Resiliency: A Dynamic View of Liquidity

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Resiliency: A Dynamic View of Liquidity

Abstract

We investigate the factors governing market resiliency, and test relevant hypotheses. Our results for spread and depth resiliency are similar, and robust with respect to the order-book depth at which liquidity is measured. We find strong commonality in resiliency across stocks, similar to that found for spread and depth. We find that resiliency increases with the proportion of patient traders, decreases with order arrival rate, and increases with tick size; providing strong support for the Foucault, Kadan, and Kandel (2005) model. Resiliency is also greater when information flow and information asymmetry are lower, and when algorithmic trading is higher.

Resiliency: A Dynamic View of Liquidity

The seminal contributions on liquidity by Garbade (1982) and Kyle (1985) identify three main dimensions of liquidity: spread, depth, and resiliency. Spread is the price dimension representing the transaction costs faced by public traders. Depth is the quantity dimension reflecting the market's ability to absorb order flow of significant size with minimal price impact. Resiliency is the time dimension that characterizes the recovery of a market after a liquidity shock, thereby providing a dynamic perspective on liquidity. In this paper, our focus – like that of Foucault, Kadan, and Kandel (2005) (hereafter "FKK") – is on the resiliency in market liquidity: specifically, spread and depth.[1] We accordingly define and empirically investigate measures of resiliency that represent the extent to which scarce liquidity gets replenished or excess liquidity gets consumed within a pre-specified time. These resiliency measures are a determinant of the volatility of trading costs and tradable quantities, and thereby of the risk arising from the price and quantity dimensions of liquidity. They also reflect the stability, or the fragility, associated with the ability of liquidity demanders to always reliably get immediate execution of their orders, even in turbulent and stressful periods. Thus, resiliency is a critically important dimension of liquidity in the context of overall market quality. Despite its key role and importance, we know relatively little about resiliency, while spread and depth are empirically well researched.[2] In this context, we provide a framework for estimating resiliency, analyse the factors governing resiliency, and test relevant hypotheses in relation to them.

The investigation of resiliency is particularly important for electronic limit order book markets, now increasingly pervasive globally for trading equities.[3] This is because new liquidity in these markets is provided only through new limit orders, and such limit order submissions by a trader are purely voluntary. There are typically no 'market-makers' obliged to stand ready to take the other side of a customer's buy or sell order at a regulated maximum spread and minimum quantity. This raises significant concerns among market participants, and implicit supervisory obligations for regulators, in relation to the quality and extent of new liquidity submitted to the book (as liquidity gets consumed), particularly in periods of market stress: for example, when buy-sell trade imbalances are significantly large, or when prices are particularly volatile. The fragility of limit order book markets is the subject of heavy regulatory attention also because of the massive growth in algorithmic trading, and the exceptionally huge and rapid liquidity changes algorithms have sometimes generated. These concerns have been exacerbated by the flash crash of May 6, 2010, and by the numerous mini-flash-crashes that have been reported from time to time.[4] An understanding of resiliency is arguably front and center in a regulatory context.

Resiliency is important for market participants, stock exchanges, and regulators also in regular market conditions. Public traders in limit order book markets can potentially face significant execution risk as they wait for spreads or depth to bounce back to normal levels through the inflow or outflow of limit orders after a trade. For example, traders of large blocks break up their trades into smaller blocks for a better execution price, and may have to wait for a non-trivial time period before they can execute successive blocks.[5] 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 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 incorporate an analysis of resiliency into their monitoring of market quality and stability.

In the context of a limit order book market, the inflow of new liquidity into the market is in the form of new "standing" limit orders, and the outflow of liquidity from the market is through cancellation of limit orders, or the execution of existing limit orders (against new market or marketable limit orders). The net liquidity flow determines the evolution of the price-quantity schedule, and consequently resiliency. Since resiliency is the extent to which liquidity recovers within a given time frame after a liquidity shock, it can be defined as the extent to which any deviations of liquidity from its long-run "normal" value are offset by the net flow of liquidity over the next time period. Accordingly, we define resiliency as the rate of mean reversion in liquidity. We investigate spread resiliency by examining mean reversion in the inside relative bid-ask spread and depth resiliency by analysing mean reversion in the depth at the inside spread.

