Resiliency in Limit Order Book Markets: A Dynamic View of Liquidity

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This Draft: November 18, 2009

Keywords: Order-Driven Markets, Resiliency, Informed Trading

JEL: G10 G14

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ABSTRACT

The seminal literature on liquidity identifies three main dimensions of liquidity: spread, depth and resiliency. While there has been extensive research focussing on spread and depth, there has been relatively little empirical investigation of resiliency, a dimension of liquidity that is also very important to market participants, stock exchanges and regulators. This paper investigates the resiliency in an electronic limit order book environment where there is centralized aggregation of liquidity and depth. We define resiliency as the speed with which the temporary order-flow related changes induced in depth and in spreads by an order-flow shock are corrected or neutralized by the flow of new orders into the market through the competitive actions of value traders, liquidity suppliers and others. We find that resiliency of each stock is consistently high and stable across different horizons, and there is strong evidence of commonality in resiliency across different stocks. Resiliency is also dependent in a stable and robust manner on microstructural determinants. The presence of informed traders leads to weaker resiliency. As predicted by Foucault, Kadan and Kandel (RFS, 2005), spread resiliency increases in the proportion of patient traders and decreases with the order arrival rate and at the end of the trading day. For depth resiliency, the proportion of patient traders, intraday order arrival rate and unsystematic risk have the same impact on depth resiliency as they do have on spread resiliency. The impact of the proportion of systematic risk on depth resiliency is positive, indicating greater willingness to provide depth replenishment in the presence of greater hedgeability. Greater long-run order arrival rate increases depth resiliency but greater intra-day order arrival rate (proxying for information flow) reduces it. In the cross section, the results show that firms with high spread resiliency also have high depth resiliency. However, we find that neither spread resiliency nor depth resiliency are significantly correlated with either spread or depth reinforcing the importance of resiliency as an independent dimension of liquidity providing significant new information.

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1. Introduction and Motivation

It is widely recognised that market liquidity cannot be captured by a single measure. The seminal literature on liquidity (Garbade (1982), Kyle (1985), and Harris (2003)) identifies three main dimensions of liquidity: spread, depth and resiliency. Spread is the price dimension and represents the transaction costs faced by public traders, and is often measured by the quoted bid-ask spread or the trade-based effective spread. Depth is the quantity dimension and reflects the market's ability to absorb and execute large orders with minimal price impact, and is often measured by the quoted depth or by *Kyle's Lambda*. Finally, resiliency is the time dimension that indicates how quickly after order-flow shocks does the spread and the depth of a market recover through the flow of new orders into the market from value traders, professional liquidity suppliers and others. This paper is an empirical investigation of resiliency, this time dimension of liquidity.

Resiliency addresses a question that is very important for market participants, stock exchanges and regulators, particularly in the context of electronic limit order markets; and most of the stock exchanges around the world now conduct trading either exclusively or significantly through an electronic order-driven market structure. Traders in such markets potentially face significant price risk and execution risk when the spread and the depth move away from their "normal" levels due to trade or order-flow related distortions. For example, block traders who break up their trades into smaller sizes for better execution may have non-trivial wait-times before they can execute successive blocks[2]. Arbitrageurs who typically work on large-volume-small-margin strategies also face similar risks; and the ability of arbitrageurs to arbitrage away small price discrepancies is essential for fair pricing and market integrity. With the market for supplying liquidity becoming increasingly competitive, and often transcending national boundaries, stock exchanges should arguably have a strong interest in understanding the replenishment mechanism of the order book in order to be able to attract and retain liquidity. Likewise, it is important for regulators to understand the resiliency dimension of liquidity, in order to factor an analysis of resiliency into their monitoring of market quality and stability[3].

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[2] This decision problem is examined in the optimal execution literature. Almgren (2003) and Huberman and Stanzl (2005) assume that trades have permanent and temporary price impacts, and that traders wait until the temporary price impact has been absorbed by the market before executing their next lot. Obizhaeva and Wang (2005) allow traders to choose whether they wait or trade before the temporary impacts have been "corrected". In their model, resiliency has a strong impact on the optimal strategy.

[3] Dynamic equilibrium models like Huang and Stoll (1996), Parlour (1998), Foucault (1999), Foucault, Kadan and Kandel (2003) and Parlour and Seppi (2003) direct little attention to the stability of limit order markets.

Spreads have been heavily researched: the literature is far too extensive to adequately summarise here[4]. Depth has also been well-researched[5]. However, while there is a developing strand of literature investigating the order-submission behavior and the order aggressiveness of market participants[6], there is little extant research on the resiliency dimension of market liquidity focusing on the continuous replenishment of the order book.

From an empirical perspective, Bhattacharya and Spiegel (1998) are the first to examine resiliency as a dimension of liquidity, but they do so from the extreme perspective of trading suspensions, defining resiliency as "the ability of a market to absorb high volatility without closing down", and conclude that their "resiliency" metric provides valuable liquidity-related information. Coppejans, Domowitz and Madhavan (2003) document "market resiliency" by analyzing the time variation of order book depth (using the Swedish index futures market), but they do so with a dominant focus on the cross-effects with time-varying returns and time-varying volatility. Gomber, Schweickert and Theissen (2004) use an intra-day event study approach to provide a largely descriptive analysis of the impact of large trades and ticker-news on their transaction cost measure, and find that "liquidity shocks dissipate quickly" while news has no impact. Finally, Degryse et. al. (2005) and Large (2007) attempt to build a picture of market resiliency by investigating the impact in an event-study framework of "aggressive orders", i.e. orders that demand more liquidity than is available at the best prices[7].

Degryse et. al. (2005), using Paris Bourse data, find that both the depth and the spread decrease significantly in the run-up to an aggressive order, and then revert back virtually immediately after the aggressive order to their pre-run-up level or higher. However, their spread-related results are more a statement about the timing of aggressive orders (i.e. such orders are made when spreads are low), than about spread resiliency in a general setting; and, for depth, they themselves acknowledge (on p232) that their results need not necessarily show resiliency (i.e. that new liquidity is quickly supplied after it is consumed), but could potentially arise because of their data limitation that they can observe only the depth at the best five quotes, and not the entire book, and hence, the consummation of an aggressive

[4] One strand of the literature decomposes the spread into three components: one component reflecting the inventory holding risk of liquidity suppliers, another component reflecting the adverse-selection losses that liquidity suppliers make to more informed investors, and the last component reflecting order-processing costs. See, for example, Huang and Stoll (1997), Stoll (1989), and Glosten and Milgram (1985). Another strand of the literature focusses on the individual trade-based effective spread, and its decomposition into the adverse selection spread and the realised spread. See, for example, Huang and Stoll (1996), Bessembinder (1997) and Naik and Yadav (2003).

[5] In particular, Hasbrouck (1991) and Kempf and Korn (1999) have analysed the effect of transactions on market prices. Additionally, for example, Glosten and Harris (1988) and Brennan and Subrahmanyam (1996) investigated the relationship between stock returns and measures of depth, similar to *Kyle's Lambda*.

[6] Biais, Hillion and Spatt (1995) empirically analyze market order flows and order aggressiveness. They document substantial serial correlation of market orders. Ahn, Bae and Chan (2001), Ranaldo (2002), Bae, Jang and Park (2003) or Grammig, Heinen and Rengifo (2004) take such analyses further.

order, by construction, exposes a hitherto unobserved part of the book. Large (2007) examines aggressive orders over 22 days in a single stock on the London Stock Exchange using the order-aggressiveness classification in Biais et. al. (2005) and an "appropriate" parametric model that views orders and cancellations as "a mutually-exciting ten-variate Hawkes point process"; and finds that the order book does not get replenished most of the time after a large trade, but when it does, it does so quickly.

Whatever we know about "resiliency" from Degryse et. al. (2005) or Large (2007) is through the prism of aggressive orders, a prism that is relatively narrow since aggressive orders constitute less than about 10% of the total order flow. This aggressive order-flow does not necessarily comprise the largest trades since the inside spread is significantly volatile. This aggressive order flow is also likely to be relatively more informed order flow since it represents "aggressive" demand for liquidity, and hence the "resiliency" related conclusions that follow are likely to be confounded by information induced changes that are not measurably controlled for. The prism of aggressive orders also means resiliency-related conclusions are clouded by the strategic timing of these potentially informed aggressive orders, and since "aggressive" is defined in terms of the depth at the best price, the probability of an order being classified as aggressive is, purely by construction, higher when the depth is low at the time of a trade, potentially generating biases at least in relation to depth resiliency.

In view of the above, given that resiliency provides a key insight into the nature of liquidity supply in the market, we believe there is a need for empirical analyses that examine resiliency in a more general setting, one that is not fettered by the prism of aggressive orders or extreme events like trading suspensions. We attempt to undertake such empirical analyses in this paper.

From a theoretical perspective, resiliency has been addressed only by Foucault, Kadan and Kandel (2005), who develop a *dynamic* model of a limit order book market with traders of different degrees of impatience. Their equilibrium limit order book dynamics are determined by two key variables: the proportion of patient traders and the order arrival rate. They conclude that, in such a market, *spread* resiliency increases as the proportion of patient traders increases, and decreases as the order arrival rate increases. They also conclude that spread resiliency increases as the conditional duration till the next transaction increases, and decreases as the tick size decreases; and also predict an increase in *spread* resiliency at the end of the trading day. Extant research has not formally tested any of the empirical implications of the Foucault, Kadan and Kandel (2005) model so far. We do so in this paper.

