

For the days immediately following the insider transactions, we would expect to observe different outcomes depending on the type of the insider transaction. For the buy transaction subsample, we would expect that the asset liquidity is impaired after the insider transaction, as the total insider ownership is in-

[136] Meulbroek (1992) amongst others also found higher trading volume on insider trading days.

[137] The increased trading volume cannot be solely attributed to the insider transactions, as the average transaction size traded by insiders in a day is 81,000 shares for buy transactions and 92,500 shares for sell transactions, which is far less than the increased volume we observe on the insider transaction day.

creased through the transaction; alread, several other studies (see, e.g., Heflin and Shaw (2000) and our research in section 5.2) have shown that market liquidity is impaired by insider ownership, due to the information asymmetry problem between the insiders and other market participants. However, as the sell transactions decrease the share of insider ownership and, therefore the share of potential information-based trading, we anticipate an asset liquidity improvement on the days following the insider sell transaction as the information asymmetry problem is attenuated through the transaction. Tables 5.26 and 5.27 show that the results are consistent with our expectations: Both the cumulative abnormal volume-weighted spread covering the period following the insider transaction and the individual abnormal volume-weighted spreads on the days after the insider transactions are all significantly negative for the subsample consisting of the insider sell transactions and all positive for the insider buy transactions.

5.3.1.3 Panel data analysis for abnormal volume-weighted spreads from the event study

Thus far, our event study design does not control for any other variable than the insider transaction. However, it has given us several interesting indications and findings, which can now be explored in more detail. We therefore scrutinize the impact of insider transactions on the standardized abnormal volume-weighted spread and the cumulative abnormal volume-weighted spread in a multivariate analysis that also controls for the following variables, that are known to at least partially explain liquidity costs: the transaction volume VO, the Xetra closing price P, the market capitalization MV and the standard deviation of daily log-returns σ_r. For the regression analysis, we transform the control variables transaction volume VO, the Xetra closing prices P and the market capitalization MV by taking their

Table 5.28: Effect of the number of insider transactions on abnormal stock market liquidity at insider trading days

This table reports company and volume-class fixed effects regressions that relate abnormal liquidity costs to the number of insider transactions for the sample period of July 2002 to December 2009. The dependent variable, abnormal liquidity costs, is represented by the standardized abnormal volume-weighted spread $SAWS(q)_{i,0,e}$ on the day of the insider transaction derived in an event study framework. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the 5-day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of insider transactions, using the number of buy and sell transactions conducted by insiders on that day. This table shows the average estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.28.1)	(5.28.2)	(5.28.3)
Price (log)	-0.145***	-0.156***	-0.154***
	(-2.94)	(-3.14)	(-3.11)
Traded volume (log)	-0.261***	-0.260***	-0.264***
	(-32.85)	(-32.64)	(-33.14)
Market cap (log)	0.169***	0.170***	0.180***
	(3.45)	(3.48)	(3.69)
Standard deviation of daily log-returns (5 days)	0.358***	0.370***	0.361***
	(21.10)	(21.80)	(21.28)
Insider transaction (buy)	0.0562***		0.0507***
	(10.90)		(9.63)
Insider transaction (sell)		-0.0404***	-0.0297***
		(-7.37)	(-5.30)
Constant	0.378*	0.465**	0.360*
	(1.74)	(2.14)	(1.66)
Observations	43229	43229	43229
Adjusted R^2	-0.019	-0.021	-0.019
F	263.4	250.1	224.3

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

natural logarithms.[138] For our panel data set with order-size-dependent abnormal volume-weighted spreads, we use a company and volume class[139] fixed effects model[140] for the estimation. The models[141] that analyze the abnormal volume-weighted spreads from the event study either include the dependent variable standardized abnormal volume-weighted spread $SAWS\,(q)_t$ or the dependent variable cumulative abnormal volume-weighted spread $CAWS\,(q)_\tau$ and all the standard control variables in the following form:

$$\left.\begin{matrix} SAWS\,(q)_t \\ CAWS\,(q)_\tau \end{matrix}\right\} = \alpha_o + \alpha_1 logVO + \alpha_2 logP + \alpha_3 logMV + \alpha_4 \sigma_r + \varepsilon \qquad (5.12)$$

First, we analyze the impact of an insider transaction on the standardized abnormal volume-weighted spread derived from the event study framework on the day of the transaction. As we expect that insider transactions have a different impact on stock market liquidity depending on the type of the transaction, e.g., either a sell or buy transaction, we separately add the number of buy (see model 5.28.1) and sell (see model 5.28.2) transactions performed by insiders and then add both together (see model 5.28.3) to the standard set of control variables.

Table 5.28 shows the results for this panel data analysis of the standardized abnormal volume-weighted spread on the day of the insider transaction. If we recall the results from the event study in section 5.3.1.2, we observed that, on days of insider purchases, the standardized abnormal volume-weighted spread was

138 This transformation is consistent with Stange and Kaserer (2008).

139 The volume class q is an inherent characteristic of our order-size-dependent liquidity costs measure.

140 The Hausman (1978) test statistic supports the usage of a fixed effects model compared with a random effects model.

141 All variables are time and company dependent, but we do not subscript the variables in the representation.

negative, although we hypothesized that an insider purchase should lead to an increase in the abnormal volume-weighted spread. We argued that this negative standardized abnormal volume-weighted spread can be explained by the increased traded volume on the day of the insider transaction, as we saw in Figure 5.7, that counteracts the expected increase induced by the insider purchase. The results in (5.28.1) provide support for this argumentation, as the coefficient for insider purchases is significantly positive and the coefficient for the traded volume is significantly negative. Specification (5.28.2) shows that insider sales decrease the abnormal volume-weighted spread, as expected. Additionally, specification (5.28.3) supports our initial hypothesis that insider purchases increase liquidity costs (positive impact on abnormal spreads) and insider sales decrease liquidity costs (negative impact on abnormal spreads).

We also analyze the same specification as in model (5.28.3) for the 5 days following the insider transactions. The results, which can be found in Table 5.29, are qualitatively the same and also significant[142] as on the day of the insider transaction and therefore support our hypotheses.

Furthermore, we redo the same analysis as in Table 5.28 for the cumulative abnormal volume-weighted spread for the 5 days following the insider transaction. The results presented in Table 5.30 are consistent with our hypotheses by showing that insider purchases lead to increased abnormal volume-weighted spreads on the 5 days following the insider transaction and insider sales induce a decrease in the abnormal volume-weighted spreads on the 5 days following the insider transaction.

After having analyzed the impact of insider transactions on abnormal volume-weighted spreads in an event study framework, we will now scrutinize our liquidity data in a panel-data regression analysis to further explore the impact of insider

[142] However, the coefficients for the sell transactions for $t = 2$ and $t = 5$ are not significant.

Table 5.29: The effect of the number of insider transactions on abnormal stock market liquidity after insider trading days

This table reports company and volume-class fixed effects regressions that relate abnormal liquidity costs to the number of insider transactions for the sample period of July 2002 to December 2009. The dependent variable, abnormal liquidity costs, is represented by the standardized abnormal volume-weighted spread $SAWS(q)_{i,t,e}$ on the 5 days $t = [1;5]$ following the insider transaction derived in an event study framework. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the 5-day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of insider transactions, using the number of buy and sell transactions performed by insiders on that day. The specifications (5.29.1) to (5.29.5) represent the 5 days $t = [1;5]$ following the insider transaction. This table shows the average estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.29.1)	(5.29.2)	(5.29.3)	(5.29.4)	(5.29.5)
Price (log)	-0.0814**	0.0908**	-0.0264	0.0940**	0.236***
	(-2.06)	(2.37)	(-0.67)	(2.37)	(6.07)
Traded volume (log)	-0.119***	-0.0426***	-0.0126**	0.0214***	0.0142**
	(-18.84)	(-6.90)	(-2.00)	(3.37)	(2.27)
Market cap (log)	0.0518	-0.0852**	0.000381	-0.114***	-0.198***
	(1.33)	(-2.25)	(0.01)	(-2.92)	(-5.14)
Standard deviation of daily log-returns (5 days)	0.186***	0.144***	0.0442***	0.00279	0.0315**
	(13.81)	(10.95)	(3.27)	(0.21)	(2.36)
Insider transaction (buy)	0.0141***	0.0151***	-0.000728	0.00784*	0.00836**
	(3.40)	(3.72)	(-0.17)	(1.87)	(2.04)
Insider transaction (sell)	-0.0399***	-0.00264	-0.0207***	-0.0160***	-0.00684
	(-9.04)	(-0.61)	(-4.67)	(-3.61)	(-1.56)
Constant	0.433**	0.484***	0.126	0.407**	0.632***
	(2.49)	(2.86)	(0.73)	(2.32)	(3.67)
Observations	42398	42222	42088	42062	41962
Adjusted R^2	-0.038	-0.048	-0.051	-0.051	-0.051
F	92.57	27.04	7.338	7.622	9.647