Spread resiliency does not appear to have been examined in the extant empirical literature at all, and depth resiliency has been examined only by looking at extreme events. Bhattacharya and Spiegel (1998) analyse the "resiliency" of the New York Stock Exchange in terms of its ability to absorb high volatility shocks without suspending trade. Coppejans, Domowitz, and Madhavan (2004) and Gomber, Schweickert, and Theissen (2015) both look at large liquidity shocks. Coppejans, Domowitz, and Madhavan (2004) are the first to analyse the time variation of order book depth, and thereby document depth resiliency, but they do so with a focus on cross-effects with time-varying returns and time-varying volatility. Gomber, Schweickert and Theissen (2015) focus on time variation in their exchange liquidity measure (which is a measure of the transaction costs for one fixed trade size) in response to the hundred largest trades. Degryse et al. (2005) and Large (2007) build a picture of market resiliency by focusing on “aggressive orders”, i.e., orders that demand more liquidity than is available at the best prices. Degryse et al. (2005) investigate limit-order book updates before and after aggressive orders in an event-study framework to examine their impact on prices, depth and spread.[6] Large (2007) estimates a continuous time impulse response function using data of a single stock. Thus, all we know empirically so far is about depth resiliency, and that is also only through the prism of relatively rare events.[7] In contrast, the analysis in this paper is general – not confined to specific periods or orders.

Our empirical analysis of spread and depth resiliency is based on data on FTSE100 stocks from the Stock Exchange Trading System (SETS) of the London Stock Exchange, and captures virtually all the limit-order-book traded liquidity flows in our sample stocks. In contradistinction, with the share of the NYSE down to under 30%, trading in U.S. stocks is fragmented across several limit order books with multiplicity of order types, different rules, and different levels of transparency (including ‘dark pools’), making overall inferences with U.S. data problematic. Our data period is July 2007 to August 2009, and thus spans the 2008 financial crisis period, providing us with a stressful sub-period with high buy-sell imbalances and high price volatility; and that is particularly relevant for an analysis of resiliency given extensive regulatory concerns about market fragility. Furthermore, even though we examine only relatively heavily traded stocks, there is considerable variation in liquidity in our sample – from a daily aggregate trading volume of less than one million British pounds-sterling to over 153 million pounds-sterling.

We find that both depth and spread resiliency are significantly greater than zero (with *p*-values << 1%) for each and every stock, and for each and every day of the sample period. The average spread and depth resiliencies over a five-minute interval are 0.60 and 0.54 respectively, implying an average half-life of only about four minutes. We also find strong evidence of commonality in resiliency, not dissimilar from the commonality in the price and quantity dimensions of liquidity (i.e., spread and depth) documented by Chordia, Roll, and Subrahmanyam (2000) and Hasbrouck and Seppi (2001) respectively. The average adjusted R^2 of regressions of individual stock resiliency on overall market resiliency is about 6.6% for spread resiliency and 5.5% for depth resiliency.

We next test the empirical predictions of the FKK theoretical model.[8] FKK address spread resiliency from a theoretical perspective by developing 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 three key variables: the proportion of patient traders, the order arrival rate, and the tick size. They conclude that, in such a market, spread resiliency increases as the proportion of patient traders increases, decreases as the order arrival rate increases, and increases with the tick size. We find strong support for the FKK hypotheses: Spread resiliency increases in the proportion of patient traders, decreases with the order arrival rate, and increases with tick size. Even though the FKK hypotheses relate only to spread resiliency, we find that depth resiliency also displays the same dependencies. The results are robust to the addition of other potentially relevant factors.

Greater information flow and/or greater information asymmetry should arguably lead to greater risk and uncertainty for liquidity suppliers, and hence reduced engagement in liquidity provision from them, potentially leading to lower resiliency and greater stresses in liquidity supply. Accordingly, we hypothesize that resiliency is inversely dependent on information flow and information asymmetry. Using intraday volatility and order imbalance as our information-related proxies, we find strong support for our hypothesis: both spread and depth resiliency decline significantly when information flow or information asymmetry are relatively high.

Algorithmic traders are increasingly becoming the principal suppliers of liquidity, and extant evidence indicates that algorithmic trading ordinarily increases liquidity (Hendershott, Jones, Menkveld, 2011), in particular on relatively low-volatility days (Raman, Robe, and Yadav, 2014) and in relatively large stocks (Hendershott, Jones, Menkveld, 2011, and Boehmer, Fong, and Wu, 2014). Hence, we hypothesize and test whether resiliency is positively related to the extent of algorithmic trading. The empirical results strongly support our hypotheses: resiliency increases with the extent of algorithmic trading.

We extend our analysis of spread and depth resiliency at best prices to resiliency deeper in the order book, i.e., the mean reversion in liquidity using the relative spread and depth at the best three price ticks, and at the best five price ticks. We find that: (i) resiliency deeper in the order book is smaller than resiliency at best prices, consistent with investors supplying limit orders mainly at best prices; (ii) the commonality of resiliency deeper in the order book is higher than commonality of resiliency at best prices suggesting that systematic liquidity risk is higher for large traders who potentially trade deeper in the order book; and (iii) resiliency deeper in the order book is driven by the same factors as resiliency at best prices. Irrespective, our overall conclusions are robust to whether we measure resiliency at best prices or deeper in the order book.