[7] A major focus of both Degryse et. al. (2005) and Large (2007) is to extend Biais et. al. (1995) to document in greater detail depth and detail the patterns in the order-flow around aggressive orders, and hence, they provide potentially useful results on the timing and frequency of different types of aggressive orders. The focus of this paper is exclusively on resiliency.

The Foucault, Kadan and Kandel (2005) model does ***not*** model *depth resiliency* since all orders are of the same size in their model, and they do not allow orders to queue at the same price. However*,* each of the factors above - proportion of patient traders, the order arrival rate and the end of the trading day – would arguably also be a factor relevant for depth resiliency, and in the same direction. A greater proportion of patient traders implies a greater volume of liquidity supplying traders, and hence greater depth resiliency. An increase in the order arrival rate would mean a greater rate of information arrival, and hence a reluctance on the part of liquidity suppliers to provide free options through their quotes, and hence a reduction in depth resiliency. Finally, at the end of the trading day, traders would be less inclined to leave open positions and hence depth resiliency would decrease. Once again, hypotheses based on these expectations have not been tested so far, and we do so in this paper.

Importantly, Foucault, Kadan and Kandel (2003) do not consider any information-related effects in their model. However, the demand curve literature[8] makes predictions about prices in the presence of trading volume, uncertainty, information asymmetry, and information flow. First, an increase in information asymmetry, information flow or uncertainty would result in greater reluctance on the part of liquidity suppliers to provide free options through their quotes, and hence a reduction in both spread and depth resiliency. Second, greater trading volume, to the extent not generated by information, would arguably result in greater spread and depth resiliency. Finally, bad news should arguably have an asymmetric effect on bid and ask side resiliency in the context of Foucault (1999) and Handa, Schwartz and Tiwari (2003).[9] We test all these predictions in this paper for the first time.

To summarize, we believe that extant research does not presently have a general framework for defining and measuring resiliency; has not analysed resiliency estimates that relate to *uninformed* order-flow, or estimates that have been generated by explicitly controlling for information; has not tested the empirical spread-resiliency related implications of the (only) theoretical model there is in this regard; has not tested corresponding implications for depth resiliency; and has not tested to what extent micro-structural factors like trading activity, uncertainty and asymmetric information, or other stock-specific factors like systematic and unsystematic risk, affect resiliency in time-series and in cross-section. We also do not know the extent of commonality in resiliency across stocks, or whether resiliency is related to the other dimensions of liquidity, spread and depth, or whether it

[8] The demand curve literature discusses whether the demand curve of stock prices is flat or sloped. For more details and evidence see Harris and Gurel (1986), Shleifer (1986), Dhillon and Johnson (1991), Beneish and Whaley (1996) or Kaul, Mehrotra and Morck (2000).

[9] Their prediction is that buy limit orders are submitted more cautiously and sell limit orders more aggressively. Holthausen, Leftwich and Mayers (1990) and Saar (2001) make a similar point by arguing that the ask and bid side of the limit order book behave asymmetrically. Brokers are particularly unwilling to take short positions to accommodate large block purchases, because they might be forced to buy the assets at unfavorable conditions later. In the case of a limit order book, the argument implies that traders on the bid side might be more hesitant to post limit orders.

provides independent new information. This paper aims to plug all these major gaps in the literature.

In this paper, we investigate resiliency in an electronic limit order book market setting rather than a dealer market setting. There are several reasons for this. First, with the enormous proliferation and growth in electronic order matching systems, stock exchanges around the world are increasingly organised as electronic order-driven markets. Except for the New York Stock Exchange, the NASDAQ and the London Stock Exchange, major stock markets conduct trading almost exclusively through open electronic limit order books.

Second, an electronic limit order market is more crucially dependent on the existence of adequate resiliency relative to a dealer or a hybrid market structure. In dealer or hybrid markets, specialists and/or market-makers are typically contractually obliged to always stand ready to buy at their quoted bid price and sell at their quoted ask price, and sometimes also obliged to maintain price continuity. Hence trade execution is guaranteed, albeit not the price. Unlike a dealer market, a limit order book market depends *only* on limit order submissions for new liquidity. This raises the issue of how a limit order book can ensure that enough new liquidity is submitted to the book as liquidity gets consumed. Clearly, trade execution cannot be guaranteed unless there is adequate resiliency. The speed of order-replenishment is critical to any trader because it determines not only the costs of trading, but also the very continuity of the trading process.

Third, order books potentially allow a cleaner estimate of resiliency. In an order book context, the resiliency is, quite literally, the rate of mean reversion in the depth and the spread of the order book, with adequate controls for the information content in trades. This is relatively straightforward to observe, since the depth and spread of the order book can be measured with precision. On the other hand, in dealer or hybrid markets, in the absence of a centralized mechanism for aggregation of available depth, the only way in which we can measure resiliency is by examining the speed with which order-induced pricing errors revert to zero. The problem there is in measuring pricing error, since that requires knowledge of the "true price". While there exist ways in which such estimations can be made[10], the associated estimates of pricing errors and resiliencies are considerably more noisy.

Finally, it is relevant to note that agents who wish to submit a new limit order can do so at a price/tick of their choice. This reveals an important facet of order-book based resiliency: the replenishment of the order book can take place at different points of the price-quantity schedule. If limit orders are submitted far from the former best price, implicit transaction costs stay high. However if the book is refilled close to the former best price, transaction costs get reduced again very quickly. Clearly, the inflow of new liquidity close to the best price is more

[10] See Holthausen, Leftwich and Mayers (1990); and Dong, Kempf and Yadav (2007).

valuable to investors than at prices far from the best price. This is a nuance that makes an order book setting much more valuable for the analysis of resiliency.

We investigate resiliency using limit order data from the electronic trading system Xetra at the German stock exchange in Frankfurt. From the perspective of this study, the German market is clearly preferable to, for example, the markets in the US and the UK, because the German market provides a purely order-driven setting without any dealers and without significant lateral linkages to external liquidity suppliers or liquidity supply systems. The behavior of limit order traders is hence not influenced by resiliency supply from external sources. The trading platform of the Frankfurt Stock Exchange also faces no competition from ECNs and hardly any competition from regional exchanges, and virtually all available liquidity is aggregated in the centralized limit order book. Limit order traders in the German market also face virtually no competition from an upstairs market as in the UK or the US[11]. Importantly, the market depth at the Frankfurt Stock Exchange is also at least as large as at NYSE or NASDAQ[12]. Overall, the limit order book of the Frankfurt Stock Exchange has relatively high depth, is affected by few external factors, and offers a clinically uncontaminated view of the behavior of limit order traders. Hence, it is clearly well-suited for an investigation of resiliency.

To summarize, this paper empirically investigates the main features of resiliency as a dimension of liquidity in an electronic limit order market. We investigate both depth resiliency and spread resiliency by examining the effect of the order-flow, duly controlled for an information measure, on the depth and the inside spread in the order book[13]. Specifically, we first address how we can formally define and measure resiliency. We accordingly set up a mean reversion model of time-varying liquidity to capture the dynamics of the spread and depth over time after controlling for informed order-flow. Second, we examine both ask-side and bid-side depth resiliency at different ticks, and both absolute and relative inside spreads, and do so across a range of different data frequencies. Third, we analyse and test hypotheses in relation to the micro-structural and stock-specific factors that affect resiliency. Fourth, we examine commonality in resiliency across stocks. Fifth, we investigate the lead-lag relationship between spread and depth resiliency. And finally, we examine the relationship between resiliency and the other two liquidity dimensions: spread and depth. Our

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[11] Grammig and Theissen (2005) report for Germany that, in 2002, only 1.5% of trades (constituting only 0.25% of market value) went through the upstairs market. In contrast, 62% of trades are reported as internalized in the UK in 1994 (Hansch, Naik and Viswanathan (1999)); and, in 2000, 52% of NYSE trades were block trades and 28% of these trades went through the upstairs market (Madhavan and Cheng (1999); New York Stock Exchange Factbook Online (2000)).

[12] In our data sample, the average of the depth of all 30 stocks at the best bid and best ask is 7,800 shares. Kavajecz (1999) observes that the average total number of shares for the largest stocks in the NYSE limit order book is 10,006, and of this depth, only 8.91%, i.e. 810 shares, corresponds to the best bid and ask price. More recent data from Bessembinder (2003) indicates that the average depth at NYSE after decimalization in 2001 was 1,937 shares for large capitalization stocks and 1,182 shares at NASDAQ. The average price per share in the US and in Germany is comparable.

[13] Resiliency results from the interaction of liquidity flowing into the market and liquidity being taken out. The inflow comes from the submission of new limit orders, while the outflow results either from the cancellation of limit orders or the execution of limit orders against newly submitted market orders. Together, inflow and outflow also determine the evolution of the price-quantity schedule.

empirical investigation is based on three-months data on the thirty stocks that constitute the DAX.