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.30: The effect of the number of insider transactions on cumulative abnormal stock market liquidity after insider trading days

This table reports company and volume-class fixed effects regressions that relate cumulative abnormal liquidity costs to the number of insider transactions for the sample period of July 2002 to December 2009. The dependent variable, cumulative abnormal liquidity costs, is represented by the cumulative standardized abnormal volume-weighted spread $CAWS(q)_{i,[1;5],e}$ on the 5 days following the insider transaction derived in an event study framework. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the 5-day standard deviation of the daily log-returns. In addtion to the aforementioned control variables, we will test the impact of insider transactions, using the number of buy and sell transactions performed by insiders on that day. This table shows the average estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.30.1)	(5.30.2)	(5.30.3)
Price (log)	0.329***	0.303***	0.305***
	(2.89)	(2.66)	(2.68)
Traded volume (log)	-0.129***	-0.133***	-0.137***
	(-7.03)	(-7.28)	(-7.47)
Market cap (log)	-0.365***	-0.341***	-0.333***
	(-3.25)	(-3.03)	(-2.95)
Standard deviation of daily log-returns (5 days)	0.385***	0.402***	0.394***
	(9.84)	(10.28)	(10.07)
Insider transaction (buy)	0.0606***		0.0447***
	(5.10)		(3.68)
Insider transaction (sell)		-0.0941***	-0.0846***
		(-7.45)	(-6.56)
Constant	2.054***	2.095***	2.002***
	(4.11)	(4.19)	(4.00)
Observations	43229	43229	43229
Adjusted R^2	-0.048	-0.047	-0.047
F	33.72	39.65	35.31

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

transactions on market liquidity.

5.3.2 Panel data analysis for the impact of insider trading on market liquidity

For our panel-data regression analysis on the impact of insider transactions on market liquidity, we once again use the log-log specification (5.1) as a basis and a company and volume-class[143] fixed effects model[144] for the estimation.

5.3.2.1 Market liquidity on the day of the insider transaction

First, we analyze the effect of an insider transaction on the day of the transaction. We expect that insider transactions have a different impact on stock market liquidity depending on the type of the transaction, e.g., either a sell or buy transaction. Initially, we verify our hypothesis by adding the log-transformed size of total volume transacted by insiders on a particular day (measured as the number of traded shares) for buy and sell transactions individually (see models 5.31.1 and 5.31.2, respectively) and then together (see model 5.31.3) to the standard set of control variables.

Table 5.31 presents the results for this set of regressions. First and foremost, we can observe that the estimates of the coefficients for the control variables price level, market capitalization, volume and return volatility are significant, have the correct signs and are, as expected, consistent with results reported in previous studies. Liquidity costs, in accord with our findings in subsection 5.1.1.2, are therefore a decreasing function of price level, market capitalization and trading

[143] The volume class q is an inherent characteristic of our order-size-dependent liquidity costs measure.

[144] The Hausman (1978) test statistic supports the usage of a fixed effects model instead of a random effects model.

Table 5.31: The effect of the nominals traded by insiders on stock market liquidity

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the nominals traded by insiders over the sample period of July 2002 to December 2009. The dependent variable, liquidity costs, is represented by the daily price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the 5-day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of insider transactions, using the log-transformed nominals bought or sold by insiders on that day. This table shows the average estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.31.1)	(5.31.2)	(5.31.3)
Price (log)	-0.496***	-0.495***	-0.495***
	(-220.79)	(-220.63)	(-220.62)
Traded volume (log)	-0.234***	-0.234***	-0.234***
	(-661.41)	(-661.08)	(-660.76)
Market cap (log)	-0.310***	-0.310***	-0.310***
	(-139.54)	(-139.61)	(-139.60)
Standard deviation of daily log-returns (5 days)	11.29***	11.29***	11.29***
	(623.59)	(624.13)	(623.61)
Insider transaction bought nominal (log)	0.00127***		0.00289***
	(3.94)		(8.90)
Insider transaction sold nominal (log)		-0.0140***	-0.0144***
		(-38.17)	(-38.99)
Constant	8.726***	8.724***	8.724***
	(903.59)	(903.64)	(903.68)
Observations	2476364	2476364	2476364
Adjusted R^2	0.536	0.537	0.537
F	573402.3	574024.7	478382.2

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

volume. By contrast, greater return volatility, which is a proxy for the general market conditions and risks, increases liquidity costs.

We also observe that the inclusion of the total volume bought by insiders support our information asymmetry hypothesis. Model (5.31.1) shows that liquidity costs, represented by the log-transformed half of our order-size-dependent volume-weighted spread measure, increase with the number of shares bought by insiders. Thus, stock market liquidity is impaired by insider purchases, as insiders have access to private, value-relevant information and in response, other market participants increase the spreads to cover potential losses to these informed traders. This is consistent with Lakonishok and Lee (2001), who showed that the informativeness of insider activities derives from insider purchases. The increase in the spread should be maintained as long as insiders hold their position, as our research on the impact of insider ownership on market liquidity showed that insider ownership impairs market liquidity. This occurs due to the same information asymmetry problem (see section 5.2), as other uninformed market participants wil continue to use the level of insider holdings as a measure of information asymmetry[145]. As a logical consequence, we should be able to see a positive impact on market liquidity immediately after the sale of an insider position, as this decreases the share of insider ownership and therefore the share of informed shareholders. Indeed, model (5.31.2) shows that an insider sale leads to a significant reduction in liquidity costs and therefore to an improved market liquidity on the day of the insider transaction. Later in this dissertation, we will determine whether this reduction persists on the days following the insider sale. The results also remain stable if we add both variables for insider purchases and sales to the model at the same time; indeed, in this case, the results are even more pronounced and signifi-

[145] See, e.g., Chiang and Venkatesh (1988).

cant (see model 5.31.3). All results, however, are significant at the 1% significance level.

We now analyze the same situation, but instead of using total volume transacted by insiders, we now add the number of insider transactions on a particular day as a proxy for insider trading activity. As before, we are able to distinguish between purchases and sales by insiders. Not surprisingly, the results are similar as before: The asset's liquidity is significantly impaired by the number of insider-initiated buy transactions (see specification 5.32.1), and the market liquidity is again improved once the insiders leave that particular stock by selling their shares, as measured by the number of individual insider sales (see specification 5.32.2). Additionally, specification (5.32.3), which includes both the number of insider purchases and sales, again displays results that are more pronounced and significant. Therefore, the results are also robust for another proxy of insider trading activity, particularly as all results are significant at the 1% significance level.

As a third analysis of the day of the insider transaction, we test the impact of an insider transaction on market liquidity using a ratio that relates the nominals bought or sold by insiders on that day to the total nominals owned by insiders[146]. We use this ratio because we assume that the perceived impact on the information asymmetry problem induced by an insider transaction is greater if insiders transact larger portions of their shareholdings. The results, as reported in Table 5.33, also reveal that the market liquidity is significantly impaired by insider purchases, while insider sales once again improve market liquidity. Therefore, these results

[146] For those insider purchases where we do not have any information on the insider holdings (either because there actually were no insider holdings at the end of the year or because the insider holdings were too small to be reported among the 12 largest shareholders in Hoppenstedt "Aktienführer"), we impute the average sample ratio. For insider sales, we presume that all shares were sold in this insider transaction, if there is no insider holding remaining at the end of the year.