We next adjust our resiliency estimation model to differentiate between replenishment resiliency, i.e., the extent to which scarce (abnormally low) liquidity is replenished, and consumption resiliency, i.e., the extent to which excess (abnormally high) liquidity is consumed. We find that replenishment resiliency is slightly smaller than consumption resiliency but the difference is only borderline significant. Overall, both replenishment and consumption resiliency are driven by the same factors as the resiliency measure estimated without allowing for any asymmetry.

Finally, we analyse resiliency during the financial crises, i.e., a period of particularly high stress. We hypothesize that consumption and replenishment resiliency should differ qualitatively between the bid and the ask side of the order book during the financial crisis period. More specifically, we expect that any excess liquidity on the bid side of the order book (where liquidity providers stand ready to buy) will be consumed quickly, leading to a high consumption resiliency. Conversely, we expect liquidity providers to replenish liquidity less aggressively, leading to a lower replenishment resiliency. However, at the ask side (where liquidity providers stand ready to sell), we expect to see the opposite pattern. Any excess liquidity will be consumed slowly and replenished quickly leading to lower consumption and higher replenishment resiliency. Our empirical results strongly support all these hypotheses. Furthermore, we find that, even in the financial crisis, resiliency depends in a stable manner on market resiliency, proportion of patient traders, order arrival rate, tick size, information, and algorithmic trading (as it does in our sample period overall).

The rest of this paper is organized as follows: Section I presents our framework for defining and measuring resiliency. Section II gives a brief outline of the market structure and the data used in the study. In Section III, we present a descriptive analysis of spread and depth resiliency. Section IV documents the results of our empirical tests: it explores commonality, tests the FKK hypotheses, and analyses the impact of information risk and algorithmic trading on resiliency. In Section V we extend our analysis to resiliency deeper in the order book. Section VI differentiates between replenishment and consumption resiliency and Section VII focuses on resiliency during the financial crisis. Finally, Section VIII offers concluding remarks.

I. Measuring Resiliency

We define resiliency as the rate of mean reversion in our liquidity measure – the relative bid-ask spread or the depth. The bulk of the analyses in the paper are based on spread and depth measured at the best quotes to buy and sell. However, for robustness, we also estimate both spread and depth resiliency deeper in the order book at the 3rd and the 5th best quotes on either side.

Resiliency is hence the extent to which any deviation of our liquidity measure from its “long-term” value is offset by the net flow of liquidity (in the form of an offsetting change in spread or depth) over the next time period. To measure resiliency, we accordingly model the relationship between the past level of liquidity L_{t-1} and the current liquidity flow $\Delta L_t = L_t - L_{t-1}$ as a mean reversion model, where liquidity reverts back to its long-run value θ with the speed of adjustment κ:

$$\Delta L_t = \kappa\left(\theta - L_{t-1}\right) + \varepsilon_t, \qquad (0)$$

where ε is a normally distributed white noise error term; and where κ measures the level of resiliency. The higher κ is, the stronger is the pull-back effect of liquidity to its long-run mean, and the higher the resiliency.

However, liquidity flows have high serial correlation; and for unbiased estimation of κ, it is necessary to eliminate the serial correlation in the residuals by including immediately preceding past liquidity changes as additional explanatory variables. For our data, five lagged liquidity change terms are adequate to eliminate serial correlation in the residuals. Accordingly, we estimate the following model separately for each stock *i,* for each trading day *T,* and for each of our two liquidity measures, spread and depth:

(0) $$\Delta L_{i,t}^{S/D} = \alpha_{i,\mathrm{T}}^{S/D} - \kappa_{i,\mathrm{T}}^{S/D} L_{i,t-1}^{S/D} + \sum_{\tau=1}^{5} \gamma_{i,t-\tau}^{S/D} \Delta L_{i,t-\tau}^{S/D} + \varepsilon_{i,t}^{S/D},$$

where *S/D* indicates whether liquidity is measured via spread (*S*) or depth (*D*), and *t* is the time index on day *T*.

II. Data

We use data from the SETS electronic order book of the London Stock Exchange (LSE). We study the resiliency of FTSE-100 stocks, with a sample ranging from July 2, 2007 to August 31, 2009. SETS is a transparent order book, where customers submit standing limit orders, marketable limit orders, and market orders. Liquidity within the order book relies totally on the anonymous submission of limit orders, i.e., there are no designated market makers providing liquidity in SETS. Trading is based on a continuous double auction with automatic order matching based on price and time priority. Continuous trading begins at 8.00 a.m. after an opening auction and ends at 4.30 p.m. with a closing auction. During our sample period, the tick size for a SETS stock was dependent on the price of the stock.[9]

The raw data used in this paper consists of 5-minute snapshots of the order book for FTSE-100 stocks. These snapshots include a time stamp, the stock identifier, the number of buy and sell trades, buy and sell trading volume, bid and ask quotes, quoted depth at best quotes as well as at level 3 and 5, the number and volume of new buy and sell limit orders, and the number and volume of cancelled buy and sell limit orders. We exclude all order books prior to 8.05 a.m. and after 4.30 p.m., and end up with 102 order books per stock and trading day. We additionally source the daily market capitalization of each stock from LSE.