We find strong evidence that the liquidity dynamics of the order book follows a stable replenishment process: the resiliency for each stock is consistently high and stable across different horizons. Relatively empty order books are refilled quickly, while relatively less new liquidity is submitted to order books that already contain many limit orders. The overall order flow reflects this resiliency, but, far more strongly, the resiliency can be seen in the behaviour of liquidity suppliers around the first few ticks of the book. Resiliency is strongest around the best price and gets steadily weaker the further we move away from the best price in the book. Clearly, trades that are executed against the book take away liquidity at the first few ticks, and traders who actively monitor the book jump in straight away to exploit these profit opportunities in the book. We find there is strong commonality in resiliency across different stocks.

We find that resiliency is dependent in a stable and robust manner on microstructural determinants. As predicted by Foucault, Kadan and Kandel (2005), the resiliency of the spread increases in the proportion of patient traders and decreases with the order arrival rate and at the end of the trading day. For depth resiliency, the proportion of patient traders, intraday order arrival rate and unsystematic risk have the same impact on depth resiliency as they do have on spread resiliency. The impact of the proportion of systematic risk on depth resiliency is positive, indicating greater willingness to provide depth replenishment in the presence of greater hedgeability. Greater long-run order arrival rate increases depth resiliency but greater intra-day order arrival rate (proxying for information flow) reduces it.

In the cross section, the results show consistently that firms with high spread resiliency also have high depth resiliency. We also find that resiliency is not significantly correlated with either spread or depth reinforcing the importance of resiliency as an independent dimension of liquidity providing significant new information.

The rest of this paper is organized as follows: Section 2 gives a brief outline of the market structure and the data used in the study. In Section 3 we present the empirical evidence on “base-case” resiliency without controlling for information flows. In Section 4, we test the impact of informed trading on resiliency. In Section 5, we test time-series based hypotheses on the impact of microstructural factors on resiliency. Section 6 examines commonality in resiliency across stocks. Section 7 analyses resiliency in the cross-section of stocks. Section 8 investigates the granger-causality relationship between spread and depth resiliency. Section 9 examines the relationships between the resiliency, the time dimension of liquidity, and the other spread and depth dimensions of liquidity. Finally, Section 10 summarizes the conclusions.

2. Data

Our study uses data from the electronic limit order market XETRA at the Frankfurt Stock Exchange (FSE). We study the resiliency of the thirty stocks which make up the blue-chip index DAX 30. Our data sample ranges from 2 January 2004 and to 31 March 2004. In that period, Xetra accounts for roughly 98% of all trading activity in these stocks. Floor trading and regional exchanges pale to insignificance.

XETRA operates as fully transparent limit order book. It contains all limit orders except the hidden part of iceberg orders (which are used rarely).[14] Liquidity of the market purely relies on the anonymous submission of limit orders, i.e. there are no designated market makers. Trading is based on a continuous double auction mechanism with automatic computer-based matching of orders. Matching takes place based on price and time priority. The continuous trading phase begins at 9.00 after an opening and ends at 17.00 with a closing auction.[15] During auctions, the order book is closed, yet during continuous trading, the whole limit order book is visible to market participants. The tick size in the book is 1 Eurocent (0.01 Euros) which corresponds to the currency's smallest possible value.[16]

The raw data used in our paper is the computerized trading protocol in which FSE keeps track of all entries, cancellations, revisions, executions and expirations of orders. Additionally, the stock exchange recorded the initial state of the order book at the beginning of our data range. From there, the order book is reconstructed by implementing the Xetra market model. This leads to an order book for each order book event. From this we take snapshots at 5-minute intervals. We exclude order books which result from auctions, since the supply mechanism for liquidity is different in auctions. Finally, we end up with 102 order books every day.

Table 1 gives some summary statistics for the stocks in our sample. It shows that the stocks vary considerably with respect to their liquidity. The stocks' market capitalizations range from 2.95 billion to 61.29 billion Euros. Average daily trading volume varies between 14.13 million Euros and 348.60 million Euros. Absolute spreads lie between 0.01 and 0.09 Euros, relative spreads between 5 and 15 basis points. The depth at the best price lies between 65,773 and 979,214 Euros. These figures show that liquidity exhibits considerable cross-sectional variation, but is pretty high on average for the stocks in our sample.

On average, 887,705 orders were submitted for a stock during the three month

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[14] Only 0.60 % of all orders are iceberg orders. The average volume of a iceberg order is 630,000 Euros, yet mostly only the tip of the iceberg gets executed and the rest is cancelled.

[15] At midday, trading is interrupted for another call auction. Furthermore, if the potential execution price of an order lies outside a prespecified range, continuous trading is interrupted by a further auction to stabilize prices.

[16] For more details on the Xetra market model at FSE see Deutsche Boerse Group (2004).

sample period. About 97.30 % of all submissions were limit orders (including marketable limit orders), 2.10 % market orders, 0.60 % iceberg orders and only 0.05 % market-to-limit orders. Of the submitted limit orders, 23 % get executed and 77 % cancelled. The average market order size is 24,000 Euros and the average limit order 35,000 Euros. The vast majority (84 %) of all trades takes place at best prices, while the remaining 16 % consume more liquidity than available at the best price.

Figure 1 shows a histogram of the number of ticks that market orders and marketable limit orders walk up the book. One sees that the largest part of the orders got settled within the first few ticks. However, some blocks clear the complete depth up to 25 ticks or more. The figure shows that the market as a whole is very liquid, that it mostly accommodates even large trades within the best spread and that even if the volume is too large, most of the matching takes place only very few ticks from the best price. Likewise, nearly all limit order activity takes place in this region as well: limit orders that are further from the best price because of price movements get cancelled or are revised to have new and more competitive price limits; nearly all new liquidity flows into the book within the first ticks from the best price. Limit orders that are far away from the best price are nearly always stale orders.

Based on the data set just described, we calculate now the variables used in our paper. We use four proxies to measure liquidity: depth at the best ask, depth at the best bid, absolute level of inside half spread in cents, and the relative inside half spread in basis points.

We now describe how we construct the variables used to test our hypotheses. We use the log of the trade volume, V_t, as our proxy of the *trading activity* in period. The *uncertainty*, U_t, is proxied by the unexpected volatility. To determine unexpected volatility we use a GARCH(1,1) model with trading volume being a conditional variable. We use this conditional variable since the conditional volatility will otherwise be strongly correlated with trading volume. We estimate the following model:

(1) $$r_t = \mu_{t-1} + \eta_t$$

(2) $$\eta_t \left| (V_t, \eta_{t-1}, \eta_{t-2}, ...) \sim N\left(0, h_t\right)\right.$$

(3) $$h_t = \gamma_0 + \gamma_1 \eta_{t-1} + \gamma_2 h_{t-1} + \gamma_3 V_t$$

r_t is the rate of return, μ_{t-1} is the mean of r_t conditional on past information and trading volume, and h_t is the conditional volatility. The residuals from this model yield the unexpected component of volatility, U_t, which, by construction, will be orthogonal to the trade volume, V_t. The *proportion of patient traders,* PP_t*,* is the number of new limit orders (corrected for cancellations) going into the book, i.e. they are not executed immediately, in relation to the overall number of new orders (corrected for cancellations) in the interval. The *arrival rate,* AR_t is simply the log of the sum of all new orders in an interval, again corrected for the number of cancellations. Finally, we define a dummy variable, D_t^E, which takes the value one if the observation is from the last 45 minutes of the day and zero otherwise.

3. Measuring Resiliency

Resiliency is the dynamic dimension of liquidity that measures how quickly after order-flow shocks does the spread and the depth of a market recover through the inflow of new orders into the market. Accordingly, to measure resiliency, we model the relationship between the current (new) liquidity flow $\Delta L_t = L_t - L_{t-1}$ and the past level of liquidity L_{t-1} as a mean reversion model where the liquidity reverts back to its long-run value θ with the speed of adjustment κ :

(4) $$\Delta L_t = \kappa\left(\theta - L_{t-1}\right) + \varepsilon_t$$

ε_t denotes a mean zero random variable. The higher the value of κ , the stronger the pull-back effect of liquidity to its long-run mean, and thus higher the resiliency. While the spirit of our model is captured by Equation (4), it is necessary to extend the model to enable unbiased estimates of resiliency by including past liquidity changes to capture autocorrelation. We accordingly estimate the extended model in Equation (5) below for all stocks simultaneously using cross-sectional SUR estimation. The constant $\alpha_i = \kappa_i \theta_i$ and the mean reversion parameter κ_i are firm-specific while the lagged values are held constant across stocks, i.e. γ is not firm specific.

(5) $$\Delta L_{i,t} = \alpha_i + \kappa_i L_{i,t-1} + \sum_{\tau=1}^{p} \gamma_\tau \Delta L_{i,t-\tau} + \varepsilon_{i,t}$$

Lags are included up to $p = 20$ since the usual diagnostic checks show no evidence of serial correlation beyond lag 20. ε is the normally distributed white noise error term. If κ in the above model equals zero, there will be a unit root.. Therefore, we test for the presence of a unit root by means of augmented Dickey-Fuller critical t-values. As the model contains no time trend, the critical value, τ_μ , is 3.43 at a 1% significance level and 2.86 at a 5% level. We estimate Equation (5) for the depth at the best price and the absolute spread and report the results are reported in Table 2 for a five-minute data frequency. Figures 2 and 3 report the variation of this aggregate “base-case” resiliency for different data-frequencies and for different number of ticks from the best price respectively.

