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Market liquidity in the financial crisis: The role of liquidity commonality and flight-to-quality

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ABSTRACT

We examine the dynamics and the drivers of market liquidity during the financial crisis, using a unique volume-weighted spread measure. According to the literature we find that market liquidity is impaired when stock markets decline, implying a positive relation between market and liquidity risk. Moreover, this relationship is the stronger the deeper one digs into the order book. Even more interestingly, this paper sheds further light on so far puzzling features of market liquidity: liquidity commonality and flight-to-quality. We show that liquidity commonality varies over time, increases during market downturns, peaks at major crisis events and becomes weaker the deeper we look 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 find that funding liquidity tightness induces an increase in liquidity commonality which then leads to market-wide liquidity dry-ups. Therefore our findings corroborate the view that market liquidity can be a driving force for financial contagion. Finally, we show that there is a positive relationship between credit risk and liquidity risk, i.e., there is a spread between 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 corroborates the existence of a flight-to-quality or flight-to-liquidity phenomenon also on the stock markets.

1. Introduction

The drying-up of market liquidity during the financial crisis is a well-documented phenomenon held, at least partially, responsible for the financial contagion experienced during that crisis. Brunnermeier and Pedersen (2009) provide an explanation for the occurrence of such liquidity spirals by linking an asset's market liquidity, i.e. the ease with which it is traded, with traders' funding liquidity, i.e. the ease with which they can obtain funding. They point out that market declines negatively affect a trader's assets, thereby increasing the probability of margin calls. This might coerce the trader to partially liquidate her portfolio putting additional price pressure on the assets. A self-enforcing liquidity spiral is likely to occur. Moreover, in such a context also other puzzling facts, like liquidity commonality across securities and the flight-to-quality or flight-to-liquidity phenomenon, can be explained.

By using a unique data set on stock market liquidity this paper aims to shed further light on these puzzling features of market liquidity. Actually, the existing literature on market liquidity in times of crises which in most cases focuses on the bid-ask spread to measure liquidity costs. We are able to extend the literature in this respect because we have access to a unique volume-weighted spread liquidity measure called XLM (Xetra liquidity measure). The data is provided by Deutsche Börse. It is a liquidity measure that measures the order-size-dependent liquidity costs of a roundtrip. Hachmeister (2007) provides theoretical background on this measure and Stange and Kaserer (2011) scrutinize its empirical properties for the German stock market. A similar measure called cost of round trip trade (CRT), which aggregates the status of the limit order book at any moment in time for a specific transaction size, was introduced by Irvine et al. (2000). Also Barclay et al. (1999), Coppejans et al. (2002), Giot and Grammig (2005), and Rösch (2012) used similar liquidity measures in a different context. The use of this order-size-dependent volume-weighted spread measure enables us to scrutinize whether specific liquidity effects hold for the whole depth of the limit order book.

On the basis of these unique data-set we aim to make a contribution to the existing market liquidity literature in several ways. First of all we investigate and try to better understand the role of market liquidity during periods of financial distress. Not surprisingly we show that market liquidity evaporates when it is most needed, i.e. in market downturns and times of crises, worryingly

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Nomenclature

DAX®	Deutscher Aktiendindex (30 largest German stocks)
MDAX®	Mid-Cap Index (50 largest stocks below DAX)
SDAX®	Small-Cap Index (50 largest stocks below MDAX)
TecDAX®	Tec-Index (30 largest technology stocks below DAX)

implying that there is a positive relationship between market risk and liquidity risk and that investors are struck by both risks at the same time. Moreover, this effect is more pronounced the deeper one digs into the limit order book, i.e. the larger traded positions are, and the less liquid stocks are, i.e. the smaller the respective companies are.

Secondly, we extend the existing literature on liquidity commonality (e.g., Chordia et al. (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001), and Brockman and Chung (2002)) by examining the dynamics and causes of it in the periods of market distress. In accordance with the literature we show that liquidity commonality significantly varies over time, increases during market downturns and peaks at major crisis events. However, because of our unique data set we can scrutinize the liquidity commonality dynamics over the whole order book depth. Interestingly, it turns out that liquidity commonality becomes weaker the deeper we look into the limit order book. As far as the drivers of liquidity commonality are concerned, our results corroborate the theoretical predictions proposed in the paper of Brunnermeier and Pedersen (2009). In fact, by using different measures of funding liquidity tightness we find evidence that by making the traders' funding situation more restrictive an increase in liquidity commonality is induced, which then leads to market-wide liquidity dry-ups. Therefore we are able to corroborate the view that market liquidity by amplifying financial market procyclicality can be a driving force for the transmission of shocks and financial contagion.

Third, we explore the phenomenon called flight-to-quality, which is also known as flight-to-liquidity. This basically states that liquidity costs are positively correlated with credit risk and that investors tend to shift their portfolio towards less risky and more liquid assets in stressed market scenarios (Beber et al., 2009). The flight-to-quality theory, to the best of our knowledge, was never tested before for stock markets and therefore we want to close this gap. In line with the existing research on the flight-to-quality phenomenon, we show that there is a positive relationship between credit risk and liquidity risk, i.e., there is a spread between 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 corroborates the idea that in times of crisis investors become increasingly risk avers and have a preference for more liquid instruments. We are therefore able to show that the flight-to-quality or flight-to-liquidity phenomenon also exists in the stock market.

To sum up, by using a sophisticated liquidity measure we are able to analyze liquidity dynamics and drivers over the whole depth of the limit order book. In this way our research helps to better understand the impact of stock market liquidity in crisis scenarios and therefore sheds further light on the characteristics of market liquidity risk. This should be helpful for institutional investors, exchange officials, financial regulators, and risk management practitioners.

The remainder of this paper is organized as follows. In Section 2, we give an overview on the literature and present our research hypotheses. Section 3 gives some background on the Xetra market structure and introduces our dataset. In Section 4 we discuss our empirical results and provide some robustness tests that support our findings. Conclusions follow in Section 5.

2. Literature review and research hypotheses

2.1. Liquidity in times of crisis

Amihud et al. (1990) were among the first to show that market liquidity can be a driving force for market declines. They argue that the stock market crash of 1987 can be at least partially explained by an across the board revision of investor's expectations about stock market liquidity. As market liquidity is priced in the stock market (e.g., Amihud and Mendelson (1986)), a drop in investor's expectation about this liquidity will lead to a decline of the stock prices.

In more recent research market declines are seen as a driver for illiquidity. In fact, 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), by using several different liquidity measures, shows that market liquidity in the US 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 LTCM hedge fund in 1998, the early 2000 burst of the high-tech bubble and the terrorist attacks on September 11, 2001. Analyzing 23 emerging markets over the period 1993–2000, Lesmond (2005) descriptively shows that bid-ask spreads as well as several other liquidity measures sharply increase during the Asian and Russian crisis. Yeyati et al. (2008) also focusing on emerging markets and using a sample of 52 stocks from seven different countries over the period April 1994–June 2004 demonstrate that crisis periods[1] 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[2] market decline. Also Naes 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 US sample that covers NYSE common shares from 1947 to 2008 and a Norwegian sample from the Oslo Stock Exchange covering the period from 1980 to 2008.