Table 5.32: The effect of the number of insider transactions on stock market liquidity

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the number of insider transactions for the sample period of July 2002 to December 2009. The dependent variable, liquidity costs, is represented by the daily price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the 5-day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of insider transactions, using the number of buy and sell transactions performed by insiders on that day. This table shows the average estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.32.1)	(5.32.2)	(5.32.3)
Price (log)	-0.496***	-0.496***	-0.496***
	(-220.81)	(-220.76)	(-220.79)
Traded volume (log)	-0.234***	-0.234***	-0.234***
	(-661.70)	(-661.69)	(-661.51)
Market cap (log)	-0.310***	-0.310***	-0.310***
	(-139.53)	(-139.52)	(-139.50)
Standard deviation of daily log-returns (5 days)	11.29***	11.30***	11.29***
	(623.67)	(624.46)	(624.11)
Insider transaction (buy)	0.00702***		0.0121***
	(4.95)		(8.50)
Insider transaction (sell)		-0.0555***	-0.0569***
		(-33.68)	(-34.38)
Constant	8.726***	8.724***	8.724***
	(903.60)	(903.59)	(903.62)
Observations	2476364	2476364	2476364
Adjusted R^2	0.536	0.537	0.537
F	573406.2	573885.3	478263.6

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

also support our earlier findings regarding the day of the insider transaction. All results are again significant at the 1% significance level.

Table 5.33: Market liquidity and insider transactions as a share of insider ownership

This table reports company and volume-class fixed effects regressions that relate liquidity costs to insider transactions as a share of insider ownership for the sample period of January 2003 to December 2009. The dependent variable, liquidity costs, is represented by the daily price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the 5-day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of insider transactions using a ratio that relates the nominals bought or sold by insiders on that day to the total nominals owned by insiders. This table shows the average estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.33.1)
Price (log)	-0.446***
	(-163.54)
Traded volume (log)	-0.219***
	(-531.40)
Market cap (log)	-0.330***
	(-123.81)
Standard deviation of daily log-returns (5 days)	10.91***
	(511.22)
Insider transaction as a share of insider ownership (buy)	0.102***
	(3.39)
Insider transaction as a share of insider ownership (sell)	-0.0507***
	(-16.25)
Constant	8.654***
	(763.14)
Observations	1832490
Adjusted R^2	0.509
F	316614.5

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These findings contribute to the existing literature by demonstrating that insider trading has a significant impact on market liquidity as measured by a liquidity price impact measure $L(q)$, which is derived from the limit order book, and that the impact of insider trading on market liquidity is not uniform; thus, a distinction between sales and purchases is necessary.

5.3.2.2 Market liquidity and the different types of insiders on the day of the insider transaction

In the previous section, we found evidence that insider trading significantly impacts stock market liquidity. However, we have the additional hypothesis that access to private or value-relevant information is not uniformly distributed across all types of insiders, causing different insider types to have different impacts on stock market liquidity. Therefore, we further scrutinize both buy and sell transactions for three mutually exclusive insider types: members of the management board, members of the supervisory board and other employees.

Table 5.34 shows the results of a specification that consists of the reference specification (5.1) and separate variables for the log-transformed daily trading volume of members of the management board, members of the supervisory board and other employees. We note that purchases initiated by members of the management board have the worst impact on market liquidity, as the market views members of the management board as the best-informed insiders. In addtion, shares bought by members of the supervisory board significantly impair the stock market liquidity, as one would expect given that supervisory board members also have access to price-sensitive information. However, in contrast to members of either the management board or the supervisory board, the shares traded by other employees improve the market liquidity. Thus, uninformed market participants assume that other employees do not have access to private information and therefore their trading activity generates additional liquidity.

We repeat the same analysis for insider sales. As uninformed market participants use the share of insider ownership as a proxy for the level of information asymmetry in a particular stock among others, we would expect a market liq-

Table 5.34: The effect of buy transactions from different types of insiders on stock market liquidity

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the number of insider buy transactions from different types of insiders over the sample period of July 2002 to December 2009. The dependent variable, liquidity costs, is represented by the daily price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the 5-day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of the number of insider buy transactions from the following insider types: management board, supervisory board and other employees. This table shows the average estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.34.1)
Price (log)	-0.748***
	(-41.14)
Traded volume (log)	-0.209***
	(-68.64)
Market cap (log)	-0.178***
	(-9.94)
Standard deviation of daily log-returns (5 days)	7.190***
	(69.60)
Insider transaction (buy) - Management board	0.0354***
	(13.94)
Insider transaction (buy) - Supervisory board	0.00784***
	(2.67)
Insider transaction (buy) - Other employees	-0.0430***
	(-5.20)
Constant	8.467***
	(105.90)
Observations	44502
Adjusted R^2	0.469
F	5918.4

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

uidity improvement for all types of insiders on the day of the insider sale. This hypothesis is supported by the results presented in Table 5.35, which shows a stock market liquidity enhancement for all types of insiders on the day of the insider transaction. This stock market liquidity improvement can further be attributed to the findings of Lakonishok and Lee (2001), who showed that insider sales have no predictive ability. All results are significant at the 1% significance level.

Table 5.35: The effect of sell transactions from different types of insiders on stock market liquidity

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the number of insider sell transactions from different types of insiders over the sample period of July 2002 to December 2009. The dependent variable, liquidity costs, is represented by the daily price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the 5-day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of the number of insider sell transactions from the following insider types: management board, supervisory board and other employees. This table shows the average estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.35.1)
Price (log)	-0.764***
	(-42.11)
Traded volume (log)	-0.210***
	(-69.07)
Market cap (log)	-0.162***
	(-9.07)
Standard deviation of daily log-returns (5 days)	7.292***
	(70.84)
Insider transaction (sell) - Management board	-0.0299***
	(-10.85)
Insider transaction (sell) - Supervisory board	-0.0490***
	(-15.58)
Insider transaction (sell) - Other employees	-0.103***
	(-10.03)
Constant	8.448***
	(106.05)
Observations	44502
Adjusted R^2	0.471
F	5975.1

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3.2.3 Market liquidity and the days following the insider transaction

After we saw that insider transactions have a significant effect on the stock market liquidity on the day of the insider transaction, we now seek to test whether this effect has a lasting impact on the post-trading period. In accord with our initial hypotheses, we expect that the liquidity effects will be persistent. Other research, such as, e.g., our work in section 5.2 and Heflin and Shaw (2000), found that insider ownership is negatively related to market liquidity; therefore, an additional insider purchase increases the share of insider ownership and thus should impair market liquidity on the days following the insider purchase. Conversely, an insider sale decreases the share of insider ownership and thus should improve the market liquidity on the days following the insider sale. This hypothesis is analyzed with the reference specification and individually adding the log-transformed size of total volume transacted by insiders on a particular day and its one- and two-day lag for both insider purchases and sales.

Table 5.36 demonstrates that the market liquidity is not only significantly improved on the day of the insider sale, which we already saw in Table 5.32, but also on the two days following the insider sale. This supports our hypothesis that a decrease in insider ownership through an insider sale leads to a lasting market liquidity improvement, as other uninformed market participants use the share of insider ownership as a proxy for the level of information asymmetry produced by insiders. Conversely, we also see that an insider purchase not only impairs market liquidity on the day of the transaction but also on the day following the transaction, due to the resulting increase in insider ownership.