Table 2 shows that there is strong spread resiliency and strong depth resiliency for each stock. The spread resiliency varies from a minimum of 0.17 (t-stat 8.8) to a maximum of 0.74 (t-stat 14.7), with an average of 0.43 (t-stat 11.8); and if we constrain the resiliency to be constant across all stocks then this common resiliency parameter is 0.40 (t-stat 62.9). The depth resiliency similarly varies from a minimum of 0.16 (t-stat 9.0) to a maximum of 0.59 (t-stat 17.5), with again an average of 0.43 (t-stat 14.7); and if we constrain the resiliency to be constant across all stocks then this common resiliency parameter is 0.34 (t-stat 76.9).

The results are qualitatively similar for resiliency over a one-minute horizon, and hence we do not report them separately. The spread resiliency varies from a minimum of 0.18 (t-stat 18.4) to a maximum of 0.58 (t-stat 47.7), with an average of 0.32 (t-stat 28.5); and if we constrain the resiliency to be constant across all stocks then this common resiliency parameter is 0.27 (t-stat 66.2). The average depth resiliency is similarly 0.33 (t-stat 29.0); and if we constrain the resiliency to be constant across all stocks then this common resiliency parameter is 0.30 (t-stat 68.9).

Figure 2 shows that the variation of resiliency with the time horizon over which it is measured. Spread (Depth) resiliency increases to about 0.7 (0.6) for a 15-minute horizon, and levels off at 0.8 (0.75) for horizons of 30 minutes or higher. Figure 3 shows the variation of the estimated depth resiliency if we vary the number of ticks for which we determine the depth and the depth resiliency. The figure shows that the limit order book is strongly resilient irrespective of the tick which is considered. However, the strength of mean reversion gets less with increasing tick size. For the depth of the limit order book, the resiliency drops from around 0.40 (on the ask side) at the best price to 0.08 ten ticks away from the best price. The bid side behaves in the same way. In all, resiliency at limit prices close to the prevailing best price is strongest. The replenishment mechanism is strongest around the best prices.

4. Impact of Informed Trading on Resiliency

We next estimate the impact of informed trading on resiliency. Arguably, an increase in information flow should result in greater reluctance on the part of liquidity suppliers to provide free options through their quotes, and hence a reduction in both spread and depth resiliency.

Since the information included in an order is not directly observable, we need a proxy for the informed trading variable. We use two proxies for informed trading both of which give qualitatively similar results. First, we use a measure based on the profit of traders demanding liquidity over any notional interval. Second, we use a measure based on absolute magnitude of the order imbalance, and split the order imbalance variable into limit order and market order imbalances. The results reported in Table 3 are based on these order imbalances. We model the resiliency as a linear function of the information proxy, and take the constant as the resiliency for uninformed order flow and the slope coefficient for the information proxy as the impact of information on resiliency. To calculate resiliency we therefore estimate the following model:

(6) $$\Delta L_t = \kappa\left(\theta - L_{t-1}\right) + \varepsilon_t$$

(7) $$\kappa = \alpha + \beta I_t$$

α denotes the mean reversion due to non-informed trades. Table 3 reports the value of α and the corresponding t-statistics for a joint estimation in which the resiliency parameter is constrained to be the same for each stock, and it represents the resiliency after controlling for informed trading.

Table 3 also reports the impact of informed trading. As expected, the impact of informed trading is strongly and significantly negative. Both Spread and Depth Resiliency decrease significantly in the presence of informed trading. The negative impact of informed trading is consistently found also in individual stock-by-stock regressions.

Given that our interest is in resiliency as a measure of liquidity, α, the resiliency parameter after controlling for informed trading, is our measure of resiliency in the remainder of the paper.

5. Time-Series Hypotheses on Resiliency

In this section we investigate how resiliency interacts in the time series with microstructural factors such as the factors suggested in Foucault, Kadan and Kandel (2005) as well as trading activity and uncertainty. In the assessment of the interaction effects of microstructural factors and resiliency, we re-estimate the basic resiliency models, yet we include the microstructural determinants as conditioning variables. In particular, the resiliency parameter now becomes a function of the conditioning variables.

We first test the Foucault, Kadan and Kandel (2005) conclusions that *spread* resiliency increases as the proportion of patient traders increases, as the order arrival rate decreases, and increases at the end of the trading day. The proportion of patient traders is measured as the number of limit order submitted divided by the total number of orders in one period. The long-run order arrival rate of stock is proxied by the average total number of market and limit orders submitted during a period. We estimate the following model:

$$\Delta L_{i,t} = \alpha_i - \kappa_{i,t} L_{i,t-1} + \sum_{\tau=1}^{p} \gamma_\tau \Delta L_{i,t-\tau} + \varepsilon_{i,t}$$

$$\kappa_{i,t} = \beta_i + \phi_i I_{i,t}$$

The results are reported in Panel A of Table 4. Clearly, Foucault et. al. hypotheses on spread resiliency are fully supported by the data. S*pread* resiliency significantly increases:

- As the proportion of patient traders increases,
- As the order arrival rate decreases,
- And increases at the end of the trading day.

However, we note that the model of Foucault, Kadan and Kandel (2005) focuses only on spread resiliency (with no hypotheses on depth resiliency) and adopt two additional simplifying assumptions: assume the order arrival rate to be constant over time; and ignore risk aversion of traders and therefore ignore the impact of risk.

As mentioned above, Foucault, Kadan and Kandel (2005) do not have any hypotheses in relation to depth resiliency. However, each of the earlier factors would arguably also be relevant for depth resiliency. First, a greater proportion of patient traders implies a greater volume of liquidity supplying traders, and hence greater depth resiliency. Second, an increase in the order arrival rate would mean a greater rate of information arrival, and hence a reluctance on the part of liquidity suppliers to provide free options through their quotes, and hence a reduction in depth resiliency. However, higher average order arrival rate also means greater trading volume, and a greater willingness to supply liquidity replenishment. Finally, at the end of the trading day, traders would be less inclined to leave open positions and hence depth resiliency would decrease.

Furthermore, since order arrival rate changes over time and limit order traders are probably risk averse, we also estimate an extended model by including the intraday order arrival rate and two measures of risk: the systematic risk and the unsystematic risk. We measure the intraday order arrival rate in a period as the sum of limit and market orders submitted during that period; systematic risk as captured by beta; and unsystematic risk as the volatility of the market-model residual. Arguably, an increase in information flow should result in greater reluctance on the part of liquidity suppliers to provide free options through their quotes, and hence a reduction in both spread and depth resiliency; and greater trading volume, to the extent not generated by information, would arguably result in greater spread and depth resiliency.

Our model consists of the equations:

(8) $$\Delta L_{i,t} = \alpha_i - \varphi_i L_{i,t-1} + \Sigma_{k=1}^{n} \gamma_k \Delta L_{i,t-k} + \varepsilon_{i,t}$$

(9) $$\varphi_{i,t} = \beta_{0,i} + \beta_1 \cdot I_{i,t} + \beta_2 \cdot D_{i,t}^{E} + \beta_3 \cdot PP_{i,t} + \beta_4 AR_{i,t} + \beta_5 V_{i,t} + \beta_6 U_{i,t}$$

In this model, I is the intraday order arrival rate, AR is the long-run order arrival rate, PP is the proportion of patient traders, END is a dummy variable for the end of the trading day, V corresponds to systematic volatility and U is the proxy for unsystematic volatility. The indices in the equations show that the conditioning variables are time-varying and stock-specific. In the SUR estimation, we let the normal level of resiliency be stock-specific (a_i), however we constrain the impact of the conditioning variables to be the same for all stocks, therefore β_1 to β_6 carry no firm indices.

Panel B of Table 4 shows the results. The table gives resiliency both for the depth as well as the spreads. A positive β coefficient means that resiliency is positively associated with the conditioning factor and a negative coefficient implies a negative association. For spread resiliency, all factors have a significant impact in the expected direction. The hypotheses of the Foucault et. al. (2005) are fully supported in the extended model:

- Spread resiliency increases with the proportion of patient traders, is lower at the end of the day and in stocks with a high long-run order arrival rate.
- It is even lower in periods where the order arrival rate is especially high.
- In high risk stocks spread resiliency is lower than in low risk stocks. This holds true for systematic risk as well as for unsystematic risk.

For depth resiliency, we do not have formal theory-based predictions. However, we can draw the following empirical conclusions:

- Proportion of patient traders, intraday order arrival rate and unsystematic risk have the same impact on depth resiliency as they do have on spread resiliency.
- The impact of the proportion of systematic risk on depth resiliency is positive, indicating greater willingness to provide depth replenishment in the presence of greater hedgeability.
- Greater long-run order arrival rate increases resiliency but greater intra-day order arrival rate (proxying for information flow) reduces it.
- The end of day dummy is positive, which we cannot explain.