All these findings lead to our first hypothesis:

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

[2] They define a large market decline as a drop of the weekly market return below more than 1.5 standard deviations of its mean.

Hypothesis 1. Market liquidity varies over time and especially is impaired during times of crisis/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.

According to theoretical research (e.g. Brunnermeier and Pedersen (2009)) an important transmission channel for causing a market liquidity impairment during periods of market downturn are the liquidity commonality and flight-to-liquidity phenomena. Therefore we look at these two phenomena in the next two sections.

2.2. 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 influencing the liquidity of an individual company's securities (Brockman et al., 2009). This phenomenon was first pointed out 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 work of Chordia et al. (2000) acknowledged the existence of liquidity commonality. E.g., Hasbrouck and Seppi (2001) use a principal component analysis to provide evidence for a single common liquidity factor influencing the liquidity of the Dow Jones 30 stocks. 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 US 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. Also the empirical results of Brockman et al. (2009) confirm that individual firm's bid-ask spreads or depths are significantly influenced by changes in the aggregate market's bid-ask spreads or depth respectively on 47 stock exchanges around the world. Besides the previously acknowledged exchange level commonality component they furthermore provide some evidence for a global liquidity commonality component.

Summing up, these findings lead to our second research hypothesis:

Hypothesis 2. Liquidity commonality exists and it exhibits a time-varying behavior.

Although the above mentioned 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 (Acharya and Pedersen, 2005; Pastor and Stambaugh, 2003; Sadka, 2006; Korajczyk and Sadka, 2008; Kuan-Hui and Lee, 2011), relatively few research has focused on the fundamental drivers affecting liquidity commonality. As a matter of fact, liquidity commonality can theoretically have three basic sources: co-variation in liquidity supply, co-movement in liquidity demand, or both. Some theoretical studies trying to explain the casual relationship between market returns and market liquidity we described above (e.g., Bookstaber (2000), Kyle and Xiong (2001), 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). Having a market-wide impact on liquidity, through simultaneously occurring transactions, we hypothesize that these market-wide liquidity demand and supply effects of market declines therefore induce co-movement in liquidity:

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

Some support for liquidity supply-side factors such as capital constraints is given by Coughenour and Saad (2004), Hameed et al. (2010) and Comerton-Forde et al. (2010), while Karolyi et al. (2012) do not find significantly consistent support for this source of liquidity commonality. Empirical support for demand-side determinants is to some extent given in the work of Huberman and Halka (2001), Kamara et al. (2008), and Karolyi et al. (2012), 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 much attention, we concentrate on this field of research with our empirical study. They propose a theoretical model that explains the spiral and dynamic interactions between funding liquidity and market liquidity.[3] In their research they argue that market declines reduce the value of financial intermediaries' assets and thus increase the probability of margin calls and higher and tighter margin requirements. At the aggregate level, this causes funding liquidity problems for the financial sector, which coerces it to partially liquidate portfolios. Those portfolio liquidations are putting 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. So 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 the funding and market liquidity spiral.

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

Hypothesis 4. Funding liquidity dry-ups lead to an increase in liquidity commonality.

2.3. Fligth-to-quality and flight-to-liquidity

Another liquidity phenomenon that prevails in times of crisis and increased market uncertainty is the flight-to-quality phenomenon, which is heavily interlinked with the flight-to-liquidity concept. In fact, often these two labels are used synonymously. This phenomenon stems from empirical investment behavior observations 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 often stated explanation that these two phenomena are intertwined is that risky

[3] 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.

assets also tend to be less liquid, see e.g., Ericsson and Renault (2006). As first we want to test whether this correlation of credit and liquidity quality is given, we formulate our next hypothesis as follows:

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

Previous theoretical and empirical research mostly indicates that there is an inverse relationship between liquidity costs and credit quality. Ericsson and Renault (2006) develop a model to illustrate the impact of liquidity risk on corporate bond yield spreads. One main result from their model is that the levels of liquidity spreads are positively correlated with credit risk/default probability. Chen et al. (2007) analyze liquidity costs for over 4000 non-callable corporate bonds from 1995 to 2003. They find that liquidity costs are decreasing with credit worthiness, as measured by the 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 unique negative correlation between credit quality and liquidity across the Euro-area government bond market.

In order to explain this relationship between market liquidity and credit risk, Vayanos (2004) theoretically shows that investors prefer more liquid instruments in times of market uncertainty (i.e., increased market volatility), which is reflected in increasing liquidity premia. He explains this phenomenon for an increased preference for liquidity with an increase in the investor's risk aversion. Longstaff (2004) finds a flight-to-liquidity premium in US Treasury bond prices, by comparing prices of Treasury bonds with identical bonds of Refcorp,[4] which basically 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 liquidity in the bond market. These findings are also consistent with Naes et al. (2011) who show, using data for Norway, that in times of increased market uncertainty some investors exit the stock market, which is perceived more risky compared to other asset classes, and others re-balance their equity portfolios towards larger and more liquid stocks.

We hypothesize that the flight-to-quality and flight-to-liquidity phenomenon also prevails in the stock market. Thereforem our last research hypothesis is formulated as follows:

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 to 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 behavior in the stock market.

[4] Refcorp is the Resolution Funding Corporation, which is a government agency created by the Financial Institutions Reform, Recovery, and Enforcement Act of 1989 (FIRREA). Refcorp bonds are fully guaranteed by the US Treasury and therefore literally have the same credit risk as Treasury bonds, however there is less liquidity for Refcorp bonds.

3. Market structure and data

3.1. Xetra market structure

The Xetra market is the electronic order-driven market system of Deutsche Börse. An electronic order book collects all limit and market orders from market 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 participants. However, market participants have the possibility to enter large orders into the order book without revealing the full volume to the market, as so called iceberg order. For an iceberg order only a specified tranche, the so called peak, which is the visible volume of an iceberg order, is introduced in the order book with the original time-stamp of the iceberg order according to price and time priority. As soon as the peak has been completely fulfilled and there is hidden volume left a new tranche is entered into the book with a new current time stamp.

Market makers, which are called designated sponsors, may provide additional liquidity, particularly for less liquid stocks. They support trading on Xetra by committing themselves to quote binding bid and ask prices for securities up to a prespecified minimum quotation volume.

3.2. Data

In our research we focus on the period from January 2003 to December 2009. We investigate the liquidity behavior of the 160 companies listed in one of the four major German stock indices (DAX, MDAX, SDAX, TecDAX), which are all traded on Xetra. It should be noted that according to market cap we cover about 90% of the German stock market. Since 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.

3.2.1. Market liquidity

To measure the liquidity costs, more precisely the roundtrip price impact, 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 round-trip order of a specific Euro volume of 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 liquidity measure of the committed liquidity available in the market. The weighted spread is a highly sophisticated liquidity measure as it combines three dimensions of liquidity in one measure: market breadth, market depth and immediacy in execution.