Table 5.36: The effect of the nominals traded by insiders (lagged) on stock market liquidity

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the nominals traded by insiders on the same and the previous two days over the sample period of July 2002 to December 2009. The dependent variable, liquidity costs, is represented by the daily price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the 5-day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of insider transactions, using the log-transformed nominals bought or sold by insiders on the same, the previous and the penultimate day. This table shows the average estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.36.1)
Price (log)	-0.483***
	(-213.53)
Traded volume (log)	-0.234***
	(-658.51)
Market cap (log)	-0.311***
	(-138.53)
Standard deviation of daily log-returns (5 days)	11.24***
	(619.20)
Insider transaction bought nominal (log)	0.00269***
	(7.93)
Insider transaction bought nominal (log) - lag 1	0.000767**
	(2.22)
Insider transaction bought nominal (log) - lag 2	-0.000181
	(-0.53)
Insider transaction sold nominal (log)	-0.0104***
	(-27.38)
Insider transaction sold nominal (log) - lag 1	-0.0106***
	(-27.47)
Insider transaction sold nominal (log) - lag 2	-0.00993***
	(-26.22)
Constant	8.659***
	(883.97)
Observations	2396026
Adjusted R^2	0.539
F	280327.2

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3.3 Robustness tests

If our hypothesis holds that market liquidity is impaired at and after insider purchases and improved at and after insider sales because uninformed market participants price protect against adverse selection and they use the share of insider ownership as a proxy for the level of information asymmetry introduced by insiders, several other expectations can be assessed. For instance, quasi-cross-sectional analysis using yearly averages for insider transactions should reveal liquidity impacts, as a higher number of average insider purchases should coincide with a higher share of insider ownership in that year, whereas a higher number of average insider sales should lead to a decrease in the insider ownership. Hence, we also expect that in our quasi-cross-sectional analysis, insider purchases have a deleterious effect on the market liquidity, whereas insider sales will improve the market liquidity. To assess these expectation, we average all variables over one-year periods; in particular, we calculate the annual average number of insider purchases and insider sales per year.

The results in Table 5.37 support our hypothesis, as average liquidity costs significantly increase with average number of insider purchases and significantly decrease with the average number of insider sales.[147]

We conduct a series of additional robustness tests[148] and therefore re-estimate the specifications of (5.31.3) and (5.32.3) for different subsamples.

First, we create two subsamples with the volume class q of our order-size-

[147] In addition, we also test a similar specification with the log-transformed annual average of nominals bought or sold by insiders instead of the annual average number of insider purchases and sales. The results are consistent with those reported in Table 5.37 and can be found in the Appendix in Table C.1.

[148] For the remaining robustness tests, we focus on the volume classes smaller than Euro 1 million, as the volume classes larger than Euro 1 million are only represented in the DAX index.

Table 5.37: The effect of the number of insider transactions on stock market liquidity

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the number of insider transactions over the sample period of July 2002 to December 2009. The dependent variable, liquidity costs, is represented by the year average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. Stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of insider transactions, using the annual average number of buy and sell transactions made by insiders. This table shows the average estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.37.1)	(5.37.2)	(5.37.3)	(5.37.4)
Price (log)	-0.668***	-0.669***	-0.664***	-0.666***
	(-30.03)	(-30.11)	(-29.95)	(-30.08)
Traded volume (log)	-0.423***	-0.425***	-0.423***	-0.425***
	(-66.94)	(-67.05)	(-67.02)	(-67.37)
Market cap (log)	-0.0165	-0.0169	-0.0185	-0.0195
	(-0.75)	(-0.76)	(-0.84)	(-0.88)
Stdev. log-returns	1.318***	1.315***	1.310***	1.303***
	(79.37)	(79.11)	(78.97)	(78.46)
Insider transaction (buy)		0.242***		0.409***
		(3.57)		(5.81)
Insider transaction (sell)			-0.674***	-0.829***
			(-7.25)	(-8.58)
Constant	8.124***	8.137***	8.136***	8.161***
	(91.04)	(91.16)	(91.39)	(91.71)
Observations	12906	12906	12906	12906
Adjusted R^2	0.644	0.645	0.646	0.647
F	6490.6	5200.9	5228.9	4376.9

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.38: The effect of the nominals traded by insiders on stock market liquidity - small vs. large volume classes

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the nominals traded by insiders for a subsample that contains all volume classes smaller than or equal to Euro 100,000 (specification 5.38.1) and a subsample that contains all volume classes larger than Euro 100,000 (specification 5.38.2) over the sample period of July 2002 to December 2009. The dependent variable, liquidity costs, is represented by the daily price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the 5-day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of insider transactions, using the log-transformed nominals bought or sold by insiders on that day. This table depicts the average estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.38.1)	(5.38.2)
Price (log)	-0.496***	-0.518***
	(-202.62)	(-120.45)
Traded volume (log)	-0.211***	-0.267***
	(-541.83)	(-398.18)
Market cap (log)	-0.247***	-0.349***
	(-102.36)	(-81.62)
Standard deviation of daily log-returns (5 days)	9.744***	12.23***
	(452.00)	(379.61)
Insider transaction bought nominal (log)	0.00373***	0.00133**
	(9.59)	(2.37)
Insider transaction sold nominal (log)	-0.0108***	-0.0158***
	(-23.92)	(-25.00)
Constant	7.458***	9.864***
	(760.29)	(530.72)
Observations	1323335	943080
Adjusted R^2	0.586	0.509
F	312131.6	163400.6

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.39: The effect of the number of insider transactions on stock market liquidity - small vs. large volume classes
This table reports company and volume-class fixed effects regressions that relate liquidity costs to the number of insider transactions for a subsample that contains all volume classes smaller than or equal to Euro 100,000 (specification 5.39.1) and a subsample that contains all volume classes larger than Euro 100,000 (specification 5.39.2) over the sample period of July 2002 to December 2009. The dependent variable, liquidity costs, is represented by the daily price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the 5-day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of insider transactions, using the number of buy and sell transactions made by insiders on that day. This table depicts the average estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.39.1)	(5.39.2)
Price (log)	-0.496***	-0.519***
	(-202.76)	(-120.55)
Traded volume (log)	-0.211***	-0.267***
	(-542.28)	(-398.78)
Market Cap (log)	-0.247***	-0.349***
	(-102.29)	(-81.54)
Standard deviation of daily log-returns (5 days)	9.751***	12.24***
	(452.36)	(379.93)
Insider transaction (buy)	0.0132***	0.00982***
	(7.61)	(4.01)
Insider transaction (sell)	-0.0401***	-0.0643***
	(-20.38)	(-22.60)
Constant	7.458***	9.864***
	(760.24)	(530.68)
Observations	1323335	943080
Adjusted R^2	0.586	0.509
F	312062.8	163363.0

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

dependent volume-weighted liquidity cost measure $L(q)$ as a split criterion. The first subsample contains all volume classes q smaller than or equal to Euro 100,000, whereas the second subsample consists of the five volume classes q which are larger than Euro 100,000. Our results for impact of insider purchases and sales on market liquidity remain robust for both the large and the small volume class subsamples. Detailed results can be found in Table 5.38 and Table 5.39.

Second, we re-estimate the same regressions considering subsamples by index affiliation. The first subsample consists of all companies listed in the SDAX or the TecDAX, which are by definition smaller companies, whereas the second subsamples contains firms from the two indices with the larger companies; namely, the DAX and MDAX. For our SDAX and TecDAX subsample, all of our model specifications remain highly significant and robust. For the larger companies in the second subsample, the results for the specification, which includes the number of insider transactions are also significant, indicating that insider purchases impair stock market liquidity, whereas insider sales improve market liquidity. Only the specification which includes the log-transformed volume transacted by insiders report a liquidity improvement by insider purchases at the 5% significance level. However, the relationship between insider sales remains also robust for this specification at the 1% significance level. Table 5.40 and Table 5.41 report more detailed results.

Thus, we can conclude overall that our findings for the relationship between insider transactions and market liquidity discussed in section 5.3.2 are robust.