6. Commonality

Next we turn to commonality in the variation of resiliency over time. We split the 62-day sample into 62 independent samples and repeat the estimation procedure earlier. Qualitatively the results are the same as in the whole data sample; the resiliency coefficients remain significantly negative. Figure 4 illustrates the time variation of the resiliency parameter for two random stocks and the market as a whole (the constrained parameter across all stocks). The figure illustrates that there is definite time variation in the daily resiliency parameters which vary between 0 and 1. Furthermore, individual resiliency seems to move parallel to the market which we explore in more detail.

We estimate commonality in resiliency with the market model approach as in Chordia, Roll and Subrahmanyam (2000). Following their market model we regress the individual resiliency parameters onto their market average. We do this with daily resiliency estimates. The regression model is the following:

$$(10) \qquad RES_{i,t} = a_i + b_i \cdot MRES_{i,t} + c \cdot MR_{i,t-k} + d \cdot SR_{i,t} + \varepsilon_{i,t}$$

In the equation, $RES_{i,t}$ is each stock's time series of daily resiliency estimates, $MRES_{i,t}$ is the time series of stock-specific market averages -- stock i's $RES_{i,t}$ is dropped for the calculation of $MRES_{i,t}$ -- and $MR_{i,t}$ is the stock-specific market return. $SR_{i,t}$ is the squared stock return which is a noise variable that might cloud commonality. a_i and b_i are assumed to vary across stocks, while the control variables have fixed coefficients c and d. ε is a normally distributed white noise error term. Table 5 gives the results. The evidence of commonality is strong: all 30 coefficients are significant on the bid side and the ask side of the order book. All these parameters are significant at the 1%-level.

7. Resiliency in the Cross-Section

If resiliency varies over time and across stocks, the choice of resilient stocks will ceteris paribus lead to more successful trading. It will be more important, the smaller the per-unit profits and the higher the turnover volume of trading strategies. In this section we focus on the cross-sectional perspective of resiliency. We ask ourselves what characteristics firms share whose stocks are particularly resilient.

An important property of a stock is its risk. We measure the overall risk of a stock i by the volatility of its return, VOL_i, which we average across time. Furthermore, we use the beta factor of stock, BF_i, for its exposure to systematic market risk. It is computed over a time series of stock returns that takes the DAX30 as the market portfolio. This data is provided publicly by the German Stock Exchange. Because the previous section showed that resiliency is negatively associated with informed trading, we also include a factor that measures such information asymmetries. In the cross section it seems plausible that informed trading has an impact on the liquidity supply if the losses of liquidity suppliers to informed traders are high. Therefore we take the stock return in each interval, sign it by the direction of order imbalance and take the sum of all signed returns. Like before we scale the signed returns by the stock's volatility. Under the assumption that order imbalance reflects information, this measure computes the overall profits of an informed traders, IP_i. Finally, we follow Banz (1981) and Fama and French (1992) in adding the firm size as a cross-sectional stock characteristic. Like in the literature, we use the log of market capitalization, MC_i, to measure size.

In a first step, Panel A of Table 6 shows the correlation of the factors among each other. Overall risk (volatility) and systematic risk (beta factor) are associated fairly strongly (0.465) which is not surprising. Otherwise, the correlations are as we would expect, yet not overly high. Panel B shows the correlations of the depth and spread resiliency with these factors. The results are averages of the ask side and the bid side. Market capitalization and the beta factor are both positively correlated with resiliency. In contrast, volatility and informed trader profits are negatively correlated with resiliency. The correlation structure is consistent for spread and depth resiliency.

Let us now turn to the cross-sectional estimation. We re-estimate Equation (5) with informed trader profits, market capitalization, beta and return volatility as conditioning variables. The estimation procedure is the same as in the time series section: again we model the resiliency parameter φ as a function of the conditioning variables. The model is:

$$(11) \qquad \Delta L_{i,t} = \alpha_i - \varphi_i L_{i,t-1} + \Sigma_{k=1}^{n} \gamma_k \Delta L_{i,t-k} + \varepsilon_{i,t}$$

$$(12) \qquad \varphi_i = \delta_0 + \delta_1 \, IP_i + \delta_2 \, BF_i + \delta_3 \, MC_i + \delta_4 \, VOL_i$$

In this model, the indices in the equations show that the conditioning variables are not time-varying yet stock-specific. In the SUR estimation, the mean reversion parameter is function of certain variables (see Equation (12)). The parameters of these conditioning variables is assumed to be the same over all stocks, therefore δ_0 to δ_4 carry no firm indices. We allow the intercept of the resiliency model to be stock-specific, α_i.[17]

Table 7 shows the results. Firstly, δ_0 reflects the base level of resiliency if all conditioning variables are zero (which we call the "base level" of resiliency). Clearly, the base level of resiliency remains strongly significant for depth and spread resiliency. The coefficients are slightly lower than without conditioning variables. The coefficients of the cross-sectional factors confirm the relationships that we observed in the correlation structure. Informed trader profits and resiliency are negatively associated (with highly significant coefficients for both spread and depth resiliency): stocks for which informed traders make higher profits have a less resilient liquidity supply. In contrast, the beta factor has strongly positive relationship with resiliency. Stocks that have a high beta factor also have a high resiliency. The results for market capitalization are not quite as strong: all coefficients are positive, however only one estimate is significant. This is evidence that large stocks tend to be more resilient, however the evidence is fairly weak. Finally, return volatility and resiliency

[17] An alternative approach is to use orthogonalized factors. We do this as a robustness check and obtain qualitatively identical results.

have a negative relationship: more volatile stocks also have a less resilient liquidity supply. This result is very strong for depth resiliency (on the bid and ask side). However, volatility has no significant impact on spread resiliency.

An interesting point to note is how consistent the cross-sectional effects are for spread and depth resiliency. The relationship with informed trader profits, beta and market capitalization is exactly the same. Volatility only has an effect on depth resiliency, while it does not affect spread resiliency. If we compare these results to the time series results, we see that spread and depth resiliency are not synchronous. This suggests a lead-lag relationship on a high frequency. In the cross section however, stocks that have a high depth resiliency also tend to have a high spread resiliency; spread and depth resiliency are linked to the same firm characteristics in the cross section.

8. Relation between Spread and Depth Resiliency

As noted in the previous section, our results arguably indicate that spread and depth resiliency are not synchronous, potentially suggesting a high frequency lead-lag relationship. Accordingly, in this section, we run a formal Granger Causality specification to test for granger causality between spread and depth resiliency.

Our first null hypothesis is that depth Resiliency has no impact on spread resiliency, and we find that this cannot be rejected at conventional significance levels. The F-STAT is 1.66 and the P-VALUE is 0.127. On the other hand, our second null hypothesis - that spread resiliency has no impact on depth resiliency - can be conclusively rejected since F-STAT is 4.30 and the P-VALUE is 0.0002.

9. Relationship with other Liquidity Measures

Evidently, the limit order book of stocks shows a strong tendency to refill once it has been cleared. The mechanism is particularly strong for larger stocks with a high exposure to risk and for stocks with low informational asymmetries. A final question that we pose is whether resiliency provides any new information in addition to depth and spread resiliency.

We re-estimate the resiliency model on a daily basis and collect a time series of resiliency estimates for the spread and depth. Then we collect time series of the average daily bid-ask spread and the average daily depth at the spread.[18] Table 8 shows the correlation structure of spread and depth resiliency with the bid-ask spread and depth. We see that the bid-ask spread and depth are significantly negatively correlated (-0.45). This

[18] We collect these time series for all 30 stocks and for each variable stack the time series into one single vector. Correlations are computed on the basis of these stacked vectors.

implies that spreads are low when depth is high and vice versa. This result is as we would have expected. However, the correlation of either spread resiliency or depth resiliency with either spread or depth, or with each other, is not statistically significant at any meaningful level.

Figure 5A indicates the time series of the correlation of spread resiliency with spread and depth, the other two measures of liquidity, and sets it in context of the correlation between spread and depth. Clearly, while the correlation between spread and depth is reasonably constant at a level of about -0.45, and always statistically significant, the correlations of spread resiliency with depth and spread are both highly variable across time, the correlation of spread resiliency with spread is never statistically significant, and the correlation of spread resiliency with depth is seldom statistically significant.

Similarly, Figure 5B indicates the time series of the correlation of depth resiliency with spread and depth, and sets it in context of the correlation between spread and depth. Once again, the correlations of depth resiliency with depth and spread are both highly variable across time, sometimes positive sometimes negative, and are never statistically significant.

In all, these results strongly indicate that the information in resiliency does not simply duplicate the information in other liquidity dimensions. Instead, it contributes to the understanding of another dimension of liquidity: the time dimension of liquidity.

10. Conclusions

The seminal literature on liquidity (Garbade (1982), Kyle (1985), and Harris (1990)) identifies three main dimensions of liquidity: spread, depth and resiliency. While there has been extensive research focussing on spread and depth, there has been relatively little empirical investigation of resiliency, a dimension of liquidity that is very important to market participants, stock exchanges and regulators. This paper investigates the resiliency in an electronic limit order book environment where there is centralized aggregation of liquidity and depth. We define resiliency as the speed with which the temporary changes induced in depth and spreads by an uninformative order-flow shock are corrected or neutralized by the flow of new orders into the market through the competitive actions of value traders, liquidity suppliers and others.