We take several measures to ensure data consistency, and to prevent the distortion of results by extreme observations. First, we omit stale quotes: we delete all observations where the best bid quote exceeds the best ask quote. Second, we exclude all observations where the best bid (ask) quote differs from the mean bid (ask) quote on that day by more than three standard deviations. Third, for each stock, we exclude all days where we have fewer than 6 order books (corresponding to 30 minutes of trading) on that day. Last, we exclude all days where we have order books for fewer than 50 stocks. This procedure leaves us with a set of 120 stocks and 486 trading days.[10]

Insert Table I about here.

Table I presents summary statistics for our sample stocks. Our sample stocks vary very considerably with respect to market capitalization and liquidity. Market capitalization ranges from 1.3 bn GBP (Ferrexpo) to 113 bn GBP (Royal Dutch Shell); average daily aggregate trading volume is between GBP 350,000 (Serco Group) and GBP 313 mn (HSBC); relative bid-ask spreads lie between 0.05% (AstraZeneca PLC) and 0.69% (Fresnillo PLC); and the depth at the best price lies between GBP 17,421 (Schroders) and GBP 622,302 (BP).

III. Descriptive Analysis of Resiliency

We estimate spread and depth resiliency $\hat{\kappa}_{i,T}^{S/D}$ for each stock and for each day of our sample period running an OLS regression based on Equation (0). We find that both depth and spread resiliency are significantly greater than zero (with *p*-values below 1%) *for each and every stock*, and *for each and every day* of the sample period. We also calculate the time-series average of the daily resiliency parameters, $\hat{\kappa}_{i}^{S/D}$, and the inter-quartile range

(75% percentile minus 25% percentile) for each stock *i*. Table II provides a summary description of our individual stock resiliency estimates.

Insert Table II about here:

Panel A of Table II shows that the average spread and depth resiliency estimates across all sample stocks are $\hat{\kappa}^S = 0.60$ and $\hat{\kappa}^D = 0.54$, respectively. Assuming an underlying arithmetic Ornstein-Uhlenbeck process, and our 5-minute data frequency, this implies that, on average, liquidity deviations have a half-life of about four minutes. Irrespective of the underlying process, it is clear that liquidity shocks in this market are neutralized fairly quickly through net flow of new orders. Panel B of Table II shows that individual stock resiliencies are fairly stable over time, even though the sample straddles the financial crisis period. The inter-quartile range across time of individual stock resiliencies is about 0.12, on average. It varies from 0.06 to 0.18 for spread resiliency, and from 0.09 to 0.18 for depth resiliency.

Even though individual stock resiliencies are large and significant for each day and each stock, there is considerable variation in the average resiliencies across sample stocks. Figure 1 show histograms of average resiliency across stocks.

Insert Figure 1 about here.

The minimum spread resiliency is 0.39, but only 4 out of the 120 stocks have a value below 0.5. Thus, the half-life of spread deviations is shorter than five minutes for almost all stocks. The minimum depth resiliency at 0.37 is lower than the minimum for spread resiliency, as is the maximum depth resiliency of 0.75 compared to 0.80 for spread resiliency. The depth resiliencies of 30 stocks, i.e., 25% of the stocks in our sample, are below 0.5.

We next split the stocks in our sample into two groups according to their market capitalization (above and below the median). We expect to see a higher resiliency for larger firms since these are known to have smaller spreads and a higher depth (see, e.g., Stoll and Whaley, 1983, Roll, 1984, and Huberman and Halka, 2001). Figure 2 shows histograms like in Figure 1 separately for large and small firms.

Insert Figure 2 about here.

Figure 2 shows that both spread and depth resiliency are clearly related to firm size. Stocks of large firms tend to be more resilient than stocks of small firms. The average spread resiliency is 0.65 for firms with a market capitalization above the median and 0.56 for firms below the median. For depth resiliency, the difference is smaller with an average of 0.57 for above-median firms and 0.52 for below-median firms. Even a simple *t*-test allows us to reject, for both spread and depth resiliency, the hypothesis of equality of mean resiliencies of above-median firms vs. below-median firms (and both with a *p*-value below 0.1%).