Table 5.40: The effect of the nominals traded by insiders on stock market liquidity - SDAX and TecDAX vs. DAX and MDAX

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the nominals traded by insiders for a subsample that contains companies listed in the SDAX or TecDAX (specification 5.40.1) and a subsample that contains companies listed in the DAX or MDAX (specification 5.40.2) over the sample period of July 2002 to December 2009. The dependent variable, liquidity costs, is represented by the daily price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the 5-day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of insider transactions, using the log-transformed nominals bought or sold by insiders on that day. This table shows the average estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.40.1)	(5.40.2)
Price (log)	-0.482***	-0.535***
	(-168.67)	(-143.16)
Traded volume (log)	-0.188***	-0.265***
	(-378.64)	(-526.14)
Market cap (log)	-0.341***	-0.219***
	(-120.17)	(-59.84)
Standard deviation of daily log-returns (5 days)	8.442***	12.54***
	(321.22)	(491.10)
Insider transaction bought nominal (log)	0.00743***	-0.000849**
	(14.77)	(-2.00)
Insider transaction sold nominal (log)	-0.0142***	-0.0117***
	(-26.49)	(-22.65)
Constant	8.449***	8.213***
	(818.15)	(485.56)
Observations	1037606	1228809
Adjusted R^2	0.487	0.574
F	164211.7	276176.9

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.41: The effect of the number of insider transactions on stock market liquidity - SDAX and TecDAX vs. DAX and MDAX

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the number of insider transactions for a subsample that contains companies listed in the SDAX or TecDAX (specification 5.41.1) and a subsample that contains companies listed in the DAX or MDAX (specification 5.41.2) over the sample period of July 2002 to December 2009. The dependent variable, liquidity costs, is represented by the daily price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the 5-day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of insider transactions, using the number of buy and sell transactions made by insiders on that day. This table shows the average estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(5.41.1)	(5.41.2)
Price (log)	-0.482***	-0.535***
	(-168.90)	(-143.25)
Traded volume (log)	-0.188***	-0.266***
	(-379.11)	(-526.65)
Market cap (log)	-0.341***	-0.219***
	(-120.03)	(-59.78)
Standard deviation of daily log-returns (5 days)	8.460***	12.54***
	(321.78)	(490.95)
Insider transaction (buy)	0.0279***	0.00346**
	(11.24)	(1.98)
Insider transaction (sell)	-0.0421***	-0.0539***
	(-19.95)	(-20.29)
Constant	8.449***	8.213***
	(817.97)	(485.55)
Observations	1037606	1228809
Adjusted R^2	0.486	0.574
F	164096.7	276128.4

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 6

Summary and conclusion

In this last chapter, we summarize the contribution of this dissertation and suggest some avenues for further research in the area of market liquidity.

6.1 Concluding remarks[149]

The literature on market microstructure has seen tremendous growth in the last two decades. In particular, market liquidity, the main topic of this dissertation, is at the core of this area of finance and has received a great deal of attention from researchers, regulators, exchange officials, traders and financial institutions in recent years. This dissertation provides a thorough discussion of market liquidity and particularly addresses the impact of the financial crisis, ownership structures and insider trading on market liquidity. It contributes to a wider understanding of the dynamics, phenomena and influencing factors that underlie stock market liquidity.

In Chapter 1, we highlighted the importance of market liquidity for today's

[149] This section is largely based on Rösch and Kaserer (2010), Rösch and Kaserer (2011) and Rösch and Kaserer (2012).

financial markets and introduced the main research questions of this dissertation.

Chapter 2 provided the foundation and basic principles of market liquidity, including a detailed delimitation and definition of market liquidity, a description of key characteristics and associated theoretical concepts, a presentation of existing liquidity measures and finally, a detailed introduction to the liquidity measure (XLM - the Xetra liquidity measure) and market structure (the Xetra market) used in our empirical analysis.

In Chapter 3, we gave an overview of the existing literature on market liquidity, especially those studies that are related to our main research questions. We also derived testable research hypotheses.

The subsequent chapter, Chapter 4, was dedicated to a detailed description of our data sets. We analyzed a highly representative sample of German companies listed in the four major German indices (DAX, MDAX, SDAX, and TecDAX) that comprise almost 90% of the total German market capitalization using a liquidity measure, called Xetra liquidity measure, that is able to simultaneously capture liquidity effects on both depth and breadth in a limit order book. Due to the fact that we were using an order-size-dependent liquidity measure derived from the limit order book, we were able to show that the presented liquidity effects in Chapter 5 hold for the entire depth of the limit order book.

In the following subsections, we summarize the key results of our main research questions on market liquidity that we analyzed in Chapter 5 and present the primary contributions of our work to the existing research on market liquidity.

6.1.1 Main results regarding market liquidity and the financial crisis

The first part of the empirical analysis of this dissertation, which addresses stock market liquidity during the financial crisis in Germany, supports our improved understanding of the dynamics and phenomena of stock market liquidity in times of crisis and increased market uncertainty. In our analysis of the effect of the financial crisis on market liquidity, we scrutinize the impact of market declines on stock market liquidity and assist in unearthing several puzzling market liquidity phenomena in the stock market during times of crisis, such as the liquidity commonality, the flight-to-quality and the flight-to-liquidity.

We empirically show that stock market liquidity is impaired during market declines and in times of crisis, implying a positive relationship between market risk and liquidity risk and resulting in investors frequently being struck by both risks at the same time. Using our order-size-dependent liquidity measure, we show that peaks in market liquidity risk in times of crisis are especially pronounced for larger volume classes, and therefore any adequate market liquidity risk management concept needs to account for this. This leads us to the conclusion that bid-ask-spread data (which is often used to measure market liquidity risk due to its easy availability) might tremendously understate the liquidity risk for larger trading positions and therefore can only poorly act as a proxy of the level and especially the variation of liquidity costs during times of crisis for larger volume classes.

The analysis of liquidity commonality demonstrates that liquidity commonality is time-varying and particularly increases in times of crisis and during market downturns, leading to soaring liquidity betas. Furthermore, peaks of liquidity commonality are associated with major crisis events. The use of our order-size-dependent liquidity measure enables us to establish that liquidity commonality becomes weaker as one probes more deeply into the limit order book. Our results present empirical evidence supportive of a supply effect in market liquidity as theoretically proposed by prior researchers e.g., Brunnermeier and Pedersen (2009). We show that liquidity commonality is induced by a lack of funding liquidity of financial intermediaries, leading to funding and market liquidity spirals.

We document that credit ratings produced by external rating agencies are able to decrease liquidity costs in the stock market by alleviating information asymmetry and hence decreasing the adverse selection component of liquidity costs. As the decision to obtain an external rating is at the discretion of the company in question, that firm can therefore opt for an external rating as a means to improve the liquidity of its own shares. We further show that liquidity costs increase with credit risk/default probability and that this effect intensifies during times of crisis, giving empirical support for the flight-to-quality or flight-to-liquidity hypothesis in the stock market.

Overall, our results clearly show that liquidity has played an important role in the current financial crisis, as the lack of market liquidity was a symptom of the crisis and at the same time responsible for exacerbating its consequences.

6.1.2 Main results regarding market liquidity and ownership structures

The second main research question focuses on the relationship between ownership concentration, blockholder types and stock market liquidity. This analysis, which also focuses on the German market, helps to shed light on the impact of ownership structure and corporate governance mechanisms on stock market liquidity.

Our results clearly show that market liquidity is significantly reduced for companies with highly concentrated ownership structures. This result is robust for various measures of ownership concentration, and it proves our initial hypothesis that stock market liquidity is affected by stock ownership concentration due to an information asymmetry problem. Specifically, it appears that large shareholders possess economies of scale in the collection of information and the ability to access private, value-relevant information and may trade on this information to extract the private benefits of control; as a consequence, other market participants increase the spreads to compensate.

Publications in the area of corporate governance have argued that ownership concentration is required as an controlling instrument. However, studies exploring the effects of blockholders on corporate governance and market liquidity demonstrated that this controlling effect results in increased liquidity costs. Therefore, they state that investors should accept a tradeoff between liquidity costs and the monitoring effect of blockholders. However, in our analyses we further consider the effect of specific types of shareholders on market liquidity. Although a highly concentrated ownership structure already reduces market liquidity, we show that insider blockholders worsen the market liquidity by even more than might be expected from structural effects alone. We pinpoint that insider, financial, and, to some extent strategic blockholders all reduce stock market liquidity. However, we find that in accordance to our second hypothesis, private blockholders and strategic majority blockholders alleviate information asymmetry and therefore improve stock market liquidity, as such blockholders are typically long-term investors.

Thus, we were able to show that not all types of blockholders impair stock market liquidity and that the apparent tradeoff between the beneficial impact of shareholders activism from blockholders and the reduced market liquidity through ownership concentration is not valid for private blockholders.