Our empirical analysis provides several interesting results. We find strong evidence of the existence of order-book resiliency. The resiliency increases with the horizon up to about the 30 minutes, and is strongest at best ticks. And informed trading reduces resiliency. There is also strong evidence of commonality in resiliency across stocks: effectively a market-model in resiliency.

The Foucault, Kadan and Kandel (2005) hypotheses on spread resiliency are fully supported by the data. *Spread* resiliency increases as the proportion of patient traders increases, as the order arrival rate decreases, and increases at the end of the trading day. Spread resiliency is also lower for higher risk stocks.

For depth resiliency, the proportion of patient traders, intraday order arrival rate and unsystematic risk have the same impact on depth resiliency as they do have on spread resiliency. The impact of the proportion of systematic risk on depth resiliency is positive, indicating greater willingness to provide depth replenishment in the presence of greater hedgeability. Greater long-run order arrival rate increases depth resiliency but greater intra-day order arrival rate (proxying for information flow) reduces it.

In the cross section, the results show that firms with high spread resiliency also have high depth resiliency. In time series, the causal relationship is much stronger from spread to depth resiliency rather than the opposite. However, there is little contemporaneous correlation of resiliency with other dimensions of liquidity, spread and depth. Resiliency is an important characteristic of liquidity that is not captured by other dimensions.

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Figures

Figure 1: Histogram of Market Order Ticks

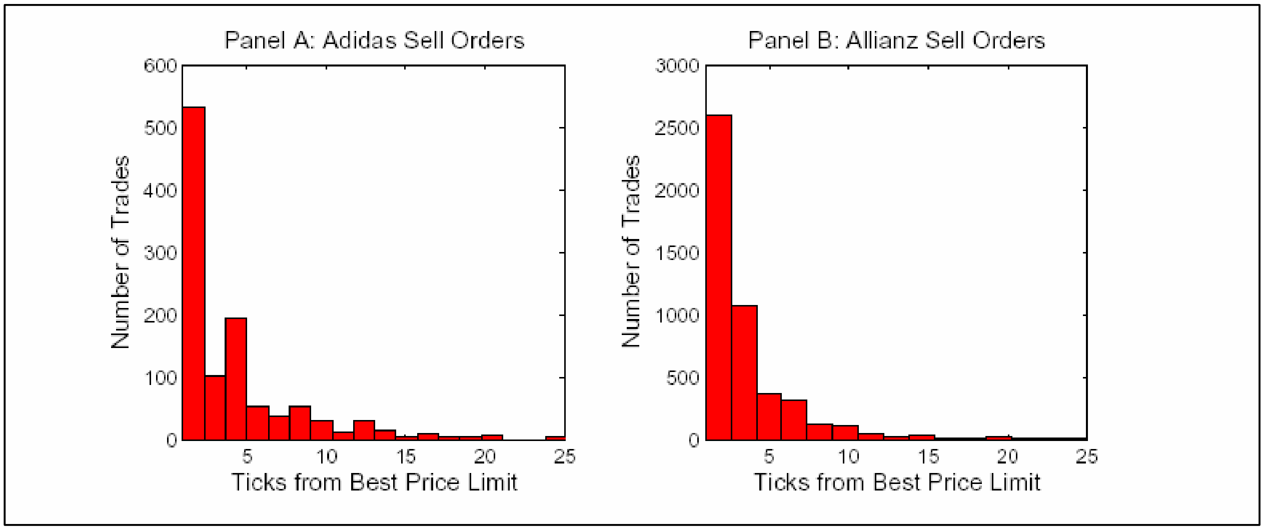

Figure 1 shows two histograms of the market order impact for two stocks, Adidas and Allianz, for trades that are too large to be settled at the best price. The x-axis gives the number of ticks that such market orders walk up the book. The y-axis counts the number of events.

Figure 2

Resiliency for different time intervals

The figure below provides the resiliency on the vertical axis and the time horizon the horizontal axis where 1, 2, 3, 4, and 5 correspond to 1,5,15,30,60 minutes respectively

