Liquidity in the German Stock Market

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Abstract

This paper presents the most extensive analysis of liquidity in the German equity market so far. We examine the evolution of liquidity over time, the determinants of liquidity, and commonality across liquidity measures and countries. We make use of a new publicly available dataset, the Market Microstructure Database Xetra (MMDB-Xetra). We find that liquidity has generally increased over time, and that in times of crisis liquidity is lower and the volatility of liquidity is significantly higher. Commonality in liquidity is highest during the financial crisis. We also find significant commonality between liquidity in the US and the German equity markets.

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1 Introduction

Equity markets have witnessed significant technological, regulatory and economic changes during the past 25 years. Among others, we have experienced the demise of floor-based trading systems, the advent of algorithmic and high frequency trading, and the coming into force of important new regulation such as MiFID in Europe and RegNMS in the US. The proportion of index investing has increased significantly and exchange traded funds have developed into an increasingly important asset class. Eventually, we have experienced the financial crisis and the European debt crisis. These events have significantly affected market liquidity, and some of them in a permanent and disruptive way. In this paper we provide an in-depth analysis of the liquidity in the German equity market. We use a new publicly available data set that spans the period from 1999 to 2013.

We start with a descriptive analysis, similar in spirit to Chordia et al. (2001) and Angel et al. (2011, 2015), of trading activity and liquidity during the sample period. We then analyze the time-series determinants of liquidity. We find that volatility and past returns have a significant impact on liquidity, and that there are systematic day-of-the-week effects in daily liquidity. What is important for asset managers is not only how market liquidity evolves in aggregate, but also how the liquidity of individual stocks co-moves. To address this issue we adopt the approach of Chordia et al. (2000) and relate stock-specific measures of liquidity to measures of market liquidity and appropriate control variables. A striking result of this analysis is that commonality in liquidity was highest during the financial crisis. This is bad news for asset managers, as it implies that low returns, low market liquidity and high commonality in liquidity tend to occur simultaneously, thus making it difficult and expensive to liquidate positions in times of stress. The liquidity of stocks does not only co-move within a country but also across countries. Therefore we also analyze the co-movement of the German and the US equity markets. We adopt the methodology of Brockman et al. (2009) and Chordia et al. (2000) and find that liquidity in the US market predicts liquidity in Germany. Consistent with our results on commonality at the national level, we find evidence suggesting that the co-movement between the German and the US markets was stronger during the financial crisis.

Our paper makes several contributions to the literature. First, it introduces a new dataset that henceforth will be available to academic researchers free of charge. Second, we provide the most extensive analysis of liquidity in the German equity market so far. Third, ours is the first analysis of commonality in liquidity focusing on the German equity market. Our empirical results provide insights that are potentially relevant for asset managers and regulators. In particular, the finding of stronger commonality in liquidity in times of crisis poses a threat to the stability of financial markets.

The remainder of the paper is organized as follows. Section 2 describes our data set. In section 3 we provide evidence on how liquidity and trading activity in the German equity market evolved since 1999. In section 4 we analyze the determinants of liquidity. Sections 5 and 6 are devoted to an analysis of commonality in liquidity within Germany and between the German and the US equity markets, respectively. Section 7 concludes.

2 Data

We use data on the German stock market from the Market Microstructure Database Xetra (MMDB-Xetra).[1] This database contains daily measures of liquidity, trading activity, and volatility for all component stocks of the German CDAX index.[2] The sample comprises 982 stocks. The data is derived from intraday trade and quote data obtained from Deutsche Börse AG for the period from January 1999 through April 2013. However, quote data, and hence all measures relying on quote data, are only available from February 2002 onwards. The intraday dataset is pre-processed by applying various filters and then aggregated to obtain daily market microstructure measures. The details of this procedure are described in Johann et al. (2018). One detail deserves mentioning, though. Some data is either missing or obviously erroneous in the raw data files. We set observations with obvious errors to missing. This applies to the periods from September 05, 2002 to November 19, 2002, and from September 01, 2011 to September 22, 2011. Thus, some variables will have gaps during these periods.[3]

In addition to the coarse filters already applied to the data when constructing the MMDB-Xetra data base, we apply several further filters. To be included in the sample, we require that a firm has a market capitalization of at least €1 mn and an average stock price between €1 and €1,000. We exclude stock days where relative spreads are larger than 50%, depth is zero, or closing midpoint returns are larger than 50% in absolute terms. The liquidity and trading activity measures are winsorized at the 0.5% (if there is no natural minimum value) and 99.5%

[1] "Xetra" and "CDAX" are registered trademarks of Deutsche Brse AG.

[2] The CDAX contains all German stocks listed on the Frankfurt Stock Exchange that are admitted to trading on a regulated market.

[3] For more details see Table B1 in Johann et al. (2018).

level.[4]

We supplement the dataset with data on market capitalization, number of shares outstanding, interest rates, and the levels of the DAX and VDAX from Thomson Reuters Eikon. This data is adjusted as in Ince and Porter (2006). For the comparison to the US market, we use data from the TAQ database. We obtain data aggregated to the daily level from the Market Microstructure Database maintained at Vanderbilt University. Dollar-Euro exchange rate information is collected from Bloomberg.

3 The Evolution of Liquidity and Trading Activity

In this section we document how liquidity and trading activity in Germany have evolved over time. We proceed in two steps. We first present and discuss summary statistics and then analyze the correlation between measures of trading activity and liquidity.

3.1 Summary Statistics

We start by presenting summary statistics on key measures of liquidity and trading activity. Most of the following statistics are based on time-series of cross-sectional averages. Unless stated otherwise we employ market-capitalization weighted cross-sectional averages. Results are shown in table 1.

<Insert table 1 about here>

The average daily trading volume in Euros (denoted the *trading value* in the sequel) of all CDAX stocks during the sample period amounts to approximately € 4.28 bn, of which € 3.78 bn is during continuous trading. Figure 1 shows how the daily value evolved over time. It was relatively stable at about € 3 bn before 2005. From 2005 to 2008 we observe an almost threefold increase in trading value, accompanied by an increase in the volatility of daily trading value. After the financial crisis of 2008, the level drops back to its pre-2005 value. For comparative purposes, the figure also shows the level of the DAX. During the financial crisis and in the time shortly after the crisis the trading value comoves with the level of the DAX. After 2009, the two time series appear to develop independently. We observe drops in trading value at the end of each year, reflecting lower trading activity during the Christmas season. Moreover, the figure

[4] We recommend any user of the MMDB-Xetra database to apply similar filtering procedures to the raw data.

reveals that the trading activity is highly concentrated in the 30 constituent stocks of the DAX index, while trading value in the remaining CDAX stocks is considerably lower.

<Insert figure 1 about here>

11.7% of the total trading value, or €500 mn per day, is traded during auctions while the rest is traded during the continuous trading sessions. Figure 2 shows the evolution of relative auction trading value. Two patterns emerge: First, there is an overall increase in the relative importance of auctions during the sample period. The auction trading value increases from about 6% to about 20%. This finding may be surprising given that the market share of high frequency traders has increased over the sample period, and that call auctions are not very attractive for these traders. However, the fragmentation of trading has also increased significantly during the sample period. Trading venues such as Cboe BXE and CXE (formerly BATS Europe and Chi-X Europe) as well as Turquoise do not offer regular call auctions. Thus, while continuous trading is now fragmented across several venues, call auction trading remains concentrated in Xetra, resulting in an increased fraction of auction volume in the total Xetra trading volume. Second, there are spikes in relative auction trading value at regular intervals. These spikes occur four times a year, namely, on the third Fridays of March, June, September, and December. These are the "triple witching days" on which derivatives on German stocks and indices expire and investors close their positions at the settlement prices.

<Insert figure 2 about here>

In the next step, we compare three different measures of volatility, (1) the daily standard deviation of 5-minute quote midpoint returns, (2) the daily number of all volatility interruptions[5] in all stocks and (3) the level of the VDAX, an index based on option implied volatilities. All three measures are highly correlated, with correlations ranging from 40% to 90%. There are three particularly volatile periods, namely 2002–2003, the financial crisis of 2008–2009, and the Euro debt crisis in 2011–2012. After the financial crisis, the number of volatility interruptions has decreased relative to the other volatility measures. A potential reason is that Deutsche Börse may have changed the threshold which triggers a trading halt.[6]

<Insert figure 3 about here>

[5] Trading in Xetra is halted when the price change exceeds a pre-specified threshold. The exact threshold value at which a halt is triggered is not disclosed. After a volatility interruption trading is restarted with a call auction.

[6] We cannot verify when and how the rules have been changed because, as noted above, the exchange does not disclose these rules.

Figure 4 shows how liquidity evolved over time. Average quoted spreads are about 0.27% while average effective spreads are about 0.16%.[7] Both quoted and effective spreads are highest during 2002-2003 and during the financial crisis, and are lowest towards the end of the sample period. The difference between the two spread measures diminishes over time and is essentially zero from 2012 onwards. Untabulated results show that average quoted and effective spreads are substantially larger, at 5% and 2%, respectively, when we consider equally-weighted rather than value-weighted cross-sectional averages. This result implies that liquidity is considerably lower for smaller stocks. A comparison of figures 3 and 4 reveals that times of high volatility coincide with times of higher spreads.

<Insert figure 4 about here>

Figure 5 shows how trading activity and depth evolved over time. The number of trades has increased considerably during the sample period, while at the same time the average trade size has declined. This is a phenomenon that has also been documented in other markets (e.g. Angel et al. (2011)), and that can be attributed to the rise of algorithmic and high-frequency trading. During the second half of the sample period, times with an abnormally high number of trades coincide with episodes of high return volatility (the latter is documented in figure 3). Depth, defined as the Euro value of quotes at the top of the orderbook, has increased from 2003 to 2007 and then dropped until the end of 2008. Thereafter depth remained approximately constant at a level below the pre-crisis level.

<Insert figure 5 about here>

3.2 Correlations between Liquidity and Trading Activity

Table 2 shows the time-series correlations between various measures of volatility, liquidity, and trading activity. Figures in the upper panel show correlations in levels while the figures in the lower panel show the correlations of daily percentage changes. The correlations are based

[7] Until September 2009 transactions in Xetra occurred either at the quoted ask or at the quoted bid price. Consequently, the effective spread was equal to the quoted spread in effect immediately before the transaction occurred. However, the effective spread is a contingent measure because an observation is only recorded when a trade occurs. If traders time their trades, i.e. if they tend to trade when the quoted spread is low, the average effective spread will be lower than the average quoted spread. In September 2009 hidden orders were introduced. Hidden orders are large, invisible limit orders. If such an order is placed between the visible best bid and ask prices and is executed, a transaction at a price within the visible quoted spread results. The MiFID pre-trade transparency requirement does not apply to hidden orders because the volume of these orders must be large enough for the large-in-scale waiver to apply.

on value-weighted averages.[8] We consider the correlations in levels first. They confirm some of the observations made in the previous section on the relation between the variables under consideration. The correlations between volatility on the one hand and spreads and price impact on the other hand are positive and significant. Moreover, depth and average trade size are negatively related to volatility while the trading value is positively related to volatility. Spreads and price impact are significantly positively correlated. Depth is not significantly correlated with the quoted spread but is significantly negatively related to the effective spread and the price impact. On the other hand, depth is highly positively related to both average trade sizes and trading value. Order imbalance is negatively correlated with all other variables, and significantly so with the quoted spread, depth, and the two trading activity variables.

The correlations in relative changes are generally lower but mostly have the same sign. The only notable differences are that changes in volatility are significantly positively related to changes in trade size, that depth is no longer significantly related to price impact, and that order imbalance is no longer significantly correlated with any of the other variables.