6.1.3 Main results regarding market liquidity and insider trading

The last major thrust of our empirical research is dedicated to one specific type of shareholder, the insider, and investigates the influence of insider trading behavior on market liquidity. The analysis of the relationship between insider trading and stock market liquidity in Germany deepens the understanding of the impact of adverse selection on stock market liquidity. We scrutinize the effect of insider trading on market liquidity both in an event study framework and through a panel data analysis.

Our study reveals that insiders trade on days that are very active, presumably to hide their own trading activity in higher trading volumes. Our results clearly show that the liquidity impact of an insider transaction is highly dependent on the type of the transaction. This is a finding that has not been featured in the previous empirical research on market liquidity. We demonstrate that market liquidity is significantly reduced on and (to some extent) after the days of insider purchases and it is significantly improved on and after the days of insider sales.

We argue that this liquidity effect is due to adverse selection as uninformed market participants price protect against the adverse selection generated by informed insiders, and this price protection is reflected in the liquidity costs. We reason that uninformed market participants use the share of insider ownership as a proxy for the level of information asymmetry induced by insiders, which links our study to our empirical research on ownership structures and to the other existing literature addressing the relationship between insider ownership and market liquidity. Hence, any transaction that alters the share of insider ownership will have a liquidity impact: Insider purchases, by increasing the insider ownership and therefore the information asymmetry generated by insiders, impair market liquidity on and after the day of the transaction. Consequently, insider sales therefore alleviate information asymmetry, as the share of insider holdings is decreased; thus, market liquidity is improved on and after the day of this insider transaction.

6.2 Outlook

Although this dissertation provides a solid and in-depth discussion of market liquidity, particularly with regard to the impact of the financial crisis, ownership structures and insider trading on market liquidity, several important questions could not be addressed by this dissertation and are left for future research. Indeed, the topic of market liquidity continues to provide an abundance of areas for future research, and we will now point out some possible avenues for such research that are related to our main research questions on market liquidity.

First, we look at possible further research that centers around the impact of crises on market liquidity. A transfer and integration of our results regarding the impact of crisis scenarios on market liquidity into (market liquidity) risk management models remains an open avenue for further investigation and would be a logical next step in this area. Current research in the area of market liquidity risk management mainly focuses upon the development of theoretical models that integrate a liquidity risk component into existing market risk frameworks that are mostly based on the value-at-risk (VaR) framework, as seen in, e.g., Stange and Kaserer (2009). However, those research efforts fail to model and integrate the special properties, dynamics and phenomena of stock market liquidity in times of crisis that we found in our dissertation and therefore underestimate the magnitude and variance of the market liquidity risk. In particular, an integration of our insights on liquidity commonality and the flight-to-quality can significantly improve existing market liquidity risk frameworks. As we empirically showed that funding and market liquidity risk are closely intertwined, another very interesting and challenging avenue for further research could be the development of a consistent and holistic risk management framework that integrates both types of risks.

At the core of our two remaining main research questions lies the impact of information asymmetry on market liquidity or, stated differently, the adverse selection component of liquidity costs. Therefore, a possible area of future research is the market liquidity impact analysis of further circumstances that should plausibly affect the information asymmetry in the market, such as analyst coverage, disclosure policies, signaling effects of share repurchases or other capital structure measures. The analysis of these circumstances using a liquidity measure derived from the limit order book would deepen the understanding of the impact of information asymmetry on market liquidity even further. In our analysis of the impact of ownership structures on market liquidity, we argued that there is a clear tradeoff between liquidity costs and the beneficial impact of shareholder activism induced by most blockholders. A future stream of literature might focus on the development of an integrated model that quantifies and optimizes this tradeoff depending on various firm characteristics, which should assist companies to optimally choose and manage their ownership and capital structures. This stream of literature would also benefit from analysis of management efforts, like an enhanced disclosure policy, to counteract and mitigate the negative liquidity impact from certain blockholders. Our research into insider trading activity used daily liquidity data, enabling us to scrutinize the liquidity impact over a relatively long period of 7.5 years; however, with the recent advent of high frequency liquidity and trading data, future research could possibly address and benefit from analyzing the impact of insider trading activity on intraday liquidity data.

As we already stated, the interest in the topic of market liquidity by researchers and practitioners is not new; however, the relevance and reoccurrence of market liquidity as a central topic in several of the recent financial crises along with the recent advent of high-frequency data, has intensified the research on this topic. However, further study in this area of finance remains possible beyond the aforementioned suggestions, which were mere refinements and extensions of the topics that were the focus of our main research questions. For instance, the role of liquidity could be elucidated in the areas of asset pricing or risk management, among other possibilities.

With this dissertation and our new empirical findings, we hope to have contributed to a better understanding about the properties, dynamics, role and impact of market liquidity.

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Appendix A

Market liquidity and the financial crisis

Table A.1: Matching of different rating categories

This table gives an overview of the different rating categories of the three major rating agencies (Standard & Poor's, Moody's and Fitch) and their respective matching. The rating scale of Euler Hermes Rating is equivalent to the S&P rating scale. The information are derived from the rating agencies' websites.

Standard & Poor's	Moody's Investors Service	Fitch Ratings	
AAA	Aaa	AAA	Investment Grade
AA+	Aa1	AA+	
AA	Aa2	AA	
AA-	Aa3	AA-	
A+	A1	A+	
A	A2	A	
A-	A3	A-	
BBB+	Baa1	BBB+	
BBB	Baa2	BBB	
BBB-	Baa3	BBB-	
BB+	Ba1	BB+	Speculative Grade
BB	Ba2	BB	
BB-	Ba3	BB-	
B+	B1	B+	
B	B2	B	
B-	B3	B-	
CCC+	Caa1		
CCC	Caa2	CCC	
CCC-	Caa3		
CC	Ca	CC	
C		C	
D	C	RD/D	

Table A.2: Rating information by company

	Rating available		**Rating range**	
Company	**from**	**to**	**lower bound**	**upper bound**
Aareal Bank AG	02.01.2003	30.12.2009	BBB+	A
Allianz SE	02.01.2003	30.12.2009	AA-	AA
AMB Generali Holding AG	01.11.2005	19.12.2008	AA	AA
BASF SE	02.01.2003	30.12.2009	A+	AA-
Bayerische Hypo-Vereinsbank AG	02.01.2003	26.01.2007	A-	A
BMW AG	01.09.2005	30.12.2009	A-	A+
Bayer AG	02.01.2003	30.12.2009	BBB+	A+
Bayer Schering Pharma AG	03.04.2003	15.09.2006	BBB+	A
C.A.T. Oil AG	03.03.2008	30.12.2009	B+	B+
Celanese AG	20.05.2004	18.06.2004	B+	B+
Commerzbank AG	02.01.2003	30.12.2009	A-	A
Continental AG	02.01.2003	30.12.2009	B+	BBB+
Daimler AG	02.01.2003	30.12.2009	BBB	A-
Degussa AG	14.11.2003	28.02.2006	BBB+	BBB+
Depfa Bank PLC	24.03.2003	28.09.2007	A+	AA-
Deutsche Bank AG	02.01.2003	30.12.2009	A+	AA
Deutsche Boerse AG	02.01.2003	30.12.2009	AA	AA+
Deutsche Post AG	02.01.2003	30.12.2009	BBB+	A+
Deutsche Postbank AG	20.09.2004	30.12.2009	A-	A
Deutsche Telekom AG	02.01.2003	30.12.2009	BBB+	A-
Duerr AG	03.05.2004	30.12.2009	B	BB-
Dyckerhoff AG	02.01.2003	30.12.2009	BB	BBB
E.ON AG	02.01.2003	30.12.2009	A	AA-
Epcos AG	02.01.2003	19.12.2008	BB+	BBB+

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Table A.2 – continued from previous page