We next analyse the time series of resiliency. To do so, we calculate market spread and market depth resiliency $MR_T^{S/D}$ as simple averages of the resiliency parameters $\hat{\kappa}_{i,T}^{S/D}$ across all stocks on day *T*. The time series are plotted in Panels A and B of Figure 3.

Insert Figure 3 about here.

The figure shows that there is only a modest variation in market spread and market depth resiliency over time. Even during the financial crisis period, resiliency remains fairly high. The minimum value of market spread resiliency MR_T^S of about 0.41 and of 0.34 for market depth resiliency MR_T^D on September 17, 2008, imply half-lives of six to seven minutes. This modest variation of resiliency is consistent with the inter-quartile ranges on individual stock resiliencies shown in Table II.

Panel C of Figure 3 shows time series of the market relative bid-ask spread in percentage points and market depth at best prices in unit of shares. We see that, in contrast to resiliency, spread and depth fluctuate very considerably over time; and as expected, the spread is highest and the depth lowest during the 2008 financial crisis. We can also see that the temporal relationship between the three dimensions of liquidity – spreads, depth, and resiliency – is quite weak.

To formalize the visual impression from Figure 3, we calculate the average correlations of spread, depth, spread resiliency, and depth resiliency. We first estimate correlation between the measures for each stock *i* over time, and then take averages across the 120 stocks. The coefficient signs are as expected: spread and depth resiliency are negatively correlated with spreads, and positively correlated with depth. Thus, the time dimension of liquidity tends to be high when the price and the quantity dimension are high. However, the correlations are small with absolute values between 0.04 and 0.17 on average, and stock specific estimates have absolute values consistently below 0.4. We conclude that resiliency is a liquidity dimension that provides information not subsumed in the information provided by the other two dimensions of liquidity – spread and depth.

IV. Empirical Tests

IV.A Commonality in Resiliency

Given the evidence of commonality in the price and quantity dimensions of liquidity (i.e., spread and depth) provided by Chordia, Roll, and Subrahmanyam (2000) and Hasbrouck and Seppi (2001), we hypothesize that there is also commonality in the time dimension of liquidity, i.e., stock resiliency depends significantly on market resiliency. To test this hypothesis, we estimate commonality in resiliency via the market model approach of

Chordia, Roll, and Subrahmanyam (2000). We regress the resiliency parameter $\hat{\kappa}_{i,T}^{S/D}$ of (each) stock *i* for each trading day *T* on market resiliency $MR_T^{S/D}$ calculated by averaging the resiliency of all sample stocks but leaving out the resiliency of the specific stock *i*. We run the following time-series regression for each stock separately:

(0) $$\hat{\kappa}_{i,T}^{S/D} = \alpha_i^{S/D} + \beta_i^{S/D} MR_T^{S/D} + \varepsilon_{i,T}^{S/D}$$

Figure 4 provides the histogram of $\hat{\beta}_i^{S/D}$ across stocks. It shows that there is considerable variation in commonality across stocks. For spread resiliency (Panel A), the loading of stock-specific resiliency on market resiliency lies between 0.20 and 1.37 with a mean of 0.86. Stock-specific depth resiliency (Panel B) loads on market depth resiliency with a factor between 0.10 and 1.41, the mean lies at 0.87. The high average loading implies that market resiliency plays an important role in determining stock-specific resiliency.

Insert Figure 4 about here.

To summarize stock-specific information, we average the stock-specific parameter $\hat{\beta}_i^{S/D}$ across stocks as in Chordia, Roll, and Subrahmanyam (2000). The average parameter estimate, average *t*-statistic (in parentheses), percentage of estimates significant at least at the 10%-level, and average adjusted R^2 are presented in Panel A of Table III.

Insert Table III about here.

The results clearly document strong commonality in resiliency. Market resiliency has a very significant impact on stock resiliency. Panel A of Table III shows that in 96% (93%) of all cases, the impact of market spread (depth) resiliency on stock spread (depth) resiliency is significant at the 10%-level at least, and the average *t*-statistic is 4.99 (4.51). The estimated average coefficient is 0.81 for spread resiliency and 0.79 for depth resiliency. The average adjusted R^2 is our measure of the strength of commonality since it indicates how much of stock specific resiliency can be explained by market resiliency. The average adjusted R^2 equals 6.6% for spread resiliency and 5.5% for depth resiliency.