<Insert table 2 about here>

4 Determinants of Liquidity

After having taken a look at the evolution of liquidity over time we now turn to a formal analysis of the determinants of liquidity. We follow the approach in Chordia et al. (2001) and estimate time-series regressions. We first calculate daily value-weighted cross-sectional averages of various measures of liquidity, namely the quoted and effective bid-ask spread, the 5-minute price impact, depth, order imbalance, average trade size, transaction value, and the standard deviation of quote midpoint returns. They serve as dependent variables in our regressions.[9]

Among the independent variables we include the contemporaneous return of the DAX and its return over the previous 5 days. Large (positive or negative) returns may induce investors to rebalance their portfolios and may affect the willingness of traders to commit capital to market making. Contrarian or momentum traders may react to lagged DAX returns, and their trading activity may affect liquidity. Chordia et al. (2001) find that liquidity reacts asymmetrically to positive and negative returns. Therefore, we split both return variables accordingly.

[8] Results for correlations based on equally-weighted rather than value-weighted averages are shown in the appendix.

[9] We repeat the analysis using equally weighted averages rather than value-weighted averages. The results can be found in the appendix.

We further include the volatility index VDAX as a measure of expected volatility. Higher levels of volatility are usually associated with lower levels of liquidity. Brunnermeier and Pedersen (2009) show that market liquidity is related to funding liquidity. Following Jank and Wedow (2015), we use the spread between the Euribor and the yield on German government bonds with the same maturity to proxy for changes in funding liquidity. The variable is similar to the US TED spread and denoted *IR Spread*.

The Markets in Financial Instruments Directive (MiFID), a EU regulation aiming at harmonizing the trading landscape in Europe, changed the regulatory framework for investment and trading services. The regulation came into force in November 2007. To capture its potential effect on liquidity we include a binary variably that takes the value 1 from the coming into force of MiFID onwards.

During the financial crisis of 2007–2009, trading activity and volatility increased while liquidity decreased. To capture this effect, we include a binary variable *Crisis* that is set to one from July 2007 to April 2009.[10]

Previous studies such as Admati and Pfleiderer (1989) and Lakonishok and Maberly (1990) have either predicted or empirically confirmed a day of the week effect for liquidity and trading activity. Therefore, we include dummy variables for the days of the week (except Friday, which is the base case).

During most of our sample period, Xetra was open for trading on some national and regional holidays. These are days which are holidays in all of Germany or in the state of Hesse, were the exchange is located, but aren't bank holidays in the US. The number of active traders may be lower on those days, the composition of the trader population may be different (e.g. the fraction of retail traders may be higher), and information may arrive at a slower rate. In order to pick up potential effects on liquidity we include a dummy variable denoted *Holiday* that identifies holidays with trading. When a Tuesday or a Thursday is a holiday many people take a day off on the Monday or Friday, respectively, between the holiday and the weekend. These days are known as "bridge days" ("Brückentage"). Because trading activity is likely to be lower on these days we use two dummies to capture any difference in liquidity between bridge days and ordinary trading days. We use two dummies in order to differentiate between the cases in which the holiday is a trading day or a day without trading, respectively. The dummy variables are denoted $Long\ Weekend_{Tr.}$ and $Long\ Weekend_{No\ Tr.}$, respectively.

[10]Our definition of the crisis period follows Bao et al. (2017) and Bessembinder et al. (2017).

The results shown in figure 2 suggest that on days on which derivatives on German stocks and indices expire, auction trading value is relatively more important than on other days. We more formally investigate the effects of these "triple witching days" on liquidity and trading activity by including a dummy variable denoted *Witching Day*.

<Insert Table 3 about here>

The results of the time-series regressions are shown in table 3. Positive contemporaneous and lagged DAX returns tend to be associated with increased volatility, higher price impacts, higher order imbalance and increased trading activity. The effects on spreads and depth are ambiguous. Positive contemporaneous returns are associated with lower quoted spreads and higher depth but have no significant impact on effective spreads. Positive lagged returns, on the other hand, are associated with higher effective spreads but do not significantly affect quoted spreads or depth.

When interpreting the coefficients on the negative contemporaneous and lagged DAX returns the change in signs needs to be accounted for. For example, a negative sign in the volatility regression implies that a smaller (i.e. more negative) DAX return increases volatility. This is indeed what we find. Moreover, the absolute values of the coefficients are much larger than those for the positive DAX returns. This finding is consistent with the leverage effect reported in the literature (e.g. Black, 1976). Further, more negative returns are associated with higher quoted and effective spreads, higher price impact, higher trading volume and lower order imbalance. The latter result is intuitive because it implies that more negative returns are associated with a higher fraction of seller-initiated trades relative to buyer-initiated trades. The results for depth are ambiguous. More negative lagged returns increase depth while more negative contemporaneous returns decrease depth.

Increases in the lagged level of the volatility index VDAX result, in line with expectations, in higher volatility and lower liquidity. The effect on trading activity is negative. The results for the interest rate spread are counterintuitive. Models such as Brunnermeier and Pedersen (2009) predict that funding liquidity and market liquidity are positively related. We find the opposite. Higher IR Spreads (implying lower funding liquidity) are associated with lower quoted and effective spreads and lower price impacts.[11]

[11] We have re-estimated all regressions using the US Ted Spread instead of the IR Spread. We still find that lower funding liquidity is associated with higher market liquidity. The coefficients on the Ted Spread in the quoted and effective spread and price impact regressions are still significantly negative while the coefficient in the depth regression is significantly positive.

The coefficients on the MiFID dummy suggest that both spreads and depth are lower in the post-MiFID period. Trading activity is also lower while order imbalance increases. We note that our analysis does not allow for a causal interpretation of these results. While the new regulation itself may have affected liquidity and trading activity, the increased fragmentation of trading (which, to a large extent, itself was a consequence of MiFID) and the proliferation of high frequency trading may also have played a role.

The results for the financial crisis dummy imply that volatility and trading value were higher during the crisis. Somewhat surprisingly, we do not observe a decline in liquidity. In fact, effective spreads are significantly *lower* and depth significantly *higher* during the crisis period. This result is obviously at odds with the univariate results presented in the previous section. Our explanation for this finding rests on the fact that the regression controls for other factors affecting liquidity, most notably volatility (captured by the VDAX). Volatility reached unprecedented levels during the crisis and negatively affects liquidity. Apparently, liquidity did not decline as much as one would have expected given the levels of volatility during the crisis.[12]

The expiration of derivatives contracts does not affect the level of quoted and effective spreads but does result in higher depth and increased trading activity. When the market is open on a national or regional holiday, trading activity, volatility and depth are lower. Price impacts are also lower, indicating lower adverse selection costs, e.g. because there might be less new information or because uninformed retail traders account for a larger fraction of traders. While quoted spreads are significantly higher, effective spreads are not larger than on non-holidays. The combined finding of quoted and effective spreads is consistent with the combined effect of volatile quoted spreads and traders timing their trades more carefully. Traders monitor the market and initiate trades when the quoted spread is low. The results for the Long Weekend dummies are mostly insignificant. However, spreads and price impacts appear to be higher on bridge days between the weekend and a holiday on which the market is closed. Finally, the results for the day of the week dummies imply that volatility, trading activity and quoted spreads are lower at the beginning of the week

[12]To further elaborate on this point we re-estimated the model but excluded the VDAX (results not shown). In this alternative specification the coefficients on the financial crisis dummy in the quoted spread and price impact regressions become positive and significant. In the effective spread regression the coefficient becomes positive but insignificant. The coefficient in the depth regression is numerically smaller but remains positive and significant.

5 Commonality in Liquidity

In this section we consider the commonality in liquidity of German stocks. We adopt the approach of Chordia et al. (2000) and estimate the following regression, separately for each liquidity measure L and each stock i. In each individual regression we use one year of daily data.

$$\Delta L_{i,t} = \alpha_i + \beta_1 \Delta L_{m,t-1} + \beta_2 \Delta L_{m,t} + \beta_3 \Delta L_{m,t+1} + \beta_4 r_{m,t-1} + \beta_5 r_{m,t} + \beta_7 r_{m,t+1} + \beta_1 \Delta r_{i,t}^2 + \varepsilon_{i,t} \quad (1)$$

$\Delta L_{i,t}$ is the relative change in liquidity measure L for stock i from trading day $t-1$ to day t. $\Delta L_{m,t}$ is the relative change in the liquidity measure of the equally-weighted market portfolio, excluding stock i, from trading day $t-1$ to day t. $r_{m,t}$ is the market return on day t, and $\Delta r_{i,t}^2$ is the change in the squared stock return from day $t-1$ to day t. For ease of exposition we do not index the coefficients by stock and time. Unlike Chordia et al. (2000), we do not only analyze commonality in spread and depth measures, but also commonality in the price impact, a measure of information asymmetry. This allows us to investigate whether different components of liquidity move together to a different extent. Furthermore, our sample period covers more than ten years (January 2003 to April 2013) rather than only one year as in Chordia et al. (2000).

We estimate the regressions in two different ways, for rolling windows of 250 trading days, or for calendar years. In the rolling-window approach the first regression uses observations 1 to 250, the second regression uses observations 2 to 251, and so on. We display the resulting time-series of coefficients in figures. The results of the calendar year regressions are tabulated. In both cases we restrict the analysis to stocks that trade on at least 100 trading days in the estimation period and that trade, on average, at least five times per day.

The degree of commonality in liquidity may be different for stocks of different size. For example, institutional investors often focus on large cap stocks. If their trades are correlated, this may result in stronger commonality. Similarly, indexing strategies have become increasingly popular. If many traders track a particular index, commonality may be stronger among the constituent stocks of that index. We therefore repeat the analysis for four subsets of stocks, namely the 30 DAX stocks, the constituents of the mid-cap index MDAX and the small-cap index SDAX, and stocks that are not included in one of these three indices (denoted "outsiders"). Note that, while the component stocks of the SDAX have much lower market capitalization than those of the DAX and MDAX stocks, the typical SDAX stock still has an above-median market capitalization. Thus, the label ”small-cap index” is somewhat misleading. The ”real” small caps are included in the fourth group.

Figure 6 shows the results of the rolling-window regressions for the full sample. The figure plots the time series of the median of the coefficients β_2 from equation 1 for the (time-weighted) relative quoted bid-ask spread, the relative effective spread, depth in Euros, and five-minute price impact. Figure 7 shows the same results for the subsamples of DAX, MDAX and SDAX stocks and the outsiders. Because we estimate separate regressions for each stock and then calculate the median of the slope coefficients, we implicitly put equal weight on all stocks. The results are thus not dominated by large-cap stocks.

<Insert figure 6 about here>

We generally observe that the time-series pattern of commonality is very similar for the different measures of liquidity. The degree of commonality is highest for the two spread measures. The lower level of commonality for depth may be a consequence of the fact that depth is measured only at the top of the order book, and differences and changes in relative tick sizes make depth less comparable across stocks than percentage spreads. The price impact displays the lowest level of commonality. This observation implies that the non-information related components of the spread (i.e. the realized spread earned by the suppliers of liquidity) contribute strongly to the commonality in spreads. Considering the evolution of commonality over time, there does not appear to be a general trend. However, we observe an increase in commonality beginning in 2007 and peaking during 2008. The pattern is most pronounced for effective spreads but clearly visible for the other measures as well. This suggests that there were market-wide changes in the cost of providing liquidity, and / or the urgency to demand liquidity, during the financial crisis. The strong increase in commonality during the financial crisis indicates that the comovement of liquidity across stocks is more pronounced in times of stress.