Mathematically, $WS(q)$ is calculated as the average volume-weighted price of all limit orders, which are required for transacting a specific Euro volume roundtrip of size q, divided by the mid-price P_{mid} of the bid-ask-spread and it is measured in basis points[5]:

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

where $a_{i,t}$ and $n_{i,t}$ 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. n represents the number of shares

[5] For a detailed analysis of this measure in a risk management context cf. Ernst et al. (2012).

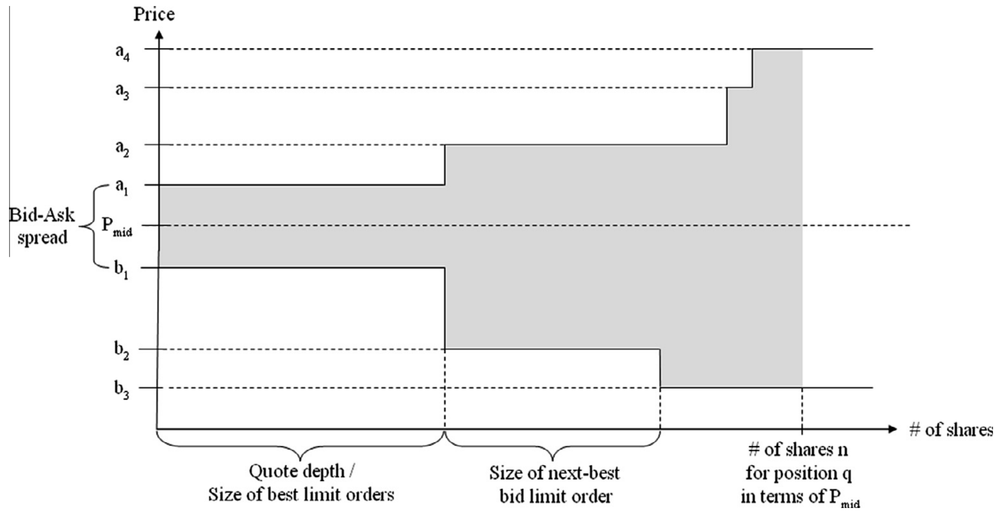

Fig. 1. Weighted spread as area between limit order bid- and ask-curves.

required to fulfill an order with a volume of size q as measured in terms of the mid-price P_{mid}. Therefore n can be calculated as $n = \frac{q}{P_{mid}}$. The individual limit orders i are added up until the sum of the individual limit order sizes $n_{i,t}$ equals n. The respective measures for the bid-side $b_{j,t}$ and $n_{j,t}$ are defined analogously. Eq. (1) can be simplified to

$$WS_t(q) = \frac{a_t(q) - b_t(q)}{P_{mid,t}} \cdot 10{,}000 \tag{2}$$

where

$$a_t(q) = \frac{1}{n}\sum_i a_{i,t} n_{i,t} \tag{3}$$

is the volume-weighted ask-price achieved when buying an order of size q through a market order and $b_t(q)$ is the respective 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 order size n (see Fig. 1) divided by the order volume q.[6]

Such a volume-weighted spread called Xetra liquidity measure (XLM) is automatically calculated by the Xetra system from the visible and invisible part, including the hidden part of iceberg orders, of the electronic limit order book.[7] The XLM was introduced in July 2002 by Deutsche Börse in order to provide its market participants with the ability to identify the implicit transaction costs. 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, TecDAX) from Deutsche Börse. Daily values of the XLM are calculated by Xetra as the equal-weighted average of all available minute-by-minute volume-weighted spread data points 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 enough 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 5 million with the exception of the following four volume classes: Euro 10, 75, 150 and 750 thousand. Whereas for the stocks in the other three indices the XLM was available for all volume classes up to Euro 1 million.

For some parts of our research we used 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. For simplicity reasons we assume that on average the limit-order book is symmetrical,[8] i.e., the liquidity costs for buying and selling are equal. Therefore, we can calculate the volume-dependent price impact $PI(q)$ per transaction as

$$L(q) = PI(q) = \frac{WS(q)}{2} \tag{4}$$

In total, our sample contained over 2.3 million observations for the 1760 trading days in our sample period. Table 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 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 order-sizes q the larger the liquidity costs $L(q)$.

3.2.2. 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, website or from the company's investor relation department. We collected the individuals company's full history of the long-term issuer ratings from Standard & Poor's (S&P) during the sample period.[9] Overall 67

[6] For similar graphical representations cf. Domowitz et al. (2005) and Stange and Kaserer (2011).

[7] For further theoretical background on the XLM see Hachmeister (2007).

[8] This is a fair assumption as Hedvall et al. (1997) found that in general the order book is quite symmetric 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.

[9] 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.

Table 1
Liquidity costs $L(q)$. Average of daily liquidity costs $L(q)$ for our sample companies 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

companies posses 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.

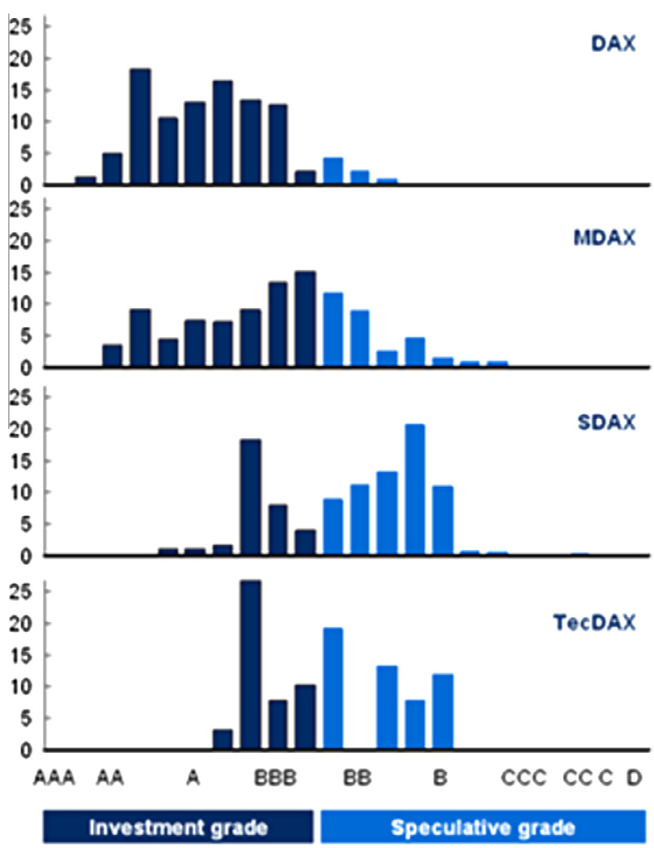

Fig. 2. Rating distribution of sample observations by index. This figure shows the distribution of our daily sample observations by rating class within one of our four major indices (DAX, MDAX, SDAX, TecDax) over the time period from January 2003 to December 2009. The distribution only includes those observations that are associated with a rating. The figure further distinguishes between investment (dark blue) and speculative (light blue) grade ratings in accordance to S&P. The relative frequencies by index are in percent. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 2 gives an overview on 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 seems to be a clear rating ranking among the indices, i.e., that companies in larger indices have better ratings than companies of smaller indices.