	Rating available		Rating range	
Company	**from**	**to**	**lower bound**	**upper bound**
Escada AG	18.03.2005	19.06.2009	CC	BB-
EADS AG	24.03.2003	30.12.2009	BBB+	A
Fresenius Medical Care KGaA	02.01.2003	30.12.2009	BB	BB+
Fresenius SE	02.01.2003	30.12.2009	BB	BB+
GEA Group AG	02.01.2003	30.12.2009	BBB-	BBB
Gerresheimer AG	06.09.2007	30.12.2009	BB	BB+
Gildemeister AG	19.07.2004	22.09.2009	B+	BB-
Grenkeleasing AG	15.05.2003	30.12.2009	BBB+	BBB+
Hannover Rückversicherungs AG	02.01.2003	30.12.2009	AA-	AA
HeidelbergCement AG	02.01.2003	30.12.2009	B-	BBB-
Henkel KGaA	02.01.2003	30.12.2009	A-	AA-
Hornbach Holding AG	01.10.2004	30.12.2009	BB	BB
Hypo Real Estate Holding AG	22.03.2004	08.10.2009	BBB	A
IKB Deutsche Industriebank AG	02.01.2003	19.12.2008	BBB-	A+
Jenoptik AG	01.10.2003	21.09.2007	B	BB-
K+S AG	23.04.2009	30.12.2009	BBB	BBB+
Klockner + Co AG	02.07.2007	30.12.2009	B+	B+
Kolbenschmidt Pierburg AG	02.01.2003	11.11.2003	BBB	BBB
Lanxess AG	20.06.2005	30.12.2009	BBB-	BBB
Linde AG	02.01.2003	30.12.2009	BBB-	A-
Lufthansa AG	02.01.2003	30.12.2009	BBB-	BBB+
MAN AG	05.08.2008	30.12.2009	A-	A-
Mannheimer AG Holding	02.01.2003	19.09.2003	A	A
Marseille-Kliniken AG	02.01.2003	21.03.2003	BB-	BB-
Merck KGAA	19.09.2003	30.12.2009	BBB	A-
Metro AG	02.01.2003	30.12.2009	BBB	BBB+

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Table A.2 – continued from previous page

	Rating available		**Rating range**	
Company	**from**	**to**	**lower bound**	**upper bound**
MTU Aero Engines Holding AG	19.09.2005	19.06.2007	BB	BB+
Munich Re AG	02.01.2003	30.12.2009	A+	AA+
Pfleiderer AG	02.01.2003	30.12.2009	BB	BB+
ProSiebenSat.1 Media AG	02.01.2003	31.07.2007	BB+	BBB-
Rheinmetall AG	02.01.2003	11.12.2008	BBB-	BBB
Rhoen-Klinikum AG	02.01.2006	30.12.2009	BBB-	BBB-
RWE AG	02.01.2003	30.12.2009	A	A+
SGL Carbon AG	02.01.2003	30.12.2009	CCC+	BB
Siemens AG	02.01.2003	30.12.2009	A+	AA-
Suedzucker AG	01.10.2003	30.12.2009	BBB	A-
T-Online International AG	24.03.2003	08.06.2006	BBB+	A-
Thiel Logistik AG	01.10.2004	15.06.2007	B	B+
ThyssenKrupp AG	02.01.2003	30.12.2009	BB+	BBB
TUI AG	31.10.2005	30.12.2009	B-	BB+
VBH Holding AG	03.03.2009	30.12.2009	BBB-	BBB-
Versatel AG	24.09.2007	19.12.2008	B+	BB-
Volkswagen AG	02.01.2003	30.12.2009	A-	A+

Table A.3: The impact of market returns on market liquidity: Crisis vs. non-crisis

This table reports company and volume-class fixed effects regressions that analyze the effect of index returns on the liquidity costs over the sample period of January 2003 to December 2009. The dependent variable, liquidity costs, is represented by the daily price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the daily Xetra closing prices. Market cap (log) is the log-transformed daily market value at day closing. Traded volume (log) represents the logarithm of the daily trading volume of traded shares. Standard deviation of daily log-returns is the annualized 5-day standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of the variable CDAX log-return, which is the daily log-return of the CDAX, which is a broad German composite index. The results are reported for three different subsamples: (A.3.1) covers the pre-crisis period from January 2003 to September 14th, 2008; (A.3.2) covers the period of financial crisis from September 15th, 2008 (collapse of Lehman Brothers) to December 2009; whereas (A.3.3) covers the whole data for our sample period of January 2003 to December 2009. This table shows the estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(A.3.1)	(A.3.2)	(A.3.3)
Price (log)	-0.440***	-0.198***	-0.507***
	(-156.10)	(-20.47)	(-225.69)
Traded volume (log)	-0.220***	-0.106***	-0.223***
	(-592.78)	(-96.33)	(-616.67)
Market cap (log)	-0.323***	-0.962***	-0.290***
	(-122.92)	(-103.53)	(-129.98)
Standard deviation of daily log-returns (5 days)	0.644***	0.433***	0.678***
	(434.41)	(221.16)	(582.68)
Log-return CDAX	-1.512***	-1.106***	-1.542***
	(-57.24)	(-35.76)	(-74.11)
Constant	8.556***	12.10***	8.559***
	(778.44)	(297.29)	(880.94)
Observations	1940124	433294	2373418
Adjusted R^2	0.485	0.393	0.524
F	365681.3	56567.3	522691.1

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

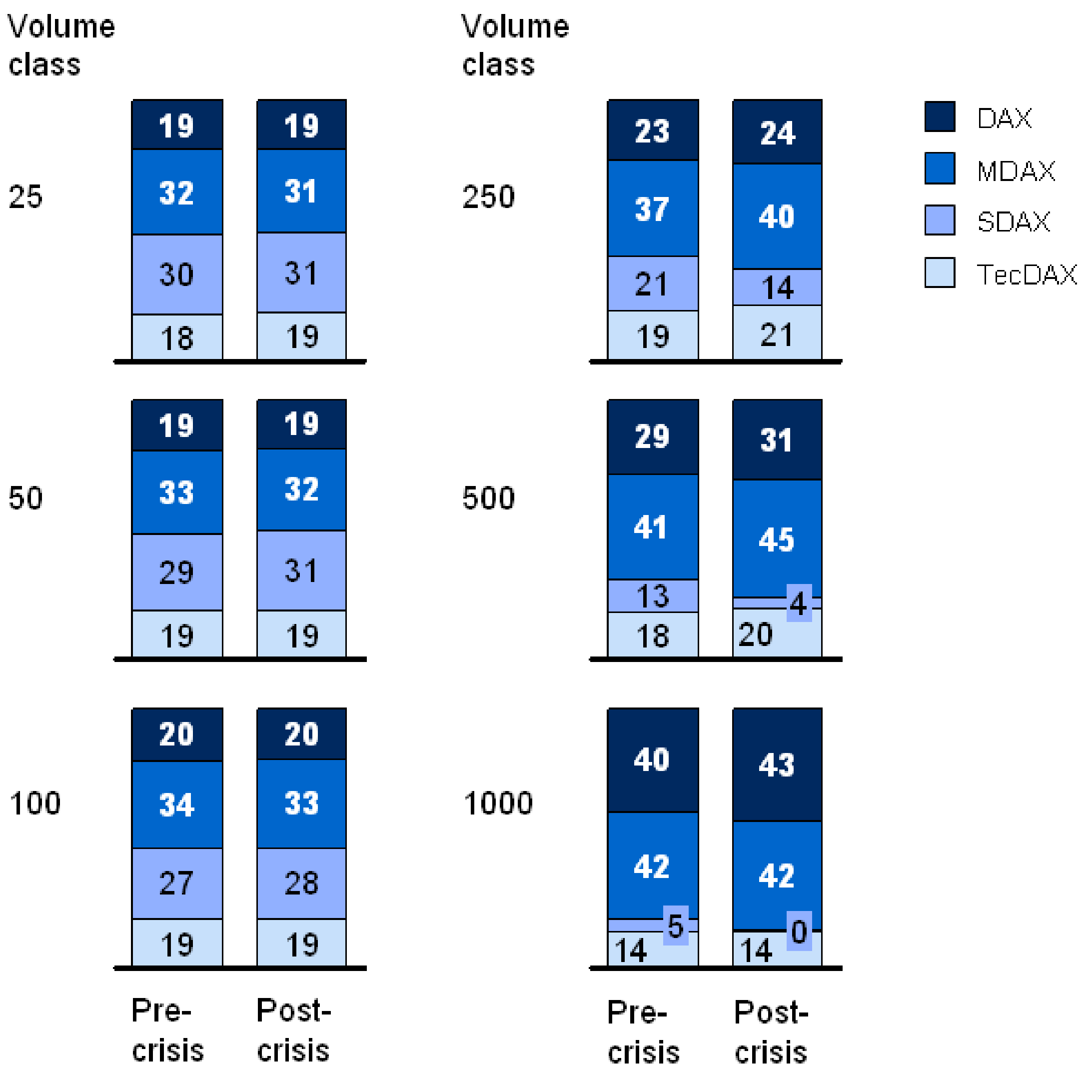

Figure A.1: Distribution of the liquidity commonality measure by index and volume class