<Insert figure 7 about here>

The commonality in liquidity for the DAX stocks (shown in the upper panel of figure 7) is generally higher than the commonality for the entire market. Further, during most of the sample period the commonality in price impacts is similar in magnitude to the commonality in spreads. The latter finding is consistent with the notion that for the most liquid stocks the non-information related components of the spread are relatively less important as compared to the average stock.

The levels of commonality for the MDAX and SDAX constituent stocks are, on average, between those for the DAX stocks and those for the outsiders. For the MDAX, we observe a general increase in commonality for all four liquidity measures beginning early during the sample period. We further find that the commonality in price impacts for MDAX stocks increased after 2007. While it previously was similar to the commonality in depth, it subsequently was at par with the commonality of the spread measures.

Table 4 summarizes the results of the calendar-year based estimations. For each year we report the median coefficient, the percentage of stocks with a positive coefficient that is significant at the 5 percent level (one-sided test), and the percentage of stocks with a negative coefficient that is significant at the 5 percent level (one-sided test). The results largely confirm those of the graphical analysis. Commonality in liquidity, while existing for all categories of stocks, is most pronounced for large-cap stocks, and during the financial crisis. Furthermore, the comovement is much stronger for the spread measures and is less pronounced for the price impact.

<Insert table 4 about here>

6 Comparing Liquidity in Germany and the US

In the previous section, we have analyzed the commonality within the German equity market. In this section, we ask whether there also exists comovement in liquidity across markets. Specifically, we test for commonality in liquidity between the German and US equities markets. While several papers have examined whether there is return comovement between these markets,[13] much less is known on the liquidity relation. Karolyi et al. (2012) use an international sample to show that the within-market commonality is driven by several supply and demand side determinants such as correlated trading by institutions or investor sentiment. Analyzing a cross-section of 47 stock-exchanges, Brockman et al. (2009) show that besides this within-market commonality, there also exists a considerable across-markets commonality in liquidity. They also show that US macroeconomic announcements influence this global commonality. Zhang et al. (2009) confirm their finding of cross-border commonality using a slightly different methodology. Frino et al. (2014) find similar results for index futures.

[13]See e.g. Copeland and Copeland (1998), Bonfiglioli and Favero (2005), Rua and Nunes (2009), Syllignakis and Kouretas (2010), Caporale et al. (2016).

Generally, commonality in liquidity might be an important determinant of asset prices and thus might influence portfolio choices. Lee (2011) shows that global commonality is an important factor in pricing international assets, while Amihud et al. (2015) show that it is the commonality in liquidity premia (not liquidity itself) that is priced. If commonality in liquidity across markets exists, illiquidity in one market may spill over to other markets and induce a global decline in liquidity. Brockman et al. (2009) consider commonality in a rather short sample period between 2002 and 2004. Zhang et al. (2009) analyze a few trading days at the end of 2004. In contrast, we are able to analyze commonality for a much longer period ranging from 2002 to 2012.[14] In addition, previous studies analyzed cross-market commonality in a bullish market environment. In contrast, our sample includes the financial crisis period. We can therefore analyze whether commonality is time-varying. It is of particular importance to know whether cross-market commonality is higher in times of crisis.

Consequently, we ask two questions. First, can we confirm previous findings of cross-border commonality in liquidity for a longer sample period? Second, is commonality particularly high in times of market turmoil? We start our analysis with a very simple graphical comparison of several liquidity measures for the two markets. US liquidity measures are derived from daily data (originally derived from TAQ intraday data) provided by Vanderbilt University and from the CRSP daily files. For both markets we construct indices which are simple averages (value-weighted wherever appropriate) of our measures of trading activity and liquidity. To enhance readability we plot weekly rather than daily values. In addition, we calculate the contemporaneous correlation between daily levels and relative changes of the liquidity measures for Germany and the US. Note that, due to the time difference between New York and Frankfurt, the actual overlap in trading hours usually is only from 9.30 AM to 11.30 AM Eastern Standard Time.[15] As a robustness check, we also calculate correlations based on weekly data. Weekly correlations are generally higher by approximately 20%.[16] As additional robustness checks we also construct equally-weighted (instead of value-weighted) averages, we consider the median instead of calculating an average, and we construct indices based on the DAX and S&P500 constituent stocks only. While (unsurprisingly) liquidity levels are affected by these design choices, correlations generally are not.

[14] Admittedly, we only consider two markets.

[15] Trading hours in Germany changed several times during our sample period.

[16] This might be due to the lower importance of the time difference at the weekly level, and to idiosyncratic variation in liquidity at the daily level, which partly cancels out at the weekly level.

<Insert figure 8 about here>

Overall, we find that the liquidity in the two markets is positively correlated in the short and long term. All correlation coefficients are significantly larger than 0. We first consider the average daily per stock trading volume in Euros, shown in figure 8. Dollar volumes are converted using daily Euro-Dollar exchange rates from Bloomberg. Because we have already discussed the evolution of the trading volume in Germany in section 3 we focus on the comparison to the US market. We observe a significantly positive correlation between the two markets which is particularly high during and after the financial crisis. Average per stock trading volume in the US and Germany is on a similar level of about €0.2 bn per day.[17] We observe that the average trading volume in Germany was actually slightly higher than in the US prior to the financial crisis. At the end of 2008 we observe a sudden drop in the German volumes. Since then the average trading volume in the US is higher, and is actually above its pre-crisis level. A possible explanation for the decline of trading activity in Xetra from 2008 onwards is the increased level of fragmentation after the the coming into force of MiFID (e.g. Hengelbrock and Theissen (2009)).[18]

<Insert figure 9 about here>

Figure 9 shows the average turnover (defined as the number of shares traded divided by the number of shares outstanding) in both markets. The plot suggests that turnover is highly correlated between the two markets. In the pre-crisis period turnover in the US was only slightly higher than the German turnover. Since 2008 the gap between the US and Germany has widened. Since then US turnover has been about twice as high as German turnover. As already noted above, the most likely reason for the decline in relative trading activity in Xetra is the increasing degree of fragmentation in European equity markets in the post-MiFID era. Quoted and effective spreads in the two countries are depicted in figures 10 and 11. Both spread measures are strongly positively correlated. Untabulated results show that the correlation is stronger during the financial crisis by about 10%. US spreads are generally smaller. The average percentage effective spread for the US is 0.11%, while it is 0.18% for Germany. Moreover, spikes in spreads are more pronounced in Germany, particularly during the financial crisis.

<Insert figure 10 about here>

[17] The dispersion in trading volume is much larger in the US.

[18] Trading in the US equity market is also fragmented. However, as documented by Angel et al. (2011), fragmentation started earlier in the US.

<Insert figure 11 about here>

Finally, we consider the average number of trades per stock in each market in figure 12. We can confirm the general finding of a positive correlation between the two markets. However, until 2006 the average number of trades remained relatively constant in the US, while in Germany there was an increase in trades until 2003 and a decrease in the number of trades between 2003 and 2006. Thereafter the correlation in the number of trades became stronger. Moreover, the average number of trades per stock and day in the US is much larger than in Germany (13,960 vs. 2,925). Together with the evidence from figure 8 this implies that the average trade size is smaller in the US.

<Insert figure 12 about here>

The graphical analysis suggests that liquidity in Germany and the US is strongly and positively related to each other. In order to test this hypothesis more formally we adopt the methodology of Brockman et al. (2009) and Chordia et al. (2000). We test for cross-country commonality in liquidity by estimating the following time-series regression.

$$\begin{aligned}\Delta Spread_t^{GER} = \alpha &+ \beta_1 \Delta Spread_{t-1}^{US} + \beta_2 \Delta Spread_t^{US} + \beta_3 \Delta Spread_{t+1}^{US} \\ &+ \gamma_1 Return_{t-1}^{US} + \gamma_2 Return_t^{US} + +\gamma_3 Return_{t+1}^{US} \\ &+ \gamma_4 \Delta Volatility_{t-1}^{GER} + \gamma_5 \Delta Volatility_t^{GER} + \gamma_6 Return_{t-1}^{DE} + \epsilon_{GER,t}\end{aligned} \tag{2}$$

$Spread_t^X$ is the equally-weighted average relative effective spread across all stocks in market X on day t, $Return_t^X$ is the equally-weighted average daily return in market X and $Volatility_t^{GER}$ is the average midpoint volatility across all German sample stocks on day t.[19] A "Δ" denotes the proportional change in a variable. Our focus is on the coefficients β_1, β_2 and β_3. These coefficients measure how liquidity in the German market reacts to lags and leads of US liquidity and thus capture the commonality in liquidity. We test the individual coefficients for significance, and we conduct an F-test to check whether the sum of the three coefficients is significantly different from zero.

<Insert table 5 about here>

[19] In line with Brockman et al. (2009) we use equally-weighted averages. We obtain qualitatively similar results when using value-weighted averages.

Specification (1) is a simplified version of equation 2. It ignores the potential impact of volatility and the lagged returns in the German equity market on liquidity. The coefficients on the lagged and contemporaneous changes in the US spread, β_1 and β_2, are positive and significant at the 1% level. Thus, there is comovement of liquidity in the US and Germany. Further, lagged changes in US liquidity affect the liquidity in the German market while the reverse is not true, as is evidenced by the small and insignificant estimate of β_3. The F-test confirms that the sum of the three beta coefficients is significant. Finally, spreads in the German market are negatively related to the lagged return in the US market. Thus, positive US returns predict lower subsequent spreads in Germany.

Specification (2) includes the volatility and the lagged return in the German equity market and is similar to equation (3) in Brockman et al. (2009). Spreads in the German equity market are significantly positively related to contemporaneous volatility and to lagged returns. Upon the inclusion of the additional variables the adjusted R^2 more than doubles. Most importantly, though, the size and significance of the coefficients β_1, β_2 and β_3 hardly change. Thus, the evidence of comovement in liquidity and of a dependene of liquidity in Germany on lagged US liquidity persists.

Specification (3) is identical to specification (1), but the role of the two markets, Germany and the US, is switched. We regress changes in US relative effective spreads on changes in German relative effective spreads. Again there is strong evidence of positive and significant contemporaneous comovement of liquidity. Spreads in the US are unrelated to lagged spreads in Germany, but are positively related to spreads in Germany on the next trading day. This result confirms the earlier evidence that spreads in Germany react to spreads in the US, but not vice versa.

Specifications (4) and (5) address the question whether commonality in liquidity was stronger during the financial crisis. The first approach, specification (4), re-estimates model (2) using the data from the crisis period. While the contemporaneous comovement is essentially unchanged (β_1 during the crisis is 0.291 as compared to 0.287 for the full sample), the dependence of spreads in Germany on lagged US spreads is somewhat stronger during the crisis (β_2 during the crisis is 0.16 as compared to 0.133). The t-statistics are smaller because of the smaller sample size. Specification (5) uses the full sample and introduces interaction terms to allow for different levels of commonality during the crisis period. The coefficients on the interaction terms are insignificant. A possible explanation for this finding is that the stronger commonality during the crisis that we have documented in the univariate analysis is already captured by the other explanatory variables in the regression model.

Finally, as in section 5, we re-estimate specification (2) using rolling 250-day windows with 1-day increments. Figure 13 plots the time series of the contemporaneous comovement and the sum of lagged, contemporaneous and next day comovement in effective spreads.

Confirming earlier results, we generally observe a significantly positive commonality in liquidity between the two countries with an average contemporaneous coefficient of 0.097. This positive relation is strongest during the financial crisis. Despite the generally positive relation, we also identify phases of zero or even negative commonality (between 2009 and early 2011 and after June 2012).