To control for other market-wide factors that might influence resiliency, we add several control variables to our basic model. We include the daily market return to control for market-wide price movements. We calculate the market return as the simple average return of the stocks (excluding the stock *i* whose resiliency is being modeled) in our sample and include the contemporaneous market return, $Ret_{-i,T}$, as well as the one-day-lagged market return, $Ret_{-i,T-1}$, in our extended model. Furthermore, we add the price range of the market to capture the uncertainty of the traders. We calculate the price range of the market as the average of the price ranges of the individual stocks (excluding the stock *i* whose resiliency is being modeled). The price range of an individual stock is calculated as the difference between the highest and the lowest price of the stock during a day scaled by the average price over this day. We include the contemporaneous market price range, $Range_{-i,T}$, and the one-day-lagged market price range, $Range_{-i,T-1}$. Furthermore, when the market resiliency changes, some stocks might lead this movement and others might follow with a lag. Therefore, we also add non-contemporaneous values of the market resiliency, $MR_{T-1}^{S/D}$ and $MR_{T+1}^{S/D}$. Thus, our extended model reads as follows:

(0)
$$\hat{\kappa}_{i,\mathrm{T}}^{S/D} = \alpha_i^{S/D} + \beta_{i,1}^{S/D} MR_{T+1}^{S/D} + \beta_{i,2}^{S/D} MR_T^{S/D} + \beta_{i,3}^{S/D} MR_{T-1}^{S/D} + \beta_{i,4}^{S/D} Ret_{-i,T} + \beta_{i,5}^{S/D} Ret_{-i,T-1} + \beta_{i,6}^{S/D} Range_{-i,T} + \beta_{i,7}^{S/D} Range_{-i,T-1} + \varepsilon_{i,\mathrm{T}}^{S/D}$$

The results of the extended model are provided in Panel B of Table III. For sake of brevity, we provide only the same information as in Panel A, i.e., we leave out the results for the control variables. The extended model leads to almost the same results as the basic model. Panel B again clearly documents commonality in resiliency. The contemporaneous market resiliency has a strong impact on individual stock resiliency, whether we consider spread or depth resiliency. In 93% (87%) of all cases, it is significant at least at the 10%-level. Both the estimated coefficients and the average *t*-statistics are similar to the ones in the base model. Including the control variables increases the average adjusted R^2 for spread (depth) resiliency by only 1.97 (0.93) percentage points.

IV.B The Foucault, Kadan, and Kandel (2005) Hypotheses

We next test the following hypotheses of the theoretical model of Foucault, Kadan, and Kandel (2005). For spread resiliency they hypothesize: (i) Resiliency increases with the proportion of patient traders. (ii) Resiliency decreases as the order arrival rate increases. (iii) Resiliency increases with tick size. FKK do not make any predictions regarding depth resiliency. However, we also examine the effect on depth resiliency of the above factors emerging from FKK. We do so by running the following pooled regression:

(0) $$\hat{\kappa}_{i,T}^{S/D} = \beta_0^{S/D} + \beta_1^{S/D} PPT_{i,T} + \beta_2^{S/D} OAR_{i,T} + \beta_3^{S/D} TS_{i,T} + \beta_4^{S/D} Size_{i,T} + \beta_5^{S/D} MR_T^{S/D} + \varepsilon_{i,T}^{S/D}$$

where the subscripts *i* and *T* all through the equation denote stock *i* and trading day *T* respectively, $\hat{\kappa}_{i,T}^{S/D}$ is the estimated resiliency of stock *i* on trading day *T* obtained from estimating Equation (0), and PPT, OAR, TS, Size, and $MR^{S/D}$ stand for proportion of patient traders, order arrival rate, tick size, market capitalization, and market resiliency respectively. The proportion of patient traders (PPT) is estimated as the logarithm of the ratio between the volume (in GBP) of new limit orders (volume of newly submitted limit orders corrected for the volume of cancelled limit orders) and the total volume of new limit and market orders. Our measure of the order arrival rate (OAR) is the logarithm of the volume of all new orders per share volume outstanding. Tick Size (TS) is a dummy variable for whether the tick size is at or above, or below, the median tick size. Size (which we include as a control given our results shown in Figure 3) is also a dummy variable and measures whether the market capitalization of a stock is at or above, or below, the median market capitalization. We use the overall market resiliency $MR^{S/D}$ as a control variable in view of our results in Section IV.A showing the strong impact of market resiliency on individual stock resiliency. The results of estimating Equation (0) are shown in Table IV.

Insert Table IV about here.

Table IV strongly supports the hypotheses of FKK. Even though the FKK model is only for spread resiliency, the results hold irrespective of whether we look at spread or at depth resiliency. Consistent with the predictions of FKK, both spread and depth resiliency increase significantly as the proportion of patient traders goes up, and as the order arrival rate goes down (with *t*-statistic > 4.0 in both cases). The coefficient of the tick size dummy is also as expected: stocks with high tick size are more resilient than those with low tick size. Hence, lower tick sizes not only reduce the price and quantity dimensions of liquidity (by increasing spreads and decreasing depth as documented by Goldstein and Kavajecz (2000)), but also reduce resiliency, the time dimension of liquidity.