3.2.3. Index and EONIA data

For the analysis of liquidity commonality we further need return data of several indices (DAX, MDAX, SDAX, TecDAX, DAX All Banks) and the EONIA. 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 listed 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 3 weeks and all monthly maturities of one to 12 months. For our analyses we use the 3-month EURIBOR.

Daily index returns of the DAX, MDAX, SDAX, TecDAX, 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.

3.2.4. Control variable

Prior research suggests that liquidity costs are at least partially explained by the variations in share price, return volatility, trading activity and firm size (Benston, 1974; Stoll, 1978; Copeland and Galai, 1983; Barclay and Smith, 1988; Hanley et al., 1993; Corwin, 1999; Stoll, 2000; Acharya and Pedersen, 2005; Stange and Kaserer, 2011). 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 (e.g., Stoll (2000) and Corwin (1999)).

The price level P controls for the effect of discreteness (Harris, 1994) and it is also a further risk proxy as lower priced stocks tend to be riskier (Bachrach and Galai, 1979). Hence, liquidity costs should theoretically be a decreasing function of the price level (Stoll, 2000). 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 is a proxy for the general market condition. Therefore, liquidity costs should increase with a rise of return volatility (Copeland and Galai, 1983). 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. Like 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 a 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,

Table 2
Descriptive statistics of variables. This table gives an overview of all variables (liquidity, indices and control variables) we will use in the following empirical analyses. 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 prices 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. 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 percent. 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

smaller stocks therefore tend to be less liquid (Pastor and Stambaugh, 2003).

Daily stock returns, daily stock prices, daily trading volume and daily market capitalization are obtained from Thomson Financial Datastream. We had to adjust daily price data, because Datastream carries forward price data if no transaction took place. We therefore removed all price data at days, when no transaction volume was recorded. Data for market value *MV* and transaction volume *VO* were used as provided by Datastream. From the daily price data we calculated a 5-days standard deviation of daily stock log-returns.

3.2.5. Descriptive information

Table 2 gives an descriptive overview of all variables used in the following empirical analyses by the four major indices. As already mentioned above, the average liquidity costs are 121 basispoints. 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 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.

4. Empirical analysis

4.1. Market liquidity over time – the impact of the financial crisis

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

First of all we try scrutinize whether 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 Fig. 3 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 pretty stable for the following years from 2005 to mid 2007. The

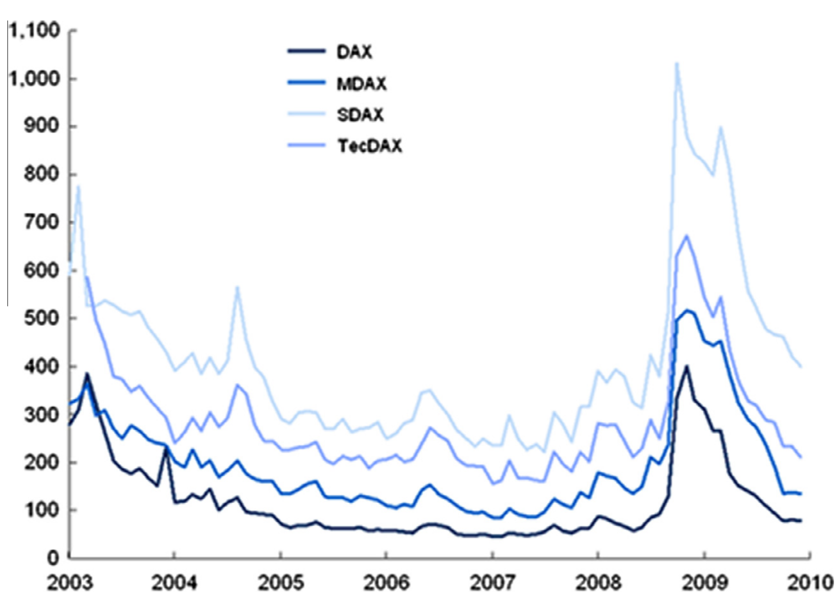

Fig. 3. Volume-weighted spread (XLM) by index. This figure shows time-series plots of monthly averages of the volume-weighted spread measure XLM for the four major German indices (DAX, MDAX, SDAX, TecDAX) over the time period from January 2003 to December 2009. The XLM is measured in basispoints.

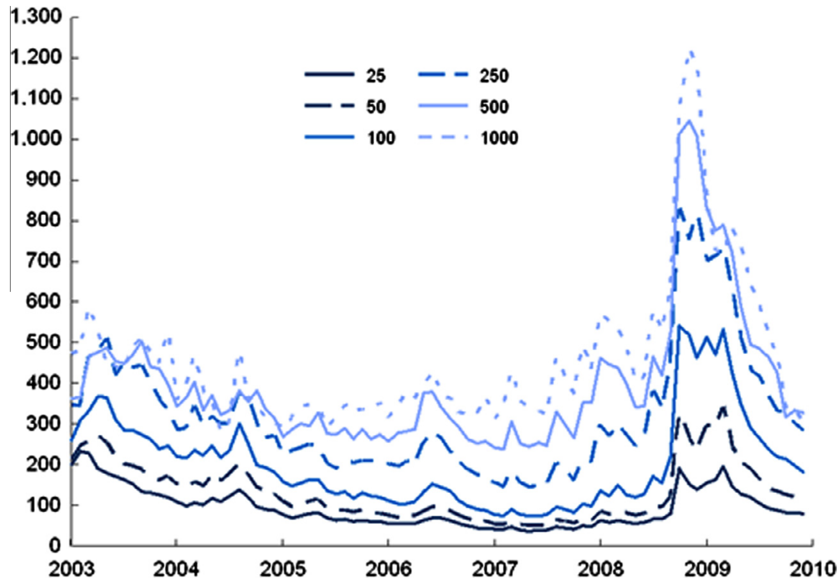

Fig. 4. Volume-weighted spread (XLM) by volume class. This figure shows time-series plots of monthly averages of the volume-weighted spread measure XLM across the six standardized volume classes q which are available for all four major indices (DAX, MDAX, SDAX, TecDax) over the time period from January 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 basispoints.

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 1000 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 slowly 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 look into the dynamics inside the limit order book. This 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. Fig. 4 displays the monthly averages of the XLM across the 6 standardized volume classes q which 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 1000 thousand. We see a similar pattern across all six volume classes to the pattern described before. However larger volume classes seem to suffer more than smaller order sizes by the financial crisis and therefore the impact of the financial crisis on market liquidity becomes stronger the deeper 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 severely to levels above 1200 basispoints for order sizes of Euro 1 million and even transaction sizes of Euro 0.5 million peaked at over 1000 basispoints. These values are almost three times as high as the initial values for these volume classes in our sample. At the same time also the volume-weighted spreads for smaller volume classes rose significantly but only reached levels of 190 and 320 basispoints for order sizes of Euro 25 and 50 thousand respectively. This unique insight is especially 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 spikes in market liquidity risk in times of crisis that are especially pronounced in larger volume classes. 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 proxy the level and especially the variation of liquidity costs during times of crisis for larger volume classes. Therefore our unique dataset with the order size-dependent volume-weighted spread measure, that better captures the liquidity dynamics of the whole limit order book, will help us to shed some further light on existing market liquidity puzzles in times of crisis.