This figure compares the distribution of the liquidity commonality measure R^2 across the four major indices (DAX, MDAX, SDAX, and TecDax) over the pre-crisis period (Jan 2003 - Aug 2008) with the distribution for the crisis-period (Sep 2008 - Dec 2009) for all of the 6 standardized volume classes q, which are available for all of the four major indices (DAX, MDAX, SDAX, and TecDax). The 6 volume classes included are those with a volume of Euro 25, 50, 100, 250, 500, 1000 thousand. The distribution is measured in percentage.

Appendix B

Market liquidity and ownership structures

Table B.1: Different measures of ownership concentration

This table reports company, volume-class and time fixed effects regressions that relate liquidity costs to various measures of ownership concentration over the sample period of 2003 to 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. In addition to the aforementioned control variables, we test the impact of the following measures of ownership concentration: share of blockholder is the total share of blockholdings as a fraction. Number of blockholders is the total count of blockholders. Herfindahl represents the sum of the squares of the individual blockholder shareholdings. Largest blockholder is the share of the largest blockholder. $C1C3$ and $C1C5$ represents the combined share of the three and five largest blockholders, respectively. This table shows the estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(B.1.1)	(B.1.2)	(B.1.3)	(B.1.4)	(B.1.5)	(B.1.6)	(B.1.7)
Price (log)	-0.335***	-0.331***	-0.331***	-0.335***	-0.336***	-0.332***	-0.331***
	(-13.60)	(-13.47)	(-13.43)	(-13.61)	(-13.65)	(-13.50)	(-13.48)
Market cap (log)	-0.258***	-0.264***	-0.262***	-0.258***	-0.259***	-0.263***	-0.263***
	(-10.61)	(-10.82)	(-10.75)	(-10.61)	(-10.62)	(-10.79)	(-10.81)
Traded volume (log)	-0.337***	-0.327***	-0.333***	-0.336***	-0.333***	-0.328***	-0.327***
	(-47.65)	(-44.19)	(-46.89)	(-46.38)	(-46.02)	(-44.48)	(-44.28)
Stdev. log-returns	0.765***	0.752***	0.763***	0.764***	0.759***	0.753***	0.752***
	(25.61)	(25.12)	(25.57)	(25.57)	(25.35)	(25.13)	(25.11)
Share of blockholders		0.101***					
		(4.40)					
Number of blockholders			0.0132***				
			(3.84)				
Herfindahl				0.0145			
				(0.51)			
Largest Blockholder					0.0679***		
					(2.61)		
C1C3						0.0968***	
						(4.06)	
C1C5							0.0989***
							(4.26)
Constant	8.832***	8.768***	8.798***	8.826***	8.798***	8.775***	8.770***
	(82.02)	(80.80)	(81.50)	(81.53)	(81.17)	(80.91)	(80.82)
Observations	9060	9060	9060	9060	9060	9060	9060
Adjusted R^2	0.696	0.697	0.696	0.696	0.696	0.697	0.697
F	2265.2	2066.4	2064.6	2059.1	2061.6	2065.3	2065.9

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Liquidity costs, ownership concentration and several blockholder types

This table reports company, volume-class and time fixed regressions that relate liquidity costs to the share of various blockholder types over the sample period of 2003 to 2009. The dependent variable, liquidity costs is represented by the yearly average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. We further include the share of blockholders, which is the total share of blockholdings as a control variable in all models. In addition to the aforementioned control variables, we test the impact of the shareholdings of following types of blockholders: insiders and financial, strategic and private investors. This table shows the estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(B.2.1)	(B.2.2)	(B.2.3)	(B.2.4)	(B.2.5)
Price (log)	-0.331***	-0.345***	-0.343***	-0.351***	-0.346***
	(-13.47)	(-13.99)	(-13.83)	(-14.15)	(-13.92)
Market cap (log)	-0.264***	-0.252***	-0.254***	-0.247***	-0.248***
	(-10.82)	(-10.33)	(-10.36)	(-10.09)	(-10.12)
Traded volume (log)	-0.327***	-0.327***	-0.324***	-0.325***	-0.329***
	(-44.19)	(-44.31)	(-43.71)	(-43.91)	(-43.51)
Stdev. log-returns	0.752***	0.752***	0.750***	0.751***	0.755***
	(25.12)	(25.15)	(25.07)	(25.11)	(25.22)
Share of blockholders	0.101***	0.134***	0.0872***	0.122***	
	(4.40)	(5.67)	(3.74)	(5.02)	
Private investors		-0.375***		-0.337***	-0.226***
		(-5.88)		(-5.12)	(-3.54)
Insider			0.146***	0.0918**	0.209***
			(3.63)	(2.20)	(4.83)
Financial investors					0.154***
					(5.50)
Strategic investors					0.0739**
					(2.31)
Constant	8.768***	8.722***	8.706***	8.687***	8.698***
	(80.80)	(80.35)	(79.30)	(79.23)	(79.28)
Observations	9060	9060	9060	9060	9060
Adjusted R^2	0.697	0.698	0.697	0.698	0.698
F	2066.4	1906.0	1898.5	1760.7	1636.3

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix C

Market liquidity and insider trading

Table C.1: The effect of the nominals traded by insiders on stock market liquidity

This table reports company and volume-class fixed effects regressions that relate liquidity costs to the nominals traded by insiders over the sample period of July 2002 to December 2009. The dependent variable, liquidity costs, is represented by the yearly average of the price impact per transaction $L(q)$, which is calculated from an order-size-dependent volume-weighted spread $WS(q)$ derived daily from the limit order book. Price (log) is the logarithm of the yearly average of the daily Xetra closing prices. Market cap (log) is the log-transformed yearly average of the daily market value at day closing. Traded volume (log) represents the logarithm of the yearly average of the daily trading volume of traded shares. The stdev. log-returns is the annualized yearly standard deviation of the daily log-returns. In addition to the aforementioned control variables, we will test the impact of insider transactions, using the log-transformed annual average of nominals bought or sold by insiders. This table shows the estimated coefficients, with the t-statistics reported in parentheses below their corresponding estimated coefficients, and the adjusted R^2 values are presented below their corresponding models.

	(C.1.1)	(C.1.2)	(C.1.3)	(C.1.4)
Price (log)	-0.668***	-0.668***	-0.652***	-0.653***
	(-30.03)	(-30.07)	(-29.48)	(-29.52)
Traded volume (log)	-0.423***	-0.426***	-0.415***	-0.419***
	(-66.94)	(-66.58)	(-65.69)	(-65.81)
Market cap (log)	-0.0165	-0.0190	-0.0162	-0.0205
	(-0.75)	(-0.86)	(-0.74)	(-0.93)
Stdev. log-returns	1.318***	1.317***	1.298***	1.296***
	(79.37)	(79.37)	(78.28)	(78.21)
Insider transaction bought nominals (log)		0.00236***		0.00414***
		(2.82)		(4.91)
Insider transaction sold nominals (log)			-0.00966***	-0.0104***
			(-11.73)	(-12.41)
Constant	8.124***	8.149***	8.076***	8.117***
	(91.04)	(90.90)	(91.01)	(91.18)
Observations	12906	12906	12906	12906
Adjusted R^2	0.644	0.645	0.649	0.650
F	6490.6	5197.6	5288.8	4421.2

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$