<Insert figure 13 about here>

In summary, the evidence in this section implies a comovement of liquidity in Germany and the US, and a dependence of liquidity in Germany on lagged US liquidity. In addition, there is some evidence that these relations were more pronounced during the financial crisis.

7 Conclusion

We conduct the most extensive study of liquidity in the German equity market so far. We examine the evolution of liquidity over time, the determinants of liquidity, and commonality across liquidity measures and across countries. In doing so we make use of a new publicly available dataset, the Market Microstructure Database Xetra (MMDB-Xetra). It covers the period from 1999 to 2013. The data set is available to academic researchers free of charge and provides daily measures of liquidity, trading activity, and volatility for all constituent stocks of the German CDAX index.

Our results show that spreads and price impacts in the German equity market have significantly declined since the early 2000s. However, liquidity was substantially reduced during the financial crisis in 2008 and 2009. Crisis times also affect other measures of trading activity and liquidity. The trading value is stable until 2006, rises during the crisis and then drops back to the pre-crisis value in 2009. A similar pattern holds for volatility which is also high in times of stress (particularly during the dot-com bubble and the financial crisis).

Interestingly, there is a steady increase in auction trading volume relative to the volume of continuous trading in Xetra. We offer an explanation that rests on the fragmentation of trading.

While continuous trading nowadays is spread across various trading venues, few of these offer auction trading. Consequently the market share of Xetra in continuous trading has declined while the market share in auction trading has not, or at least not to the same extent. As a result, the fraction of trading on Xetra that occurs during the daily auctions has increased.

We analyze the determinants of liquidity adopting the methodology of Chordia et al. (2001) and Angel et al. (2011). Our findings suggest that measures of illiquidity such as bid-ask spreads and price impacts are negatively related to returns. Moreover, there is a systematic day-of-the-week effect. Liquidity is lower at the beginning of the week.

We further analyze commonality in liquidity. We adopt the methodology of Chordia et al. (2000) and Brockman et al. (2009) but use a much longer sample period than these authors did. We find that there is significant comovement of liquidity across stocks. The comovement is stronger for more liquid stocks (the DAX constituents in particular), and it is stronger in times of market stress.

When comparing the German and US equity markets we find that average trading value per stock and day and turnover move in lockstep until the financial crisis. Since then trading activity in Germany's Xetra system is considerably lower than activity in the US markets, potentially because of the increased fragmentation of trading in the post-MiFID era. Average bid-ask spreads are higher in Germany throughout the entire sample period. We further find that there is commonality in liquidity between the German and the US market. There is a tendency for commonality between the two markets to be more pronounced in times of stress. Moreover, there is evidence that liquidity in Germany depends on lagged liquidity in the US, but not vice versa.

Overall, our results allow several conclusions. Liquidity has generally increased over time. However (and unsurprisingly), liquidity is significantly lower and volatility higher in times of stress. Liquidity co-moves across stocks and across countries. This comovement is particularly pronounced in times of stress. Thus, low returns, low liquidity and high commonality in liquidity go hand in hand. This is important (and bad) information for asset managers and regulators. It implies that it is particularly expensive to liquidate positions in times of crisis and is a potential threat to the stability of financial markets.

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Tables and Figures

Table 1: Summary statistics of liquidity and trading activity measures

This table shows summary statistics for the time-series of volatility, liquidity, and trading activity. *Trading Value* is the daily sum of all trading volume in €1 bn, either during the continuous trading session or during all auctions of that day. The other daily time-series comprise value-weighted cross-sectional means of the respective variables. *SD Midquote* is the standard deviation of 5 minute returns of the quote midpoint in percent. *Quoted Spread* is the time-weighted spread as a percentage of the quote midpoint. *Effective Spread* is the (trading-)value-weighted effective spread as a percentage of the quote midpoint. *Price Impact*$_t$ is twice the signed change in the quote midpoint from immediately prior to a trade until 5 minutes after the trade, expressed as a percentage of the quote midpoint. *Depth* is the time-weighted average depth at the best bid and ask in €1 mn. *OIB* is the relative value-weighted order imbalance in terms of Euro volume. *Trade Size* is the average volume of a trade in €1,000.

	Mean	SD	P1	P50	P99	Skew.	Kurt.	N
Trading Value$_{\text{cont.}}$	3.84	2.10	1.24	3.27	10.85	3.05	23.98	3642
Trading Value$_{\text{auction}}$	0.49	0.71	0.00	0.41	3.56	8.51	145.99	3642
SD Midquote	0.16	0.07	0.08	0.14	0.44	2.96	19.38	2790
Vola Interrupt.	137.39	73.62	40.00	129.00	404.00	3.71	31.37	2860
Quoted Spread	0.27	0.11	0.12	0.24	0.58	1.07	3.92	2790
Eff. Spread	0.17	0.07	0.10	0.14	0.36	5.28	95.17	2790
Price Impact$_5$	0.13	0.05	0.08	0.12	0.30	1.87	7.48	2790
Depth	6.45	2.25	2.64	6.13	10.90	0.16	1.80	2790
OIB	–0.91	5.87	–14.82	–0.79	11.85	–0.54	15.27	3642
Trade Size	37.71	25.20	10.78	34.47	99.65	2.62	22.09	3642

Table 2: Correlations of liquidity and trading activity measures

This table shows time-series correlations between measures of volatility, liquidity, and trading activity. The daily market-wide measures are constructed as value-weighted averages of the individual stock-level measures. The measures are defined as in table 1. Panel A shows correlations in levels while Panel B shows the correlations of relative daily percentage changes, denoted by Δ. Numbers in **boldface** indicate significance at the 5% level.

Panel A: Levels	SD Mid	Q. Spr.	Eff. Spr.	PI_5	Depth	OIB	Tr. Size
Q. Spr.	**0.43**						
Eff. Spr.	**0.62**	**0.69**					
PI_5	**0.79**	**0.69**	**0.81**				
Depth	**–0.45**	**0.08**	**–0.23**	**–0.24**			
OIB	**–0.05**	**–0.05**	–0.01	–0.04	**–0.06**		
Tr. Size	**–0.29**	**0.30**	0.03	–0.01	**0.93**	**–0.19**	
Tr. $Val._{total}$	**0.22**	**–0.17**	**–0.12**	–0.02	**0.30**	**–0.09**	**–0.04**
Panel B: Changes	Δ SD Mid	Δ Q. Spr.	Δ Eff. Spr.	$\Delta\, PI_5$	Δ Depth	Δ OIB	Δ Tr. Size
Δ Q. Spr.	**0.11**						
Δ Eff. Spr.	**0.18**	**0.06**					
$\Delta\, PI_5$	**0.49**	0.04	**0.17**				
Δ Depth	**–0.07**	**–0.07**	**–0.13**	–0.04			
Δ OIB	–0.01	0.01	–0.01	–0.02	0.01		
Δ Tr. Size	**0.25**	–0.04	0.02	**0.08**	**0.63**	**–0.06**	
Δ Tr. $Val._{total}$	**0.56**	–0.00	**0.05**	**0.13**	**0.34**	**–0.05**	**0.72**

Table 3: Time-series regressions of liquidity measures

This table shows time-series regression results, where the dependent variables are daily market-wide measures of liquidity and trading activity. The market-wide measures are constructed as value-weighted cross-sectional averages. The measures are defined as in table 1. ΔDAX^{+} (ΔDAX^{-}) is the contemporaneous return of the DAX if the return is positive (negative) and zero otherwise. ΔDAX_5^{+} (ΔDAX_5^{-}) is the return of the DAX during the five previous days if the return is positive (negative) and zero otherwise. $VDAX_{t-1}$ is the closing level of the VDAX of the previous day. *IR Spread* is the spread between the 12month Euribor and the return of a 12month German government zero-coupon bond, similar to the Ted spread. *Post MiFID* is an indicator variable for the period after the introduction of MiFID. *Financial Crisis* is an indicator variable for the period from July 2007 through April 2009. *Witching Day* is an indicator variable for days on which derivatives on German stocks and indices expire. $Holiday_{Tr.}$ is an indicator variable for holidays on which Xetra is open for trading. *Long* $Weekend_{Tr.}$ and *Long* $Weekend_{No\ Tr.}$ are indicator variables for so called Brückentage, where on the holiday Xetra is open or closed for trading, respectively. *Monday* through *Thursday* are indicator variables for the respective weekdays. Newey and West (1987) adjusted t-statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

	SD Mid	Q. Spr.	Eff. Spr.	PI_5	Depth	OIB	Tr. Size	Tr. $Val._{total}$
ΔDAX^{+}	0.411***	-0.289*	0.001	0.325***	12.937***	238.764***	80.287*	41.067***
	(3.07)	(-1.66)	(0.01)	(3.88)	(5.11)	(21.27)	(1.83)	(8.67)
ΔDAX^{-}	-1.396***	-0.631***	-0.818***	-0.845***	1.872	245.795***	-58.494	-44.521***
	(-8.28)	(-3.75)	(-8.00)	(-9.83)	(0.77)	(20.88)	(-1.40)	(-9.18)
ΔDAX_5^{+}	0.223***	0.072	0.283**	0.150***	0.184	15.937***	44.227	4.536*
	(3.70)	(0.77)	(2.43)	(3.70)	(0.13)	(2.91)	(1.62)	(1.94)
ΔDAX_5^{-}	-0.667***	-0.085	-0.183***	-0.220***	-4.120***	27.368***	-25.976	-20.096***
	(-5.25)	(-0.83)	(-2.78)	(-3.84)	(-2.99)	(4.95)	(-1.13)	(-5.68)
$VDAX_{t-1}$	0.004***	0.008***	0.005***	0.004***	-0.104***	0.020*	-0.145***	-0.101***
	(23.85)	(32.67)	(38.43)	(32.80)	(-24.42)	(1.74)	(-2.66)	(-15.88)
IR Spread	1.693***	-9.031***	-3.589***	-2.249***	-12.286	54.907*	-599.264***	84.813***
	(2.93)	(-17.52)	(-7.46)	(-7.68)	(-1.30)	(1.66)	(-7.03)	(5.44)
Post MiFID	0.000	-0.055***	-0.008**	-0.006***	-3.404***	1.426***	-28.997***	-0.760***
	(0.08)	(-11.92)	(-2.15)	(-2.98)	(-35.90)	(5.30)	(-33.24)	(-5.01)
Financial Crisis	0.023***	0.005	-0.013***	0.002	1.577***	-0.462**	4.452***	3.732***
	(8.55)	(1.22)	(-3.31)	(1.39)	(20.41)	(-1.98)	(5.81)	(20.85)
Witching Day	0.002	0.009	0.002	-0.005	0.730***	-0.598	28.893***	6.039***
	(0.48)	(0.66)	(0.28)	(-1.31)	(4.62)	(-0.25)	(2.73)	(8.26)
$Holiday_{Tr.}$	-0.017***	0.035***	-0.007	-0.007**	-0.281*	0.666	-5.312***	-1.075***
	(-4.70)	(2.62)	(-1.38)	(-2.08)	(-1.91)	(0.91)	(-3.23)	(-4.48)
Long $Weekend_{Tr.}$	0.000	-0.005	0.002	0.003	0.089	-2.416	-0.977	0.523
	(0.03)	(-0.51)	(0.35)	(0.66)	(0.51)	(-1.41)	(-0.15)	(0.87)
Long $Weekend_{No\ Tr.}$	-0.009	0.011	0.032***	0.030***	-0.277	-1.899	0.497	-1.203*
	(-0.59)	(0.63)	(3.01)	(2.65)	(-0.91)	(-1.17)	(0.08)	(-1.89)
Monday	-0.014***	-0.010***	-0.001	-0.001	-0.093**	-0.069	-1.945***	-0.819***
	(-8.02)	(-3.18)	(-1.02)	(-0.53)	(-2.04)	(-0.32)	(-2.81)	(-10.62)
Tuesday	-0.008***	-0.007*	-0.006***	-0.003**	0.052	-0.281	-0.540	-0.199**
	(-3.47)	(-1.85)	(-3.28)	(-2.16)	(0.90)	(-1.29)	(-0.58)	(-2.07)
Wednesday	-0.006***	-0.011***	-0.007***	-0.004**	0.119**	0.070	0.126	-0.001
	(-2.58)	(-2.91)	(-3.88)	(-2.54)	(2.05)	(0.32)	(0.14)	(-0.01)
Thursday	-0.000	-0.005	-0.001	-0.002	0.054	-0.007	0.149	0.118
	(-0.04)	(-1.55)	(-0.26)	(-1.28)	(1.20)	(-0.03)	(0.21)	(1.48)
Observations	2790	2790	2790	2790	2790	3642	3642	3642
Adj. R^2	0.80	0.68	0.64	0.74	0.83	0.44	0.44	0.43