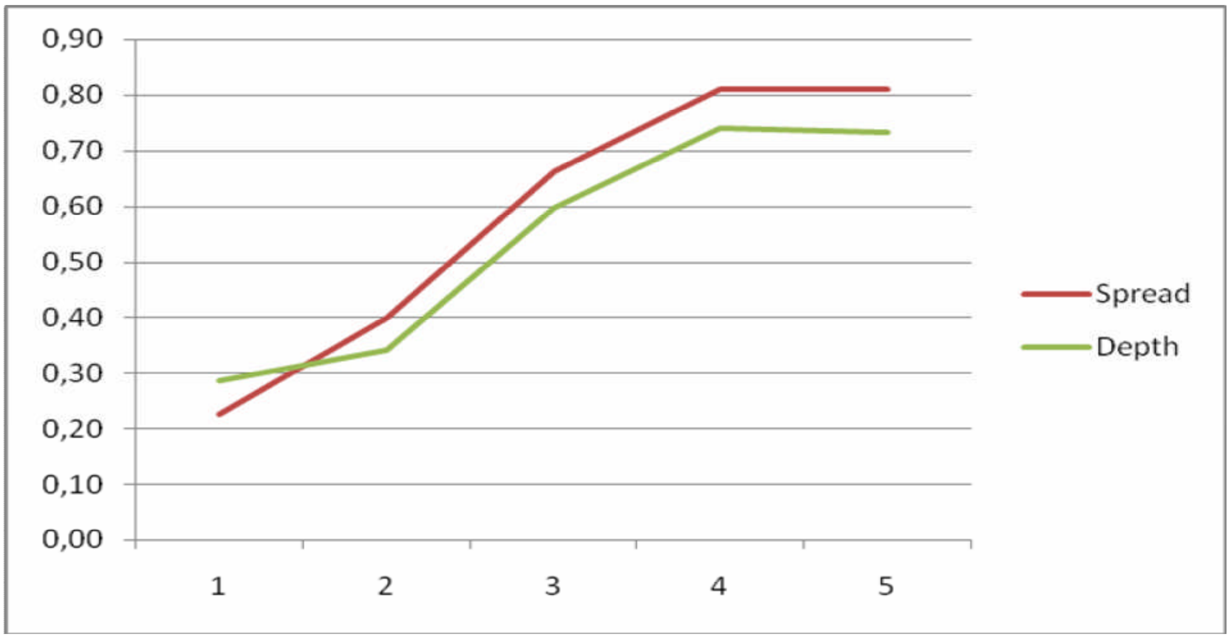

Figure 3

Resiliency for different ticks

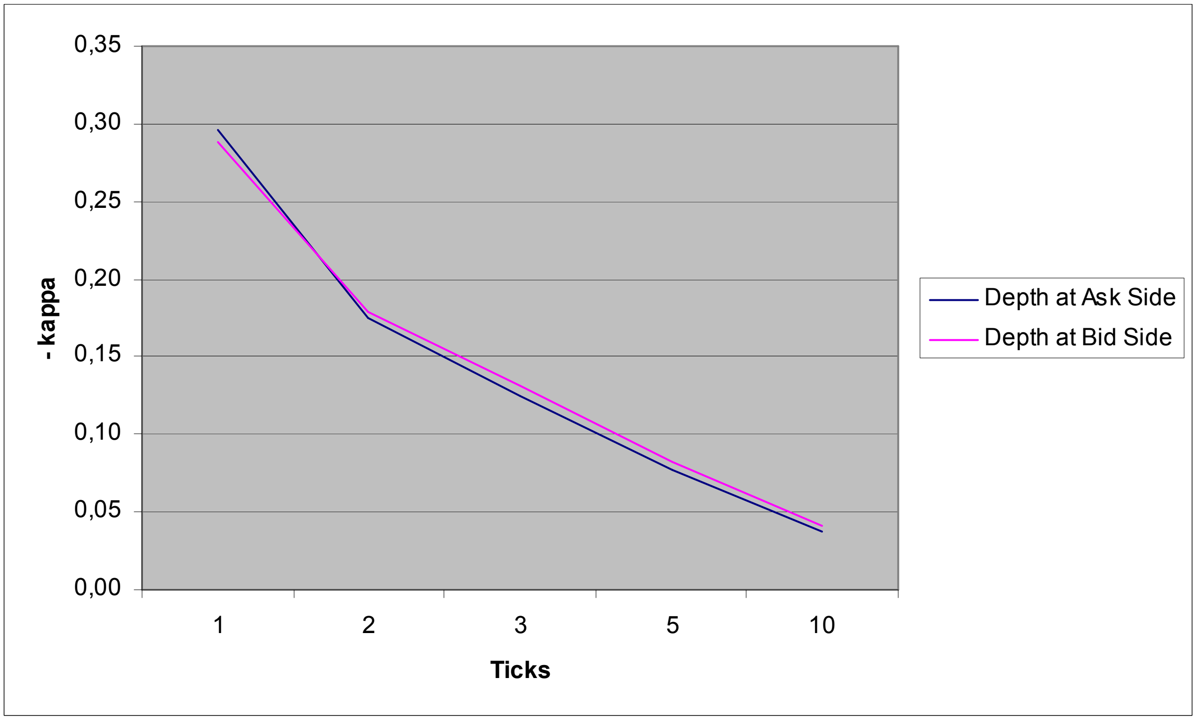

Figure 4: Commonality in Resiliency

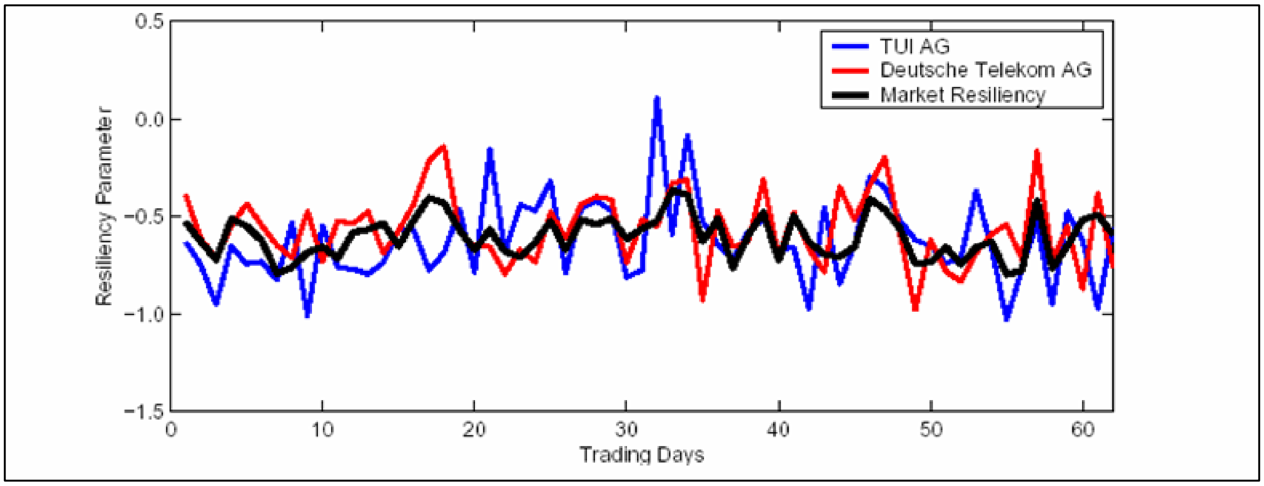

Figure 4 shows the time variation in resiliency of two stocks -- Deutsche Telekom (red graph) and TUI (blue graph) -- as well as the variation of the market average (black graph). The parameters are estimated for each separately and then plotted against a time axis.

Figure 5A: Correlations over Time: Spread Resiliency

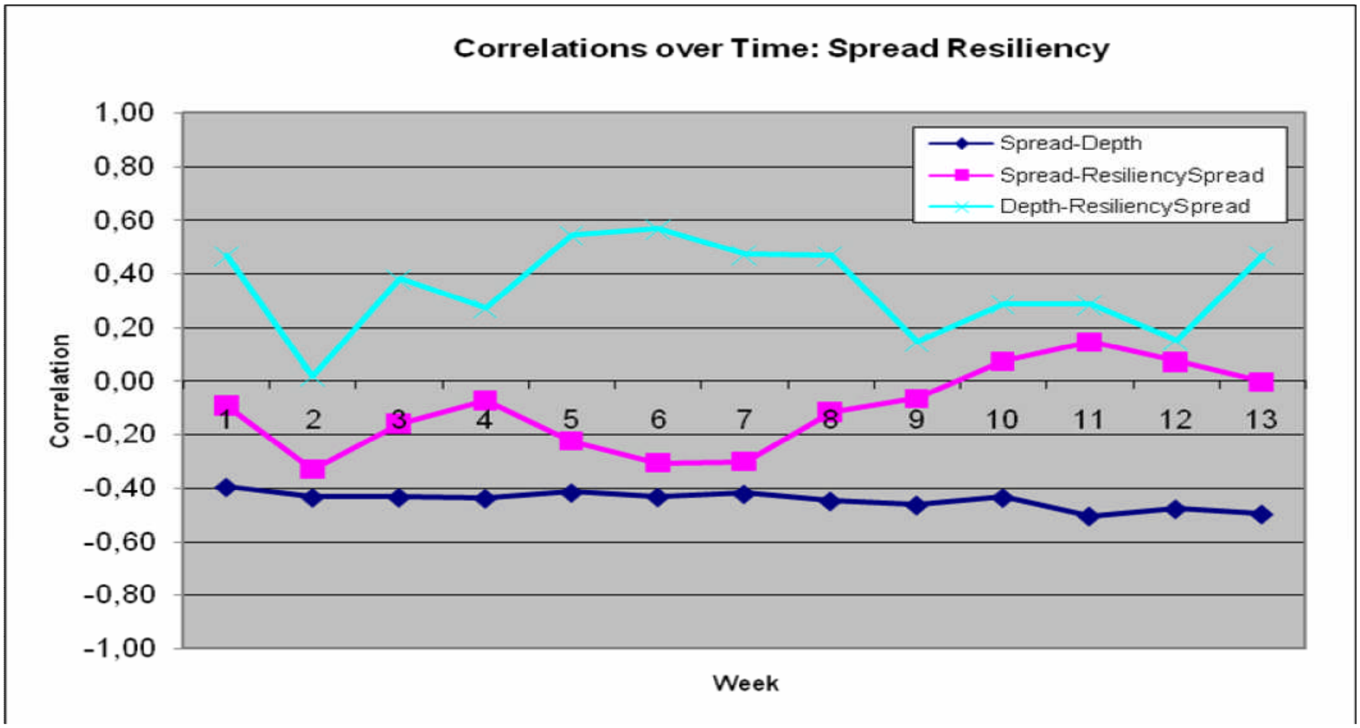

Figure 5B: Correlations over Time: Depth Resiliency

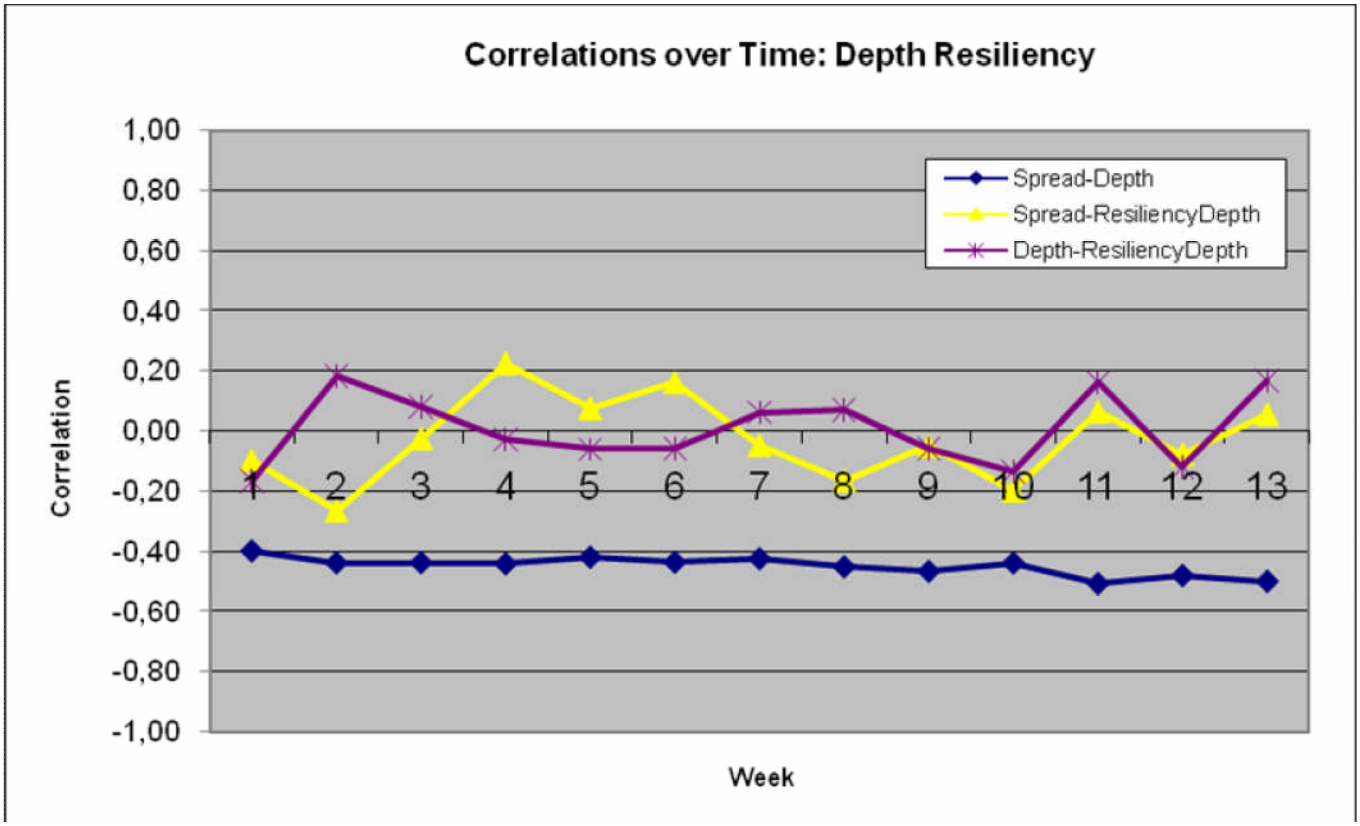

Table 1A: Summary Statistics of the Data Set

	Mean	Median	Max	Min
Market Capitalization	18.20	10.39	61.29	2.95
Daily Trading Volume	114.19	75.22	348.60	14.13
Bid-Ask Spread (in €)	0.04	0.03	0.09	0.01
Bid-Ask Spread (in %)	0.09	0.10	0.15	0.05
Depth (at best prices)	180,487	148,461	979,214	65,773

Table 1A summarizes the main characteristics of the stocks in our data set. Market capitalization is given in billions of Euros and log returns in %. Trading volume is the average daily trading volume in millions of Euros. Absolute spreads and depth at the best price are in Euros and relative spreads in %.