Looking at the control variables shows that stocks of large companies are more resilient than stocks of small companies. This clearly shows that size has an independent impact on resiliency. Also, the loading of individual stock resiliency on market-wide resiliency increases compared to Table III. The adjusted R^2 approximately doubles through our inclusion of stock-specific determinants, suggesting the importance of these variables.

IV.C Information and Resiliency

As discussed earlier, greater information flow and/or greater information asymmetry should arguably lead to greater risk and uncertainty for both liquidity suppliers and liquidity consumers, and hence reduced engagement from them, leading to lower resiliency. Accordingly, we test whether resiliency is inversely related to two different information-related proxies: first, intraday volatility as a proxy for information flow; and second, the imbalance between buyer-initiated and seller initiated trades as a proxy for information asymmetry.

Volatility is a widely used proxy for information flow.[11] In an efficient market, prices change in response to new information. Therefore, relatively higher intra-day volatility of price changes on a particular day should arguably correspond to greater information flow that day. We compute our volatility measure as the annualized volatility of intra-day log mid-price returns over all five-minute intervals within a day. Hence, $Vola_{i,T}$ is the estimated intra-daily volatility of stock *i* on trading day *T*. We extend Equation (5) by adding $Vola_{i,T}$ as an additional explanatory variable and estimate the following regression model:

$$\hat{\kappa}_{i,T}^{S/D} = \beta_0^{S/D} + \beta_1^{S/D} PPT_{i,T} + \beta_2^{S/D} OAR_{i,T} + \beta_3^{S/D} TS_{i,T} + \beta_4^{S/D} Size_{i,T} + \beta_5^{S/D} Vola_{i,T} + \beta_6^{S/D} MR_T^{S/D} + \varepsilon_{i,T}^{S/D} \quad (0)$$

Panel A of Table V shows the results of estimating Equation (0). It clearly shows that information flow (proxied by intraday volatility) has a statistically significant and negative impact on both spread and depth resiliency (with *t*-statistics below -2.8). Thus, the greater the flow of information into the market, the less willing investors are to replenish the liquidity shortage or consume the excess liquidity of the order book.

Insert Table V about here.

At the same time, the impact of the variables suggested by FKK remains qualitatively the same. After controlling for information flow, both spread and depth resiliencies continue to be significantly higher when the proportion of patient traders is higher, when the order arrival rate is lower, and for stocks with higher tick size and large market capitalization.

Our proxy for information asymmetry is the imbalance between buyer-initiated and seller-initiated trades. The argument is as follows: if new information comes into the market, new market orders (including marketable limit orders) of informed traders are likely to be on the same side of the order book, while uninformed traders place their orders on the buy and sell side evenly. Hence, one should expect to see a larger absolute imbalance in executed orders when information asymmetry is relatively higher.[12] We calculate the imbalance in executed orders for each stock within each 5-minute interval as the absolute difference between market buy and market sell orders divided by all market orders; and take the average over the day to get the daily imbalance in executed orders.

We examine the incremental impact of information asymmetry (measured by the imbalance in executed orders) on resiliency by using Equation (0) but replacing the information proxy $Vola_{i,T}$ by the imbalance in executed orders, $OI_{i,T}$. Hence, we estimate the following regression equation:

$$\hat{\kappa}_{i,T}^{S/D} = \beta_0^{S/D} + \beta_1^{S/D} PPT_{i,T} + \beta_2^{S/D} OAR_{i,T} + \beta_3^{S/D} TS_{i,T} + \beta_4^{S/D} Size_{i,T} + \beta_5^{S/D} OI_{i,T} + \beta_6^{S/D} MR_T^{S/D} + \varepsilon_{i,T}^{S/D} \quad (0)$$

The results from estimating Equation (0) are presented in Panel B of Table V. They show a negative and statistically significant impact of order imbalance on both spread and depth resiliency. This again shows that, when the information asymmetry in the market is relatively high, investors are relatively less willing to neutralize liquidity shortages and excesses. The impact of the remaining factors is mostly unchanged.

Overall, our results in this sub-section show that both spread and depth resiliency are significantly lower when information flow or information asymmetry are relatively higher. This is consistent with our hypothesis that the greater risk and uncertainty associated with greater information flow and/or greater information asymmetry leads to reduced propensity to engage in liquidity supply or consumption, and hence lower resiliency.

IV.D Algorithmic Traders and Resiliency

Algorithmic traders are increasingly becoming the principal suppliers of liquidity, and extant evidence indicates that algorithmic trading ordinarily increases liquidity (see, e.g., Hendershott, Jones, and Menkveld, 2011). Hence, we hypothesize and test in this sub-section whether resiliency is positively related to the extent of algorithmic trading.