Table 4: Commonality in Liquidity in different market segments over time

This table shows, for the relative quoted spread, the time-weighted euro depth, the equal-weighted effective spread, and the equal-weighted 5-minute price impact, for each year separately, the median estimate of β_2 from equation 1 and the percentage of stocks with coefficients that are positively or negatively significant at the 5% level (one-sided test), respectively. Estimations are based on periods of one calendar year each. Panel A shows results for the aggregate market, panel B for the DAX, panel C for the MDAX, panel D for the SDAX, and panel E for stocks outside of these three indices.

Year	Quoted	% sig. +	% sig. -	Depth	% sig. +	% sig. -	Effective	% sig. +	% sig. -	Price Impact	% sig. +	% sig. -
						A: Marketwide						
2002	0.68	25.58%	0.39%	0.47	16.67%	2.71%	0.60	24.03%	0.39%	0.47	7.36%	0.39%
2003	0.62	30.83%	1.19%	0.47	24.11%	3.56%	0.53	23.72%	1.58%	0.39	7.91%	1.98%
2004	0.68	36.82%	0.34%	0.47	16.55%	2.36%	0.57	25.68%	0.34%	0.27	7.09%	2.70%
2005	0.62	30.00%	0.00%	0.48	19.69%	2.19%	0.67	30.00%	0.63%	0.60	11.87%	2.19%
2006	0.56	23.34%	1.33%	0.50	20.42%	1.59%	0.67	31.83%	0.80%	0.38	8.49%	3.98%
2007	0.82	40.24%	0.49%	0.63	24.15%	1.46%	0.93	45.12%	0.73%	0.56	14.88%	1.71%
2008	1.05	74.78%	0.00%	0.67	24.93%	0.89%	1.06	70.62%	0.00%	0.89	29.38%	0.89%
2009	0.41	23.69%	0.35%	0.58	22.65%	0.70%	0.51	28.22%	0.70%	0.52	15.33%	1.74%
2010	0.47	26.73%	0.66%	0.46	16.50%	1.65%	0.61	30.36%	0.99%	0.19	5.28%	2.97%
2011	0.68	50.78%	0.31%	0.56	24.61%	0.93%	0.77	49.53%	0.31%	0.44	15.58%	1.56%
2012	0.43	26.55%	0.69%	0.42	18.62%	1.72%	0.33	13.10%	2.07%	0.30	9.66%	1.38%
						B: DAX						
2002	0.85	26.67%	0.00%	0.61	53.33%	0.00%	0.81	63.33%	0.00%	1.05	6.67%	0.00%
2003	0.80	50.00%	0.00%	0.77	83.33%	0.00%	0.77	53.33%	0.00%	0.86	6.67%	0.00%
2004	0.96	96.67%	0.00%	0.79	93.33%	0.00%	0.76	76.67%	0.00%	0.77	6.67%	0.00%
2005	0.81	66.67%	0.00%	0.88	93.33%	0.00%	0.76	93.33%	0.00%	0.82	16.67%	3.33%
2006	0.83	43.33%	0.00%	0.72	60.00%	0.00%	0.73	73.33%	0.00%	0.83	0.00%	6.67%
2007	0.82	76.67%	0.00%	0.77	80.00%	0.00%	0.88	96.67%	0.00%	0.87	10.00%	0.00%
2008	0.89	100.00%	0.00%	1.02	80.00%	0.00%	1.07	100.00%	0.00%	0.99	30.00%	0.00%
2009	0.81	50.00%	0.00%	0.75	63.33%	0.00%	0.56	83.33%	0.00%	0.85	30.00%	0.00%
2010	1.04	56.67%	0.00%	0.67	76.67%	0.00%	1.07	86.67%	0.00%	0.86	0.00%	3.33%
2011	0.95	79.31%	0.00%	0.56	79.31%	0.00%	0.90	93.10%	0.00%	0.91	13.79%	0.00%
2012	0.94	43.33%	0.00%	0.68	80.00%	0.00%	0.97	40.00%	0.00%	0.84	10.00%	0.00%

Table 4: Commonality in Liquidity in different market segments over time

(continued from previous page)

Year	Quoted	% sig. +	% sig. -	Depth	% sig. +	% sig. -	Effective	% sig. +	% sig. -	Price Impact	% sig. +	% sig. -
C: MDAX												
2002	0.52	31.82%	0.00%	0.48	21.21%	0.00%	0.59	28.79%	0.00%	0.39	7.58%	0.00%
2003	0.44	39.13%	0.00%	0.41	32.61%	2.17%	0.33	28.26%	0.00%	0.26	10.87%	4.35%
2004	0.62	43.48%	0.00%	0.23	17.39%	0.00%	0.41	34.78%	0.00%	0.30	6.52%	0.00%
2005	0.61	29.79%	0.00%	0.30	25.53%	0.00%	0.40	40.43%	0.00%	0.41	10.64%	2.13%
2006	0.86	41.30%	0.00%	0.67	56.52%	0.00%	0.60	67.39%	0.00%	0.62	10.87%	2.17%
2007	0.93	59.57%	0.00%	0.69	63.83%	0.00%	0.89	80.85%	0.00%	0.90	27.66%	0.00%
2008	0.96	97.87%	0.00%	0.79	63.83%	0.00%	0.93	97.87%	0.00%	1.02	59.57%	0.00%
2009	0.66	34.04%	0.00%	0.54	36.17%	0.00%	0.44	44.68%	0.00%	0.75	29.79%	0.00%
2010	0.92	42.55%	0.00%	0.52	25.53%	0.00%	0.43	53.19%	0.00%	0.67	6.38%	6.38%
2011	1.00	57.45%	0.00%	0.56	46.81%	0.00%	0.67	80.85%	0.00%	0.85	25.53%	0.00%
2012	0.83	30.43%	0.00%	0.48	36.96%	0.00%	0.49	17.39%	0.00%	0.67	17.39%	0.00%
D: SDAX												
2002	0.19	10.00%	0.00%	0.00	20.00%	10.00%	0.08	10.00%	0.00%	-0.31	0.00%	0.00%
2003	0.21	30.77%	2.56%	0.13	12.82%	7.69%	0.13	10.26%	0.00%	0.01	7.69%	2.56%
2004	0.27	28.89%	0.00%	-0.05	4.44%	8.89%	0.21	17.78%	0.00%	0.22	6.67%	6.67%
2005	0.46	27.27%	0.00%	0.08	22.73%	4.55%	0.31	27.27%	0.00%	0.56	11.36%	0.00%
2006	0.42	27.27%	0.00%	0.23	13.64%	0.00%	0.40	36.36%	0.00%	0.05	15.91%	2.27%
2007	0.49	50.00%	0.00%	0.29	26.09%	0.00%	0.45	56.52%	0.00%	0.47	28.26%	2.17%
2008	0.89	89.13%	0.00%	0.27	8.70%	0.00%	0.79	91.30%	0.00%	1.00	30.43%	2.17%
2009	0.41	27.27%	0.00%	0.21	11.36%	0.00%	0.29	20.45%	0.00%	0.35	15.91%	6.82%
2010	0.44	20.45%	0.00%	0.22	6.82%	0.00%	0.21	25.00%	0.00%	0.15	4.55%	2.27%
2011	0.74	51.16%	0.00%	0.23	9.30%	0.00%	0.50	58.14%	0.00%	0.49	13.95%	2.33%
2012	0.42	27.91%	2.33%	0.12	9.30%	2.33%	0.26	13.95%	4.65%	0.06	9.30%	0.00%
E: Outside												
2002	0.62	23.68%	0.66%	0.08	7.24%	3.95%	0.37	15.13%	0.66%	0.42	7.89%	0.66%
2003	0.55	23.91%	1.45%	-0.03	11.59%	3.62%	0.32	19.57%	2.90%	0.25	7.25%	1.45%
2004	0.59	26.86%	0.57%	0.15	6.29%	1.71%	0.41	16.57%	0.57%	0.08	7.43%	2.86%
2005	0.60	25.13%	0.00%	0.07	6.53%	2.51%	0.43	18.59%	1.01%	0.57	11.56%	2.51%
2006	0.52	17.12%	1.95%	0.22	10.51%	2.33%	0.50	19.84%	1.17%	0.50	7.78%	4.28%
2007	0.81	31.71%	0.70%	0.26	11.50%	2.09%	0.70	32.06%	1.05%	0.68	11.15%	2.09%
2008	0.99	63.08%	0.00%	0.26	12.15%	1.40%	0.89	56.07%	0.00%	0.85	22.43%	0.93%
2009	0.30	15.06%	0.60%	0.19	14.46%	1.20%	0.31	15.66%	1.20%	0.54	8.43%	1.20%
2010	0.47	19.23%	1.10%	0.17	6.59%	2.75%	0.40	16.48%	1.65%	0.30	6.04%	2.20%
2011	0.83	45.05%	0.50%	0.33	14.85%	1.49%	0.61	34.16%	0.50%	0.53	13.86%	1.98%
2012	0.49	22.22%	0.58%	0.04	5.26%	2.34%	0.21	7.02%	2.34%	0.21	7.60%	2.34%

Table 5: Commonality Germany - US

This table shows results for time-series regressions of daily changes in liquidity in one market on daily changes in liquidity in the other market and several control variables, as specified in equation 2. The daily measures are constructed using value-weighting of individual stock measures. The measures are defined as in table 1. Δ denotes daily proportional changes.$\Delta Spread_{[t-1,t+1]}$ is the relative effective spread of the "other" market (i.e. of the US market in models (1), (2), (4) and (5), and of the German market in model (3)) for the previous, the same, or the following day. *Crisis* is a dummy that takes value 1 in the period between July 2007 and April 2009. Newey and West (1987) adjusted t-statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively. F-Test provides the p-value for an F-test of $\sum_{t=-1}^{T=+1} \Delta Spread_t = 0$.