4.1.2. 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. In line with Stange and Kaserer (2011) 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 very unique panel data set with order-size-dependent liquidity costs, we use a company and volume class fixed effects model for the estimation.[10] In the remainder of the paper all our panel data models include the dependent variable $logL(q)$ and all the standard control variables in the following form, where time and company subscripts are neglected for simplification:

$$logL(q) = a_o + a_1 logVO + a_2 logP + a_3 logMV + a_4 \sigma_r + e \quad (5)$$

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

[10] The Hausman (1978) test statistic supports the usage of a fixed effects model in comparison to a random effects model.

Table 3
The effect of the financial crisis on market liquidity. This table reports company and volume class fixed effects regressions that analyze the effect of the financial crisis on liquidity costs during the sample period January 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. Standard deviation of daily log-returns is the annualized 5 days standard deviation of daily log-returns. Besides the above mentioned control variables we will test the impact of the financial crisis using three different dummy variables: Lehman week (3.1), which equals 1 during the week following the collapse of Lehman Brothers (September 15th–September 19th, 2008), Lehman month (3.2), which equals 1 during the month following the collapse of Lehman Brothers (September 15th–October 14th, 2008) and Financial crisis (3.3), 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, the t-statistics are reported between parentheses below the respective estimated coefficients and the adjusted R^2 are presented below the respective model.

	(3.1)	(3.2)	(3.3)
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.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

financial crisis dummy covering the period from the Lehman collapse until the end of 2009 (September 15th, 2008–December 31st, 2009). Based on our more descriptive results in Figs. 3 and 4 and on other studies that discovered liquidity dry-ups during times of crisis (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 market's turmoil. Therefore, a positive relation between these dummy variables and the liquidity costs would show that there are unexplained crisis specific liquidity dynamics.

Table 3 presents the results for these regressions. First of all we can assert that the estimates of the coefficients for all 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 liquidity costs are increasing with the return volatility, which is a proxy for the general market risk. These results are consistent with results reported in previous studies (e.g. e.g. Yeyati et al. (2008) and Naes et al. (2011)).

Furthermore, Table 3 gives ample evidence that the financial crisis had a major impact on market liquidity, as all our three dummy variables are positive significant on a 1% significance level, with the Lehman week dummy having the largest impact on liquidity costs. This 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. This positive relationship between liquidity costs and our dummy variables for the financial crisis justify to further explore the liquidity dynamics during times of crisis, as there are so far unexplained crisis specific liquidity dynamics.

4.1.3. The impact of market returns on market liquidity

Here we explore the relationship between individual stock liquidity and aggregate index returns. For that purpose we add the variable index log-return, which is the daily log-return of the index (DAX, MDAX, SDAX, TecDAX) in which the respective stock is a constituent to our reference specification (see Eq. (5)).[11] We analyze this relation for three different sub-samples to test if there are variations in the relationship in times of crises and non-crises: (4.1) covers the pre-crisis period from January 2003 to September 14th, 2008, (4.2) covers the period of financial crisis from September 15th, 2008 (collapse of Lehman Brothers) to December 2009, while (4.3) covers the whole data for our sample period January 2003–December 2009.

Table 4 shows the results for our three different sub-samples. Across all sub-samples we see a negative significant relationship between aggregate index returns and individual stock liquidity, indicating that in all kind of general market conditions market declines (negative index returns) impair individual stock liquidity as measured by an increase in liquidity costs, while rising markets improve individual stock liquidity. This analysis gives support for former theoretical works and is also consistent with findings of Chen and Poon (2008), who attribute 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

[11] As an alternative we also analyzed the same regressions for the CDAX, which is a broad German market index. Unreported tables show that this does not materially impact the results.

Table 4
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 during the sample period January 2003–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. Standard deviation of daily log-returns is the annualized 5 days standard deviation of daily log-returns. Besides the above mentioned 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, TecDAX) of which the respective stock is a constituent. The results are reported for three different sub-samples: (4.1) covers the pre-crisis period from January 2003 to September 14th, 2008, (4.2) covers the period of financial crisis from September 15th, 2008 (collapse of Lehman Brothers) to December 2009, while (4.3) covers the whole data for our sample period January 2003–December 2009. This table shows the estimated coefficients, the t-statistics are reported between parentheses below the respective estimated coefficients and the adjusted R^2 are presented below the respective model.

	(4.1)	(4.2)	(4.3)
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.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

market downturns, and further demonstrates that there clearly is a positive relationship between market risk and liquidity risk.

4.2. Liquidity commonality

Fig. 3 and our empirical results in Tables 3 and 4 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. Therefore, we start-off with an analysis of a widely stated phenomenon in market liquidity: liquidity commonality.

In brief, liquidity commonality describes the phenomenon of synchronicity of individual asset's liquidity variation with aggregate market-wide liquidity movements and was initially discovered by Chordia et al. (2000). Extending the stream of research presented in subsection 2.2 we first of all want to explore two characteristics of the liquidity commonality by 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, like the financial crises? We then will pick-up a line of possible further research suggested by above mentioned research and look at factors determining the observed liquidity commonality.

4.2.1. Liquidity commonality and the financial crisis

Following 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 we therefore estimate the following time-series regression:

$$\Delta WS(q)_{i,t} = \alpha_i + \beta_i \cdot \Delta WS(q)_{M,i,t} + X \cdot A + \varepsilon_{i,t} \tag{6}$$

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

$$\Delta WS(q)_{i,t} = \frac{WS(q)_{i,t} - WS(q)_{i,t-1}}{WS(q)_{i,t-1}} \tag{7}$$

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 the volume-weighted spread of firm i, i.e., the dependent variable (cf. Chordia et al. (2000) and Coughenour and Saad (2004)). The proportional change in the market volume-weighted spread $\Delta\, WS(q)_{M,i}$ is derived as in Eq. (7). Following Chordia et al. (2000) we include further variables represented by the vector (A). These are lead and lag variables[12] 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[13]; 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, while 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, which we label liquidity beta. Analog to asset pricing the liquidity beta can be seen 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 Table 5. Based on Kamara et al. (2008) who found a strong time variation in commonality, we want to analyze if the sudden liquidity dry-up in

[12] Lead and lag variables refer to the previous and next trading day observations of the variable.
[13] Analog to the market volume-weighted spread we exclude the dependent variable stock from the calculation of the market averages.