To measure the extent of algorithmic trading, we follow the approach of Hendershott, Jones, and Menkveld (2011) by using the intensity of the order-flow as a proxy for algorithmic trading. Whereas they look at overall order-flow, we focus on the flow of cancelled orders. The rationale is that algorithmic traders frequently cancel submitted orders, leading to a lower message-to-trade ratio for algorithmic traders than for other traders (Angel, Harris, and Spatt, 2011, Hendershott, Jones, and Menkveld, 2011, and Hasbrouck and Saar, 2013). Hence, a higher proportion of algorithmic traders should arguably lead to a higher proportion of cancelled trades. Specifically, we compute the logarithm of the total volume of cancelled limit orders, divided by the volume of all limit and market orders, minus the volume of all cancelled limit orders. We calculate this proportion for each 5-minute interval, and then aggregate over the day to come up with a daily measure.

To test our hypothesis we extend the previous equations by adding our algorithmic trading variable (*Algo*) as an explanatory variable:

(0) $$\hat{\kappa}_{i,T}^{S/D} = \beta_0^{S/D} + \beta_1^{S/D} PPT_{i,T} + \beta_2^{S/D} OAR_{i,T} + \beta_3^{S/D} TS_{i,T} + \beta_4^{S/D} Size_{i,T} + \beta_5^{S/D} Vola_{i,T} + \beta_6^{S/D} OI_{i,\mathrm{T}} + \beta_7^{S/D} Algo_{i,\mathrm{T}} + \beta_8^{S/D} MR_T^{S/D} + \varepsilon_{i,T}^{S/D}$$

The proportion of patient traders (PPT), order arrival rate (OAR), tick size (TS), size, volatility, and market resiliency $MR^{S/D}$ are included as in the previous sections. We use volatility as the information flow proxy, and order imbalance as the information asymmetry proxy (as in Table V).

Insert Table VI about here.

Our results on the impact of our algorithmic trading proxy are presented in Panel A of Table VI. They provide strong support for our hypothesis: Algorithmic trading has a large, positive, and highly significant impact on both spread and depth resiliency with *t*-statistics of 4.9 and 7.8 respectively. The dependence of resiliency on each of the other variables remains unchanged, and continues to be highly significant.

Raman, Robe, and Yadav (2014) show that algorithmic traders provide less liquidity on days with high volatility. We therefore hypothesize that algorithmic trading increases resiliency to a lesser extent when volatility is high. To test this hypothesis, we interact the algorithmic trading with volatility and extend Equation (0) by adding this interaction variable:

(0) $$\hat{\kappa}_{i,T}^{S/D} = \beta_0^{S/D} + \beta_1^{S/D} PPT_{i,T} + \beta_2^{S/D} OAR_{i,T} + \beta_3^{S/D} TS_{i,T} + \beta_4^{S/D} Size_{i,T} + \beta_5^{S/D} Vola_{i,T} + \beta_6^{S/D} OI_{i,\mathrm{T}} + \beta_7^{S/D} Algo_{i,\mathrm{T}} + \beta_8^{S/D} Vola_{i,T} \cdot Algo_{i,\mathrm{T}} + \beta_9^{S/D} MR_T^{SD} + \varepsilon_{i,T}^{S/D}$$

The results are presented in Panel B of Table VI and provide strong evidence in favor of our hypothesis. The positive impact of algorithmic trading on spread (depth) resiliency becomes significantly weaker when information flow is relatively higher.[13]

Hendershott, Jones, and Menkveld (2011) and Boehmer, Fong, and Wu (2014) both document that algorithmic trading leads to an increase in the liquidity of relatively large stocks. Therefore, we hypothesize that the positive impact of algorithmic traders on resiliency is higher for stocks with higher market capitalization. To test this hypothesis, we add another variable that interacts algorithmic trading with size:

$$\hat{\kappa}_{i,T}^{S/D} = \beta_0^{S/D} + \beta_1^{S/D} PPT_{i,T} + \beta_2^{S/D} OAR_{i,T} + \beta_3^{S/D} TS_{i,T} + \beta_4^{S/D} Size_{i,T} + \beta_5^{S/D} Vola_{i,T} + \beta_6^{S/D} OI_{i,\mathrm{T}} + \beta_7^{S/D} Algo_{i,\mathrm{T}} + \beta_8^{S/D} Vola_{i,T} \cdot Algo_{i,\mathrm{T}} + \beta_9^{S/D} Size_{i,\mathrm{T}} \cdot Algo_{i,\mathrm{T}} + \beta_{10}^{S/D} MR_T^{S/D} + \varepsilon_{i,T}^{S/D} \quad (0)$$

The results are presented in Panel C of Table VI, and provide strong support for our hypothesis. The positive impact of algorithmic trading on