Dependent Spread	(1) Germany	(2) Germany	(3) US	(4) Germany (crisis only)	(5) Germany (crisis dummy)
ΔSpread$_{t-1}$	0.133***	0.114***	0.002	0.160*	0.119***
	(3.74)	(3.36)	(0.07)	(1.90)	(3.46)
ΔSpread$_{t}$	0.287***	0.196***	0.219***	0.291***	0.186***
	(6.99)	(4.38)	(6.47)	(2.66)	(4.29)
ΔSpread$_{t+1}$	-0.003	0.007	0.117***	-0.014	0.026
	(-0.10)	(0.26)	(3.93)	(-0.28)	(0.86)
Return$_{t-1}^{US}$	-0.827***	-0.804***		-0.858***	-0.803***
	(-6.14)	(-5.24)		(-3.03)	(-5.20)
Return$_{t}^{US}$	-0.211	-0.173		0.092	-0.185
	(-1.41)	(-1.34)		(0.36)	(-1.42)
Return$_{t+1}^{US}$	-0.049	-0.043		-0.085	-0.045
	(-0.31)	(-0.33)		(-0.37)	(-0.36)
Volatility$_{t}^{GER}$		0.082***		0.026	0.082***
		(3.71)		(0.45)	(3.70)
Volatility$_{t-1}^{GER}$		-0.004		-0.014	-0.004
		(-0.56)		(-0.95)	(-0.58)
Return$_{t-1}^{GER}$		0.497**	0.173	0.507	0.486**
		(2.25)	(0.94)	(0.99)	(2.18)
Return$_{t}^{GER}$			-1.545***		
			(-6.36)		
Return$_{t+1}^{GER}$			0.086		
			(0.50)		
Crisis					-0.000
					(-0.00)
Crisis $\times$ ΔSpread$_{t-1}$					-0.016
					(-0.25)
Crisis $\times$ ΔSpread$_{t}$					0.011
					(0.15)
Crisis $\times$ ΔSpread$_{t+1}$					-0.052
					(-0.83)
Constant	0.002	-0.001	0.001	0.002	-0.001
	(1.30)	(-0.74)	(0.77)	(0.34)	(-0.66)
F-Test	0.000	0.000	0.000	0.027	0.000
Adj. R^2	0.120	0.242	0.129	0.176	0.241
Observations	2392	2357	2461	406	2357

Figure 1: Total trading value

This graph shows total Euro trading volume (denoted trading value) for all constituent stocks of the CDAX and for the subsample of DAX-constituents. In addition the level of the DAX index is shown.

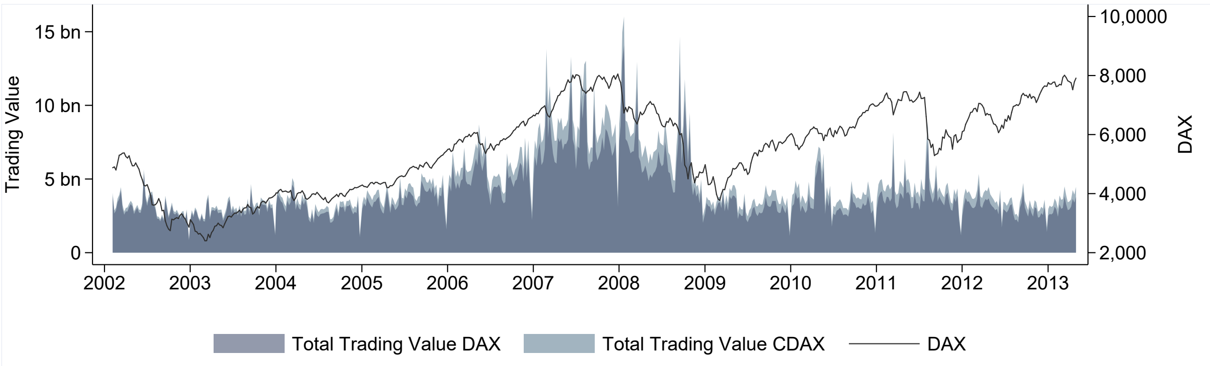


Figure 2: Relative auction value

This graph shows the fraction of trading value that is traded during an auction relative to the total trading value of that day.

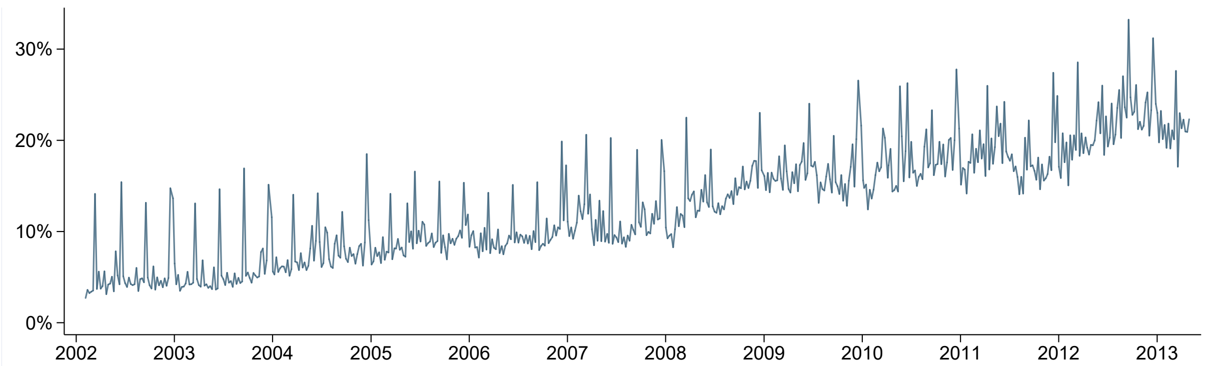


Figure 3: Volatility measures

This graph shows the evolution of various volatility measures over time. *Midquote SD* is the value-weighted average of the daily standard deviation of 5 minute returns based on the quote midpoints. *Vola Interruptions* is the total number of volatility interruptions per day, in 10th. *VDAX* is the level of the VDAX volatility index.

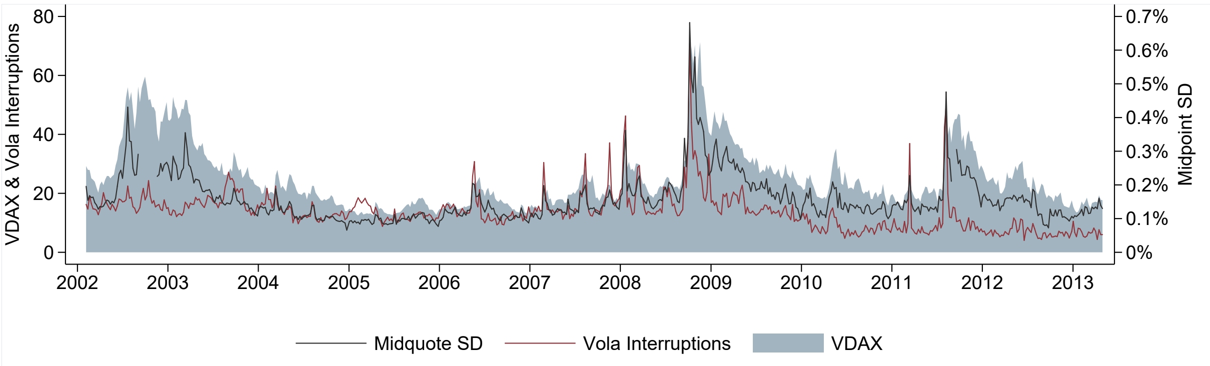


Figure 4: Trading cost measures

This graph shows the evolution of transaction costs over time. *Relative Quoted Spread* is the quoted bid–ask spread as a percentage of the quote midpoint. *Relative Effective Spread* is the effective spread as a percentage of the quote midpoint. *Price Impact* is twice the signed change in the quote midpoint from immediately prior to a trade until 5 minutes after the trade, expressed as a percentage of the quote midpoint. Cross-sectional averages are value-weighted.

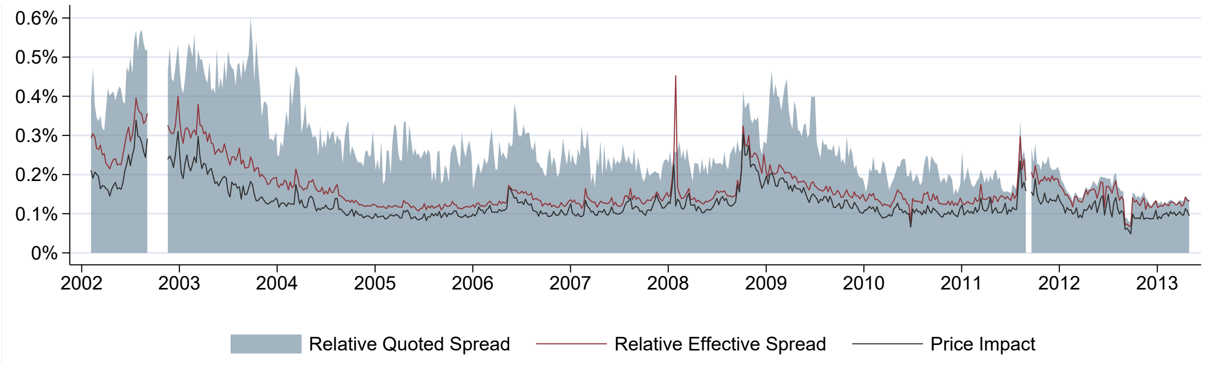


Figure 5: Trades and depth

This graph shows the evolution of depth and trading activity over time. *Depth* is the time-weighted total depth at the best bid and ask in Euro. *Average Trade Value* is the average size of trades in Euro. *Trades* is the total number of trades. Cross-sectional averages are value-weighted.

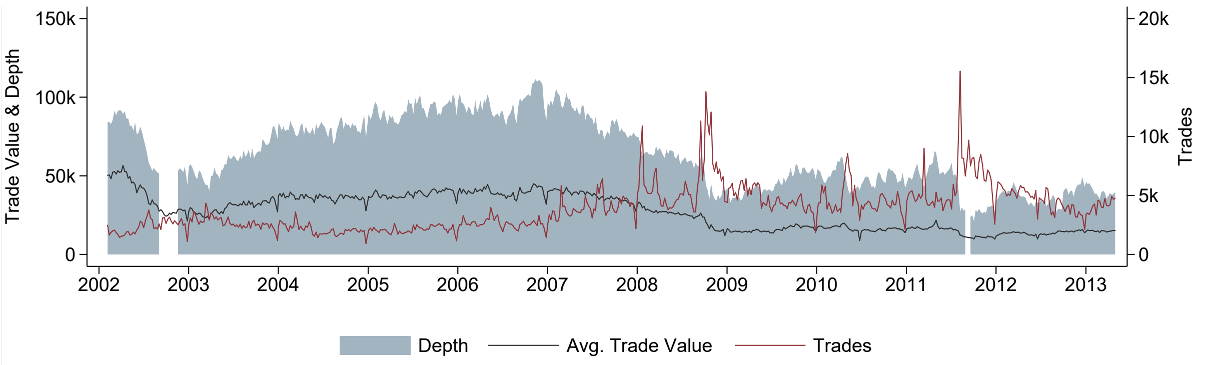


Figure 6: Market-Wide Commonality in Liquidity

This graph shows the time series of the median coefficient β_2 obtained from estimating regression equation 1.