Table 1B: Average Number of Order Submissions

Order Types	Bid Side (Buys)	Ask Side (Sells)	All Orders (Sum)
Market Orders	9,512	9,563	19,075
Limit Orders	433,346	448,878	882,224
Market-to-Limit Orders	204	195	399
Iceberg Orders	2,568	2,514	5,082

Table 1B gives an overview over the average number of order submissions in our data sample. The averages are computed over all 30 stocks in the blue-chip segment of FSE. Column 1 lists the bid side of the book, column 2 the ask side and the third column gives figures for all orders.

Table 2: "Base Case" Resiliency on a 5-minute Frequency

This Table reports regression results for each stock for "base-case" resiliency, i.e. without incorporation of informed trading into the estimation. The columns give the resiliency parameter with its corresponding t-values. The final row gives the resiliency parameter if constrained to be equal across stocks.

Estimated equation for the spread model:

$$\Delta L_{i,t} = \alpha_i - \kappa_i L_{i,t-1} + \sum_{\tau=1}^{p} \gamma_\tau \Delta L_{i,t-\tau} + \varepsilon_{i,t}$$

Estimated equation for the depth model:

$$\Delta L_{i,t} = \alpha_i - \kappa_{i,t} L_{i,t-1} + \sum_{\tau=1}^{p} \gamma_\tau \Delta L_{i,t-\tau} + \varepsilon_{i,t}$$

$$\kappa_{i,t} = \beta_i + \delta_i D_{i,t}^{BID}$$

	Spread		**Depth at Best Price**	
Stock	**K**	**t-stat**	**K**	**t-stat**
Adidas	0.42	12.85	0.41	14.02
Allianz	0.39	10.66	0.57	15.65
Altana	0.42	12.93	0.42	15.08
BASF	0.40	10.68	0.50	14.62
Bayer	0.50	11.75	0.48	14.85
BMW	0.41	11.20	0.53	17.51
Commerzbank	0.52	12.98	0.43	15.25
Continental	0.38	11.71	0.41	16.30
Daimler	0.51	12.45	0.42	13.08
Deutsche Bank	0.45	11.56	0.61	17.40
Deutsche Börse	0.38	11.95	0.41	15.29
Deutsche Post	0.54	13.19	0.53	16.28
Deutsche Telekom	0.70	13.34	0.34	13.97
EON	0.55	13.14	0.49	14.03
Fresenius	0.38	12.66	0.29	12.52
Henkel	0.37	13.19	0.35	12.96
HypoVereinsbank	0.29	9.81	0.14	7.41
Infineon	0.74	14.99	0.35	14.31
Linde	0.41	11.83	0.47	17.67
Lufthansa	0.54	13.00	0.51	17.46
MAN	0.39	12.48	0.39	14.96
Metro	0.46	13.75	0.41	14.21
Münchener Rück	0.35	10.94	0.52	15.14
RWE	0.38	10.02	0.46	15.62
SAP	0.46	12.16	0.42	12.88
Schering	0.44	12.61	0.45	15.32
Siemens	0.08	5.46	0.44	13.48
Thyssen Krupp	0.09	5.03	0.21	7.55
TUI	0.46	13.22	0.56	18.44
Volkswagen	0.50	11.98	0.54	16.62
Average	0.43	11.78	0.43	14.66
Restricted Estimation	0.40	66.55	0.34	75.54

Table 3: The Impact of Informed Trading on Resiliency

Table 3 reports the results of estimating resiliency for the entire sample of stocks constraining the resiliency parameter to be the same across stocks and after controlling for informed trading and the impact of the informed trading parameter.

$$\Delta L_{i,t} = \alpha_i + \kappa_i L_{i,t-1} + \sum_{\tau=1}^{p} \gamma_\tau \Delta L_{i,t-\tau} + \varepsilon_{i,t}$$

$$\kappa_i = \alpha_i + \beta_i I_t$$

	Spread Resiliency	**Depth Resiliency**
Resiliency after controlling for informed Trading	0.42 (62.9***)	0.39 (76.1***)
Impact of Information	-0.06 (-11.0***)	-0.08 (-12.6***)

Table 4: Hypotheses on Time-Series Variation in Resiliency

Table 4 reports the results of testing hypotheses on time series variation in resiliency. The resiliency coefficient is conditioned on time series factors.

PANEL A
Foucault, Kadan and Kandel (2005) Hypothesis on Spread Resiliency

Conditioning Variable	Hypothesis	Coefficient	T
Proportion of Patient Traders	+	0.05	5.96
Long-run Order Arrival Rate	-	-1.14	-18.98
End of Day Dummy	-	-0.03	-8.26

PANEL B

	Spread		**Depth**	
Conditioning Variable	Coef.	T-stat	Coef.	T-stat
Proportion of Patient Traders	0.07	7.97	0.17	7.19
Long-run Order Arrival Rate	-1.43	-13.16	0.94	11.14
End of Day Dummy	-0.02	-7.43	0.05	14.10
Intraday Order Arrival Rate	-0.07	-7.53	-0.16	-4.38
Systematic Risk	-2.80	-2.82	2.10	1.51
Unsystematic Risk	-4.52	-3.88	-6.82	-4.17

Table 5: Commonality in Resiliency

Table 5 reports the regression results of commonality in order book resiliency. The individual resiliency estimates are regressed onto the market average. The market return and squared individual stock return are included as control variables. The coefficient of market liquidity is firm-specific and the t-statistics of market liquidity give the percentage of significant t-values.

		Depth		Spread	
		Ask	Bid	Ask	Bid
Constant	A	-0.006	-0.018	-0.005	-0.017
	t(a)	-2.155	-6.447	-2.774	-3.931
Market Liquidity	B	0.995	0.982	0.985	0.982
	% t(b)	100.00	100.00	100.00	100.00
Market Return	C	0.004	-0.011	-0.001	-0.025
	t(c)	0.265	-0.623	-0.099	-1.575
Squared Return	D	0.000	0.000	0.000	0.000
	t(d)	-0.511	-0.109	0.011	0.192

Table 6: Correlation of Cross-Sectional Factors and Resiliency

Table 6 reports correlation of cross-sectional factors and resiliency measures. Panel A shows the top half of the correlation matrix of the cross-sectional factors amongst each other. Panel B shows the correlation of the resiliency measures with these cross-sectional factors. The critical value at the 5%-quantile is +/- 0.153.

Panel A: Correlation Matrix of Cross-Sectional Factors

		BF	IMB	MC	VOL
Beta Factor	BF	1.000	0.086	0.250	0.465
Informed Trader Profits	IP		1.000	0.194	-0.126
Market Capitalization	MC			1.000	-0.161
Return Volatility	VOL				1.000

Panel B: Correlation Matrix of Resiliency and Cross-Sectional Factors

		BF	IMB	MC	VOL
Resiliency of Depth	φ_D	0.085	-0.161	0.268	-0.198
Resiliency of Spread	φ_S	0.356	-0.221	0.210	-0.223

Table 7: Resiliency Conditional on Cross-sectional Factors

Table 7 shows the results for cross-sectional variation in resiliency. The first column is the estimate of the coefficient and the second column always gives the corresponding t-statistic. Trading volume has been scaled by 10^{-4} and order imbalance by 10^{7} to obtain more presentable coefficient levels.

	Depth				Spread			
	Ask		Bid		Ask		Bid	
	Coeff	T	Coeff	T	Coeff	T	Coeff	T
Constant	-0.81	-40.39	-0.86	-41.03	-0.02	-45.93	-0.02	-45.42
Resiliency (other variables=0)	0.34	17.30	0.27	13.87	0.27	15.43	0.29	15.60
Information	-1.84	-8.98	-1.36	-6.53	-1.20	-8.17	-1.07	-6.88
Beta Factor	0.03	2.72	0.04	4.02	0.05	7.54	0.06	8.68
Firm size (in logarithms)	0.00	0.48	0.01	3.90	0.00	1.36	0.00	1.07
Return volatility	-9.48	-7.57	-6.59	-5.16	0.63	0.58	-1.39	-1.23

Table 8: Correlation of Resiliency Measures

Table 8 reports correlation of the various measures of resiliency with each other. In particular, we correlate the bid-ask spread and depth at the spread with resiliency. The table shows the results for the resiliency of the spread and depth. The diagonal consists of ones and only the top half of the table is reported for the sake of brevity. The critical value at the 5\%-quantile is +/- 0.153.

	Spread	Depth	Spread Resiliency	Depth Resiliency
Spread	1	-0.45**	-0.09	-0.04
Depth		1	0.29	-0.13
Spread Resiliency			1	0.28
Depth Resiliency				1