Table 5
Market-wide commonality in liquidity: Crisis vs. non-crisis. 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). 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. $\Delta WS(q)_{i,t} = \frac{WS(q)_{i,t} - WS(q)_{i,t-1}}{WS(q)_{i,t-1}}$. The main regressors $\Delta WS(q)_{M,i,t}$, $\Delta WS(q)_{M,i,t-1}$, and $\Delta WS(q)_{M,i,t+1}$ are the contemporaneous, lag, and lead daily changes of market average liquidity costs. We do not report the following additional regressors of the regression: 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 cross-sectional averages of time series slope coefficients, the respective 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%. The results are reported for three different sub-samples: Panel A covers the whole data for our sample period January 2003–December 2009, Panel B covers the pre-crisis period from January 2003 to September 14th, 2008, while Panel C covers the period of financial crisis from September 15th, 2008 (collapse of Lehman Brothers) to December 2009.

	Coefficient	*t*-Statistic	% Positive	% Positive significant
Sample A: all (January 1, 2003–December 31, 2009)				
$\Delta WS(q)_{M,t}$	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			
Sample B: non-financial crisis (January 1, 2003–September 14, 2008)				
$\Delta WS(q)y_{M,t}$	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			
Sample C: financial crisis (September 15, 2008–December 31, 2009)				
$\Delta WS(q)_{M,t}$	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			

** $p < 0.05$.
* $p < 0.10$.
*** $p < 0.01$.

the market induced by the financial crisis can at least to some extent be explained by an increase in the liquidity commonality. 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.

Table 5 provides 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 stock's liquidity with the aggregate market liquidity. We further see in sample A, which covers the whole 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 sub-sample are very much in the range of liquidity betas reported in earlier research (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. In line 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 times higher ($\beta = 2.51$) during the financial crisis in sample C as compared to the non-crisis period ($\beta = 0.45$) in sample B, as one can see in Table 5. Therefore, the relation between individual stock liquidity and aggregate market liquidity becomes much stronger in times of crisis, i.e. 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.

4.2.2. 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 of the existence of commonality in liquidity, few research has focused on the drivers of liquidity co-movement. We especially 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 R^2 statistic 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 amongst others by Morck et al. (2000) and Chen et al. (2007). The market model return R^2s were also recently used by Hameed et al. (2010) and also used by Karolyi et al. (2012) to measure the degree of individual stock liquidity synchronicity. This measure for the degree of liquidity commonality simply is the coefficient of determination R^2 resulting from a regression of the following single-factor liquidity market model, which is a simplification of the specification (6):

$$\Delta WS(q)_{i,t} = \alpha_i + \beta_i \cdot \Delta WS(q)_{M,i,t} + \varepsilon_{i,t} \qquad (8)$$

For every stock and each month in our sample we estimate the R^2 statistic if there are at least 15 observations[14] available for the respective company in 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

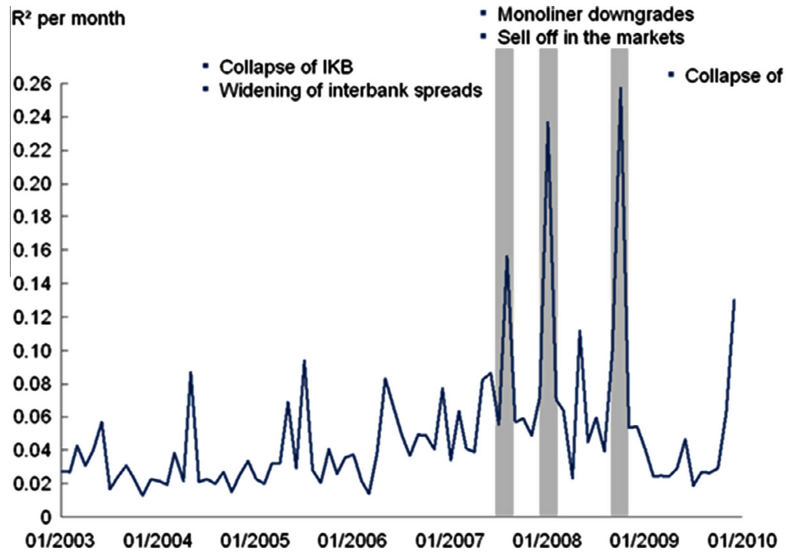

Fig. 5. Liquidity commonality over time. This figure shows a time-series plot of monthly cross-sectional averages of the R^2 statistic which serves as a proxy for the degree of liquidity commonality over the time period from January 2003 to December 2009. The R^2 statistic is derived by an equal-weighted average individual stocks R^2 statistic estimated by a single-factor liquidity market regression model.

can be explained by aggregate market liquidity movements, and vice versa.

Fig. 5 shows some interesting facts about the development of liquidity commonality over time. First of all, it gives additional support for the existence of liquidity commonality and therefore for a systematic liquidity risk component, as the R^2 statistic indicates that some portion of the individuals stock's innovations in daily liquidity can be explained by the innovations in daily market liquidity. Furthermore, we can observe that liquidity commonality heavily varies over time during our sample period from 2003 to 2009. Moreover, the level of liquidity commonality seems to be higher on average during the financial crisis compared to the non-crisis period before. But most interestingly there are large spikes 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. But also other large spikes coincide with major crisis events, e.g., the collapse of IKB Deutsche Industriebank, a German bank which 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 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 spikes and the high level of liquidity commonality during the financial crisis confirm our earlier finding that liquidity betas are higher during times of crises.

4.2.3. Liquidity commonality and the impact of different order sizes

In Fig. 5 we have shown 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. Therefore we redo the same analysis using specification (8), 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 this monthly individual estimates we are able to calculate monthly equal-weighted average R^2 statistics for every standardized volume class q across all companies.

Fig. 6 basically shows the same liquidity commonality development over time as Fig. 5. 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, Fig. 6 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 six standardized volume class q which are available for all four major German indices (DAX, MDAX, SDAX and TecDAX).

Fig. 7 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 gets. While 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 the deeper we look into the limit order book. These findings however contradict those of Kempf and Mayston (2008), who showed in their analysis that commonality in liquidity becomes stronger the deeper they look into the limit order book.

4.2.4. Liquidity commonality and market declines

So far we basically can record four interesting facts about liquidity commonality: liquidity commonality exists (in the whole limit order book), it varies over time, it is especially pronounced in times of crisis and it becomes weaker the deeper we look into the limit order book. In the next step we want to put our attention on the drivers behind 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 saw that individual stock liquidity is influenced by index returns (see Table 4), i.e., aggregate stock market declines reduce individual stock liquidity. Furthermore, some research on return co-movement (e.g., Ang and Chen (2002)) showed that co-variation in stock returns increases after large market declines. We now want to see if there is a similar pattern in liquidity

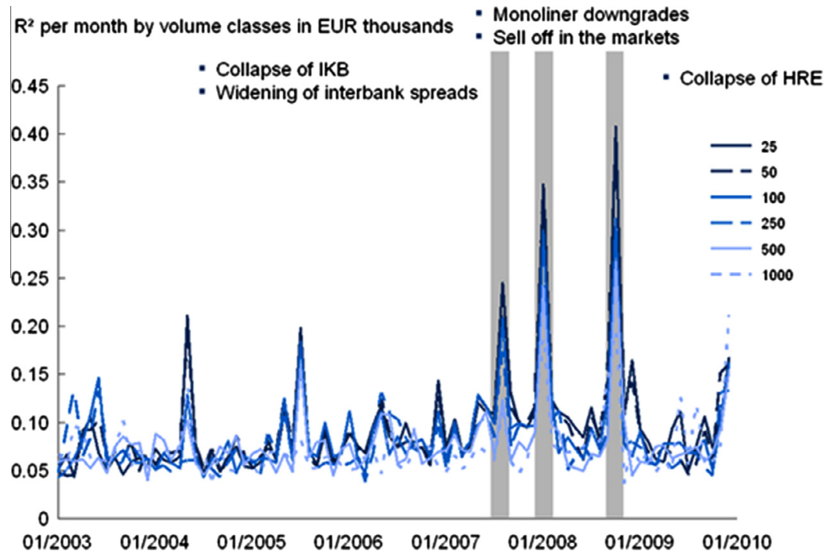

Fig. 6. Liquidity commonality over time by different volume classes. This figure shows time-series plots of monthly averages of the R^2 statistic across the six standardized volume classes q which are available for all four major indices (DAX, MDAX, SDAX, TecDax) over the time period from January 2003 to December 2009.

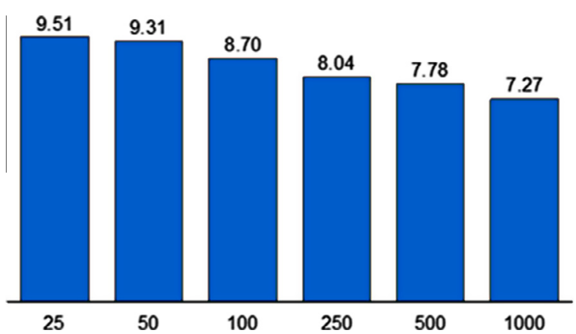

Fig. 7. Average liquidity commonality by different volume classes. This figure shows averages of the monthly R^2 measure, a measure for the degree of liquidity commonality, for six standardized volume classes q (in EUR thousand) which are available for all four major indices (DAX, MDAX, SDAX, TecDax) over the time period from January 2003 to December 2009.

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, e.g., Bookstaber (2000), Kyle and Xiong (2001), Vayanos (2004), Garleanu and Pedersen (2007) and Brunnermeier and Pedersen (2009), where it is argued 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 induce co-movement in liquidity.

We start our regression analysis by applying a logistic transformation to our R^2 statistic (Morck et al., 2000; Hameed et al., 2010; Karolyi et al., 2012). Thus we calculate *LiqCom* as:

$$LiqCom = ln\left[\frac{R^2}{1-R^2}\right] \tag{9}$$

First of all 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, TecDAX) and the standard deviation of the index log-returns as independent variables in specification 6.1 in Table 6. We see that there is clear negative relationship between index returns and liquidity commonality. This shows that liquidity commonality is increased in market declines and supports our Hypothesis 3. 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. Based on the theoretical work of Vayanos (2004) 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, 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 1-day returns and a variable that captures abnormally large positive returns in specifications 6.2 and 6.3 respectively. Technically these two variables are interaction terms of a dummy variable, that equals one if the 1-day index return is at least 1.5 standard deviations[15] above its sample mean 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 the above mentioned control variables alltogether in the specification 6.4.

The results in model 6.2 show that large negative market shocks even significantly magnify the liquidity co-movement induced by index returns. This gives further support to the theoretical liquidity demand and supply explanations, as most of them should only loom large for large market drops. This interesting fact for unusual high market downturns also confirms other empirical results of Chordia et al. (2001), Chordia et al. (2002) and Hameed et al. (2010) who found a highly significant bid-ask spread widening at days of or days following negative market returns. This

[15] In line 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, lead to similar results.

Table 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 January 2003–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 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, TecDAX). Standard deviation of index log-return (monthly) is the annualized standard deviation of 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 between parentheses below the respective estimated coefficients and the adjusted R^2 are presented below the respective model.

	(6.1)	(6.2)	(6.3)	(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.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

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 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 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 is an important result 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.

4.2.5. 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 (Brunnermeier and Pedersen, 2009) has recently received huge attention. 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 Euro OverNight Index Average (EONIA).

Banking sector returns measure the change in the aggregate market value of the banking sector and therefore proxy 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 7.1 in Table 7 that adds the DAX Banks log-returns to specification 7.1 in Table 6. 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 1-day returns in specification 7.2, we see that the index return becomes insignificant, the impact of abnormally large negative and large positive 1-day returns remains significant, however. This is consistent with the view 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 us a second proxy for funding liquidity tightness: the EURIBOR-EONIA-spread. To finance themselves, banks, amongst other possibilities, participate in the interbank market, where banks make unsecured, short-term loans to each other. The Euro OverNight Index Average (EONIA) is the interest rate for such unsecured, overnight interbank loans. The 3-month EURIBOR is the average rate at which the same panel banks offer to lend unsecured funds to other banks in the interbank market for maturities of 3 months. Therefore, the level of the EURIBOR-EONIA-spread can be seen as the proxy for ease of funding liquidity available to banks, i.e., the spread will widen in tight liquidity conditions as well as in situations where the banks' liquidity uncertainty increases.

Analog to specification 7.1 we add the EURIBOR-EONIA-spread to the index returns and the standard deviation of the index log-returns. In specification 8.1 of Table 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 1-day index returns in specification 8.2.

Table 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 January 2003–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 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, TecDAX). DAX Banks log-return (mnthly) 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 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 between parentheses below the respective estimated coefficients and the adjusted R^2 are presented below the respective model.

	(1)	(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.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 8
The effect of funding liquidity (measured by EONIA) 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 January 2003–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 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 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, TecDAX). The EURIBOR (3M)-EONIA-spread is the spread between the 3-month EURIBOR and the EONIA. Standard deviation of index log-return (monthly) is the annualized standard deviation of 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 between parentheses below the respective estimated coefficients and the adjusted R^2 are presented below the respective model.

	(8.1)	(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.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Overall our findings consistently 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). Our results corroborate the view that the rather elusive theoretical concept, where the lack of market liquidity is a symptom of the financial crisis and at the same time responsible for exacerbating its consequences, holds.

4.3. Flight-to-quality or flight-to-liquidity in the stock market

Previous research indicates that there is an inverse relationship between liquidity costs and credit quality (Longstaff et al., 2005; Ericsson and Renault, 2006; Chen et al., 2007). 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 becoming more liquid compared to low credit quality assets during times of 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 (Vayanos, 2004; Longstaff, 2004; Acharya and Pedersen, 2005; Beber et al., 2009).

4.3.1. Descriptive statistics uncovering the flight-to-quality

To analyze the flight-to-quality effect, we will first of all have a look at some univariate statistics. This 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 of all, we want to get an impression how liquidity costs differ across rating categories and what influence the financial crisis has on these differences. Table 9 shows average volume-weighted spreads $WS(q)$ for three different rating categories (investment grade, speculative grade and non-rated) and for two different periods (pre-crisis vs. crisis). We can see that there is a clear liquidity ranking across rating categories during both pre-crisis and crisis period. Liquidity costs for investment grade stocks are lowest, followed by speculative grade stocks and companies which do not posses 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

Table 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 January 2003–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 thousand Euro. 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 observation of companies that do not posses a rating of 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 posses an investment grade rating and companies that have an speculative grade rating. Difference Rated – Non-rated gives the difference of the weighted spreads between the observations of companies that posses 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 sub-samples: 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 (January 1, 2003–September 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 (September 15, 2008–December 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***

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

introduced by Copeland and Galai (1983) and Glosten and Milgrom (1985). Rating agencies are a means of private information production and therefore alleviate the adverse selection component of liquidity costs by decreasing the information asymmetry problem. 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 shows that stocks of a higher credit quality firms posses 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 previous findings in the bond and CDS markets (e.g., Ericsson and Renault (2006) and Chen et al. (2007)). Moreover, according to the flight-to-quality phenomenon we find that in times of increased market uncertainty, e.g., during the financial crisis, the impact of credit risk on liquidity risk is intensified. Therefore, these findings give support to assertion that the flight-to-quality phenomenon is not only present on the bond markets but also on the stock markets.

4.3.2. The impact of rating information on market liquidity

To show that these findings based on univariate test statistics are robust we proceed with a multivariate analysis. For that purpose we extend the panel data regression specification (5) to analyze the impact of ratings on market liquidity. We start off with an analysis of the impact of rating information in general by introducing a dummy variable that indicates if a company possesses an agency rating. This setting should analyze if a rating produced by an external rating agency conveys additional private information to reduce the information asymmetry, leading to a reduction of the adverse selection component of the weighted spread and finally leading to lower liquidity costs.

The negative impact of the rating dummy presented in Table 10 gives 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. To quantify the impact of external ratings, we can see that an external rating reduces the liquidity costs by roughly 10%. The result is also significant on a 1 percent significance level.

4.3.3. The flight-to-quality - the impact of credit quality on market liquidity during the financial crisis

We now want to turn our focus on the multivariate analysis of the flight-to-quality or flight-to-liquidity phenomenon. We especially aim to answer two fundamental questions with 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?

Therefore we add a dummy variable to our panel data regression specification (5) 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 we separately estimate the impact of this dummy for three different sub-samples: specification (11.1) in Table 11 covers the pre-crisis period, (11.2) covers the period of the financial crisis, while (11.3) covers our entire sample period. Especially a comparison of the two first sub-samples will yield some insight into the flight-to-quality phenomenon.

Table 11 shows that the coefficient of our dummy variable is significantly negative across all sub-samples and that therefore investment grade stocks have liquidity costs that are roughly 5% less than those of speculative grade stocks. This clearly indicates that also 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 (11.1) with the coefficient during the financial crisis (11.2), we clearly see that the impact of credit risk intensifies during the financial crisis. This shows that the

Table 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 2003–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. Standard deviation of daily log-returns is the annualized 5 days standard deviation of daily log-returns. Besides the above mentioned 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 between parentheses below the respective estimated coefficients and the adjusted R^2 are presented below the respective model.

	(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.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

flight-to-quality or flight-to-liquidity phenomenon also holds for the stock market. It corroborates the perception that in times of crisis investors become increasingly risk avers and have a preference for more liquid instruments. As we are using a volume-weighted spread measure derived from the limit order book, our results, that are all significant on a 1% significance level, show that the flight-to-quality phenomenon holds for the whole depth of the limit order book in the stock market.

5. Summary and conclusion

Market liquidity was a huge issue during the financial crisis. This study contributes to a better understanding of market liquidity behavior during periods of market distress by analyzing liquidity costs on the German stock market. We aim to make a contribution to a better understanding of the dynamics of stock market liquidity in situations of financial turmoil. We used a quite representative sample of German companies comprising almost 90% of the total German market capitalization. As for the liquidity measure we had access to a unique variable, called Xetra liquidity measure. By construction this variable is able to simultaneously capture liquidity effects on both depth and breadth in the electronic limit-order book of the trading system Xetra run by the Deutsche Börse. On the basis of these data we scrutinized the impact of market declines on stock market liquidity. By doing so we aimed to uncover several market liquidity puzzles in the stock market during times of crisis, most importantly the liquidity commonality, the flight-to-quality and the flight-to-liquidity phenomenon.

Our main results can be summarized as follows. First, we showed that stock market liquidity is impaired during market declines and in times of crisis, implying a positive relation between market and liquidity risk. 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

Table 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 January 2003–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. Standard deviation of daily log-returns is the annualized 5 days standard deviation of daily log-returns. Besides the above mentioned control variables we will test the impact of 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 sample consists only of those companies that posses a rating by an external rating agency and therefore non-rated companies are excluded. The results are reported for three different sub-samples: (11.1) covers the pre-crisis period from January 2003 to September 14th, 2008, (11.2) covers the period of financial crisis from September 15th, 2008 (collapse of Lehman Brothers) to December 2009, while (11.3) covers the whole data for our sample period January 2003–December 2009. This table shows the estimated coefficients, the t-statistics are reported between parentheses below the respective estimated coefficients and the adjusted R^2 are presented below the respective model.

	(11.1)	(11.2)	(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.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

the liquidity risk for larger trading positions and therefore can only poorly proxy the level and especially the variation of liquidity costs during times of crisis for larger volume classes.

Second, the analysis of liquidity commonality documented that it is time-varying and especially 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 show that liquidity commonality becomes weaker the deeper we look into the limit order book. Our results present empirical evidence supportive of a supply effect in market liquidity as theoretically proposed by Brunnermeier and Pedersen (2009), as we show that liquidity commonality is induced by a lack of funding liquidity of financial intermediaries, leading to funding and market liquidity spirals.

Third, we show that credit ratings produced by external rating agencies are able to decrease liquidity costs in the stock market by alleviating the information asymmetry and hence decreasing the adverse selection component of liquidity costs. Even more interesting, we show that liquidity costs increase with credit risk/default probability and that this effect intensifies during times of crisis. This empirically corroborates the flight-to-quality or flight-to-liquidity hypothesis in the stock market. Moreover, it should be noted that these liquidity effects hold for the whole depth of the limit order book.

Overall, our results are in line with the perception that liquidity spirals have played an important role in the financial crisis. Even though it is true that the lack of market liquidity was a crisis symptom, by the same time drying-up market liquidity was responsible for exacerbating its consequences.

These results may be of importance for risk management officers as well as for regulators. The former should care about the fact that liquidity costs are negatively related to market returns. This effect is the more pronounced the larger risk positions are. Moreover, liquidity costs, especially during times of crisis, are strongly driven by a common risk factor. The latter may use this paper as a piece of evidence that liquidity spirals are driven by supply side effects. Hence, any effective intervention during a market turmoil should focus on how to improve funding liquidity for financial intermediaries.

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