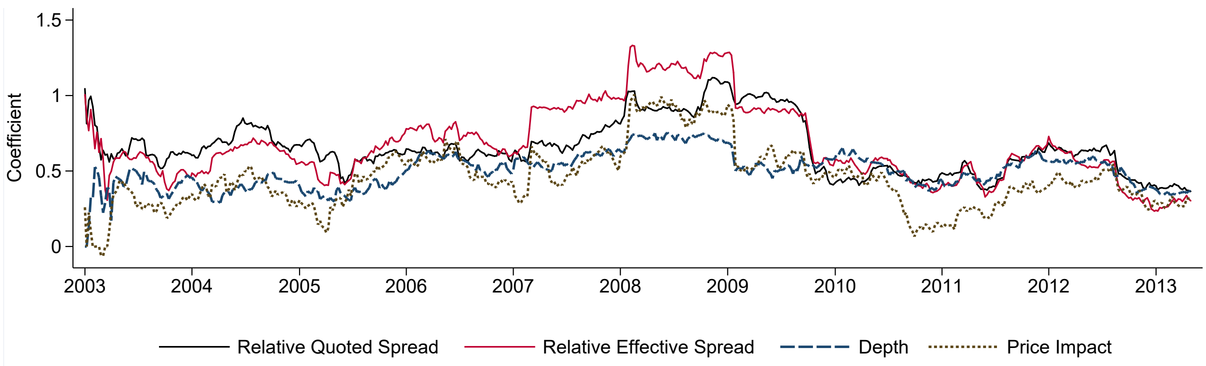


Figure 7: Commonality in Liquidity for Sub-Samples

This graph shows the time series of the median coefficient β_2 obtained from estimating regression equation 1 seperately for DAX, MDAX and SDAX constituents, and for stocks that are not members of one of these three indices.

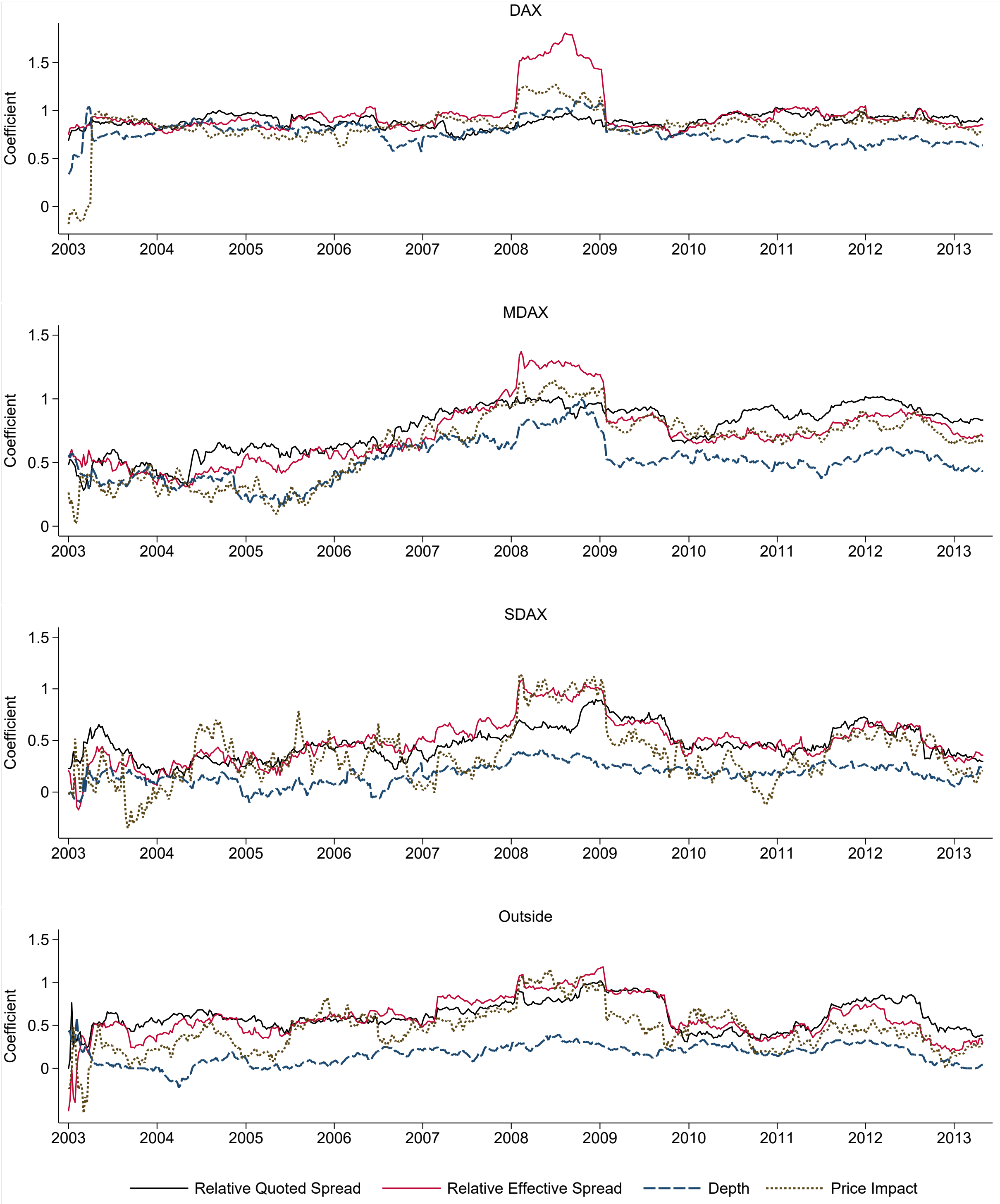


Figure 8: Germany vs. US - Total trading value

This graph shows the value-weighted average daily trading volume in Euro for the average German and US stock in our sample. US volumes are converted into Euro using daily USD - EUR exchange rates from Bloomberg. Delta/Level is the correlation of the relative 1-day changes/levels of trading volume based on daily observations.

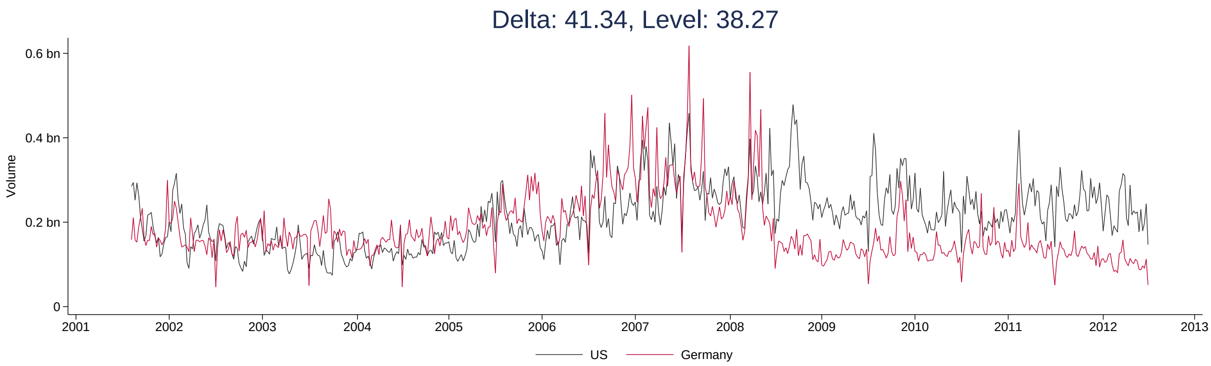


Figure 9: Germany vs. US - Turnover

This graph shows the value-weighted average daily turnover for a German/US stock. Turnover is defined as the number of traded shares divided by the number of shares outstanding of a given stock. Delta/Level is the correlation of the relative 1-day changes/levels of turnover based on daily observations.

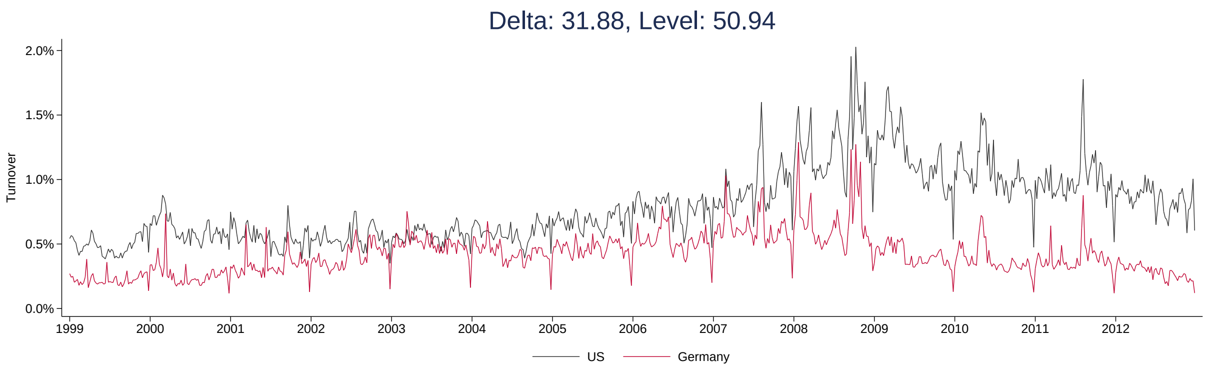


Figure 10: Germany vs. US - Relative Quoted Spread

This graph shows the evolution of the value-weighted average daily *Relative Quoted Spread* for Germany and the US. Within a day, spreads are time-weighted. Delta/Level is the correlation of the relative 1-day changes/levels of the relative quoted spread based on daily observations.

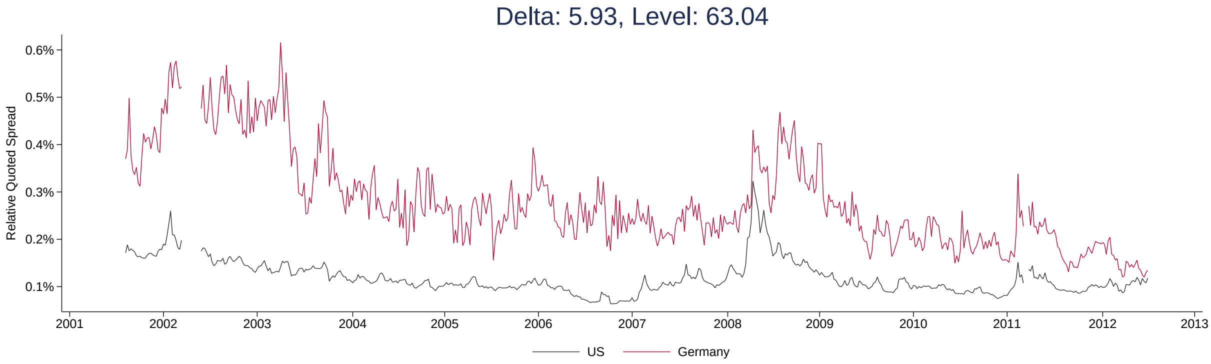


Figure 11: Germany vs. US - Relative Effective Spread

This graph shows the evolution of the value-weighted average daily *Relative Effective Spread* for Germany and the US. Within a day, spreads are weighted by trading value. Delta/Level is the correlation of the relative 1-day changes/levels of the relative effective spread based on daily observations.

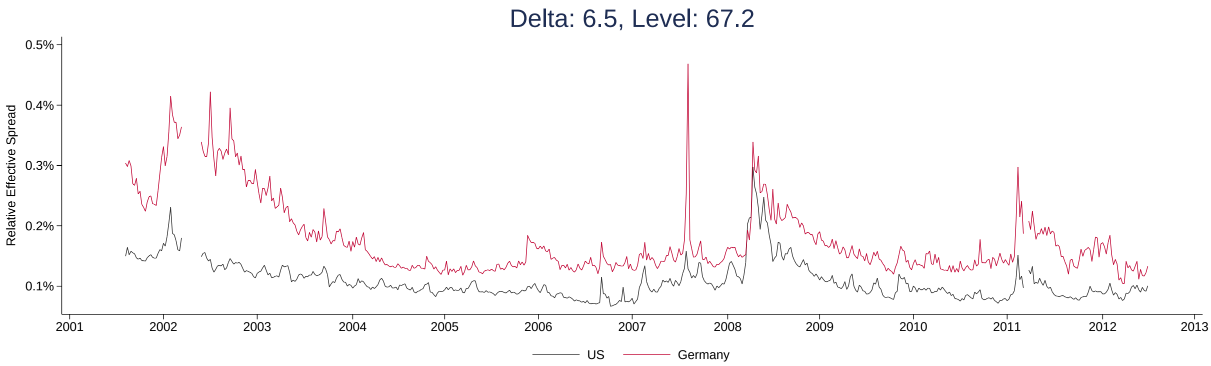


Figure 12: Germany vs. US - Trades

This graph shows the value-weighted average daily number of *Trades* for Germany (right axis/red) and the US (left axis/black). Delta/Level is the correlation of the relative 1-day changes/levels of the first-differences/levels of trades based on daily observations.

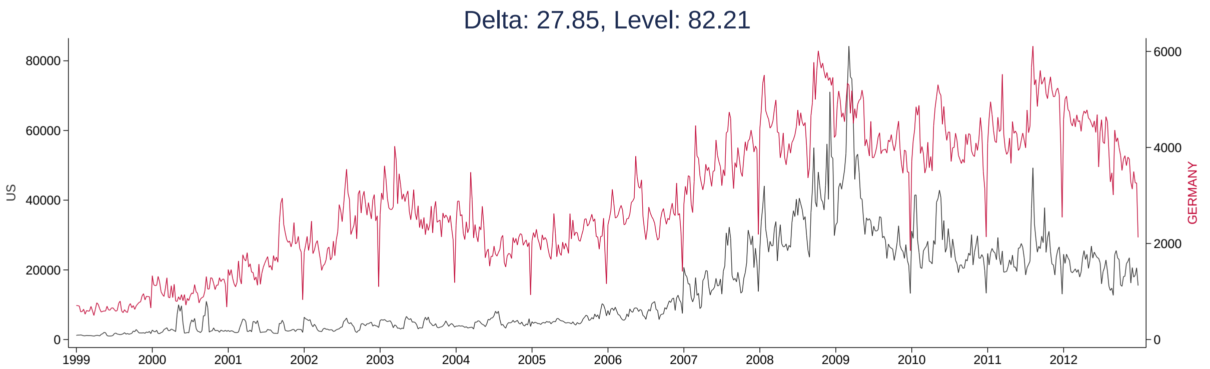
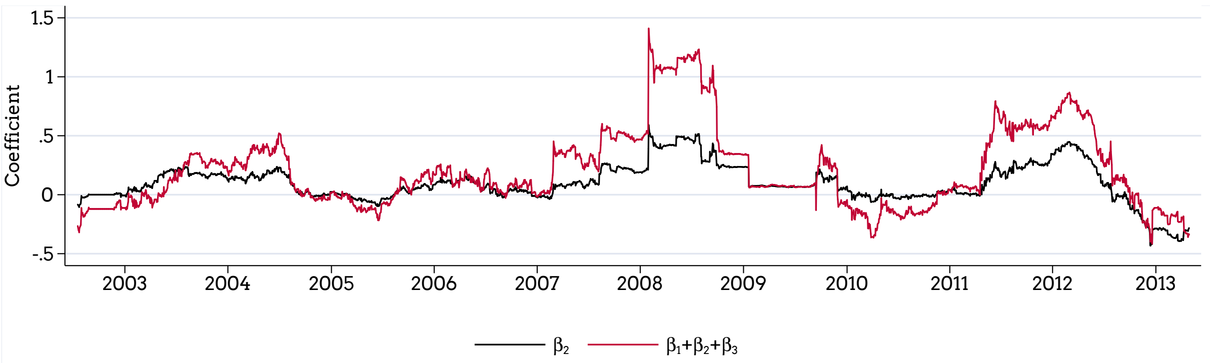


Figure 13: Germany vs. US - Rolling Regression

This graph shows the time series of the median coefficient β_2 and the sum of the coefficients $(\beta_1+\beta_2+\beta_3)$ obtained from estimating regression equation 2 on a rolling 250-day window.



Appendix

Table A1: Correlations of liquidity and trading activity measures using equal weighting

This table shows time-series correlations between contemporaneous daily changes of various measures of volatility, liquidity, and trading activity. The daily market-wide measures are constructed using equal-weighting of the individual stock measures. The measures are defined as in table 1. Δ denotes daily percentage changes. **Bold** numbers indicate significance at the 5% level.

Panel A: Levels	SD Mid	Q. Spr.	Eff. Spr.	PI_5	Depth	OIB	Tr. Size
Q. Spr.	**0.51**						
Eff. Spr.	**0.78**	**0.78**					
PI_5	**0.86**	**0.67**	**0.92**				
Depth	**–0.23**	**–0.08**	**–0.25**	**–0.20**			
OIB	**–0.17**	**–0.11**	**–0.18**	**–0.14**	**–0.09**		
Tr. Size	**–0.16**	**0.08**	**–0.11**	**–0.09**	**0.95**	**–0.59**	
Tr. $Val._{total}$	**0.20**	**–0.20**	**–0.17**	–0.04	**0.38**	**0.15**	**–0.09**
Panel B: Changes	Δ SD Mid	Δ Q. Spr.	Δ Eff. Spr.	Δ PI_5	Δ Depth	Δ OIB	Δ Tr. Size
Δ Q. Spr.	–0.01						
Δ Eff. Spr.	**0.45**	**0.18**					
Δ PI_5	**0.56**	–0.01	**0.24**				
Δ Depth	**0.14**	**–0.23**	**–0.08**	**0.07**			
Δ OIB	**0.07**	–0.03	0.02	0.02	0.00		
Δ Tr. Size	**0.14**	–0.03	**–0.11**	**0.07**	**0.43**	0.01	
Δ Tr. $Val._{total}$	**0.35**	**0.05**	**0.11**	**0.07**	**0.29**	0.01	**0.62**

Table A2: Time-series regressions of liquidity measures using equal weighting

This table shows time-series regression results, where the dependent variables are daily market-wide measures of liquidity and trading activity. The market-wide measures are constructed using equal-weighting of the individual stock measures. The measures are defined as in table 1. ΔDAX^{+} (ΔDAX^{-}) is the contemporaneous return of the DAX if the return is positive (negative) and zero otherwise. ΔDAX_5^{+} (ΔDAX_5^{-}) is the return of the DAX of the five previous days if the return is positive (negative) and zero otherwise. $VDAX_{t-1}$ is the closing level of the VDAX of the previous day. *IR Spread* is the spread between the 12month Euribor and the return of a 12month German government zero-coupon bond, similar to the Ted spread. *Post MiFID* is an indicator variable for the period after the introduction of MiFID. *Financial Crisis* is an indicator variable for the period from July 2007 through April 2009. *Witching Day* is an indicator variable for days on which derivatives on German stocks and indices expire. $Holiday_{Tr.}$ is an indicator variable for holidays on which Xetra is open for trading. $Long\ Weekend_{Tr.}$ and $Long\ Weekend_{No\ Tr.}$ are indicator variables for so called Brückentage, where on the holiday Xetra is open or closed for trading, respectively. *Monday* through *Thursday* are indicator variables for the respective weekdays. Newey and West (1987) adjusted t-statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

	SD Mid	Q. Spr.	Eff. Spr.	PI_5	Depth	OIB	Tr. Size	Tr. Val.$_{total}$
ΔDAX^{+}	0.772***	-2.064*	0.825	2.299***	1.972***	337.087***	0.611	41.067***
	(5.66)	(-1.79)	(1.49)	(4.79)	(4.42)	(13.50)	(0.06)	(8.67)
ΔDAX^{-}	-1.499***	-2.843**	-4.798***	-3.655***	0.124	417.381***	6.892	-44.521***
	(-7.55)	(-2.12)	(-7.65)	(-7.12)	(0.28)	(18.99)	(0.78)	(-9.18)
ΔDAX_5^{+}	0.322***	0.810	0.928***	1.064***	0.148	28.885*	3.328	4.536*
	(4.19)	(1.15)	(2.82)	(4.32)	(0.56)	(1.91)	(0.51)	(1.94)
ΔDAX_5^{-}	-0.726***	0.242	-0.712*	-1.155***	-0.916***	77.632***	1.075	-20.096***
	(-4.49)	(0.28)	(-1.73)	(-3.53)	(-3.49)	(6.07)	(0.19)	(-5.68)
$VDAX_{t-1}$	0.003***	0.055***	0.032***	0.020***	-0.019***	-0.129***	-0.021	-0.101***
	(15.18)	(32.63)	(41.44)	(32.30)	(-24.74)	(-4.47)	(-1.53)	(-15.88)
IR Spread	0.037	-72.222***	-31.587***	-17.382***	-1.248	397.765***	-92.777***	84.813***
	(0.06)	(-15.19)	(-13.76)	(-9.59)	(-0.76)	(6.24)	(-5.05)	(5.44)
Post MiFID	-0.013***	-0.128***	0.012	-0.008	-0.559***	7.298***	-5.665***	-0.760***
	(-2.74)	(-3.14)	(0.72)	(-0.63)	(-33.90)	(12.93)	(-34.86)	(-5.01)
Financial Crisis	0.029***	0.049	-0.002	0.096***	0.392***	2.134***	1.098***	3.732***
	(8.24)	(1.60)	(-0.16)	(8.77)	(28.25)	(4.63)	(7.22)	(20.85)
Witching Day	0.002	0.050	0.009	-0.022	0.062**	-2.071	2.658*	6.039***
	(0.40)	(0.77)	(0.33)	(-1.13)	(2.23)	(-1.44)	(1.89)	(8.26)
$Holiday_{Tr.}$	-0.044***	0.191**	-0.044	-0.100***	-0.039	6.001***	-1.544***	-1.075***
	(-9.62)	(2.34)	(-1.24)	(-4.07)	(-1.48)	(2.84)	(-5.48)	(-4.48)
$Long\ Weekend_{Tr.}$	0.003	-0.069	0.007	0.028	0.019	2.028	-0.963*	0.523
	(0.51)	(-0.69)	(0.15)	(0.95)	(0.59)	(1.07)	(-1.66)	(0.87)
$Long\ Weekend_{No\ Tr.}$	0.026*	-0.086	0.119*	0.135**	-0.020	0.200	0.858	-1.203*
	(1.90)	(-1.18)	(1.76)	(2.22)	(-0.50)	(0.04)	(0.43)	(-1.89)
Monday	0.002	-0.058***	0.010	0.024***	-0.020**	-1.554***	-0.324**	-0.819***
	(0.83)	(-2.64)	(1.10)	(3.21)	(-2.52)	(-3.41)	(-2.00)	(-10.62)
Tuesday	-0.002	-0.042	-0.017	-0.002	0.002	-2.054***	-0.024	-0.199**
	(-0.79)	(-1.49)	(-1.44)	(-0.22)	(0.23)	(-3.62)	(-0.11)	(-2.07)
Wednesday	-0.004	-0.034	-0.026**	-0.004	0.009	-0.983*	0.097	-0.001
	(-1.49)	(-1.20)	(-2.22)	(-0.44)	(0.87)	(-1.73)	(0.44)	(-0.01)
Thursday	-0.002	0.003	-0.012	-0.005	0.004	-1.184***	0.084	0.118
	(-1.03)	(0.15)	(-1.26)	(-0.70)	(0.52)	(-2.63)	(0.52)	(1.48)
Observations	2790	2790	2790	2790	2790	3642	3642	3642
Adj. R^2	0.64	0.61	0.74	0.69	0.80	0.38	0.34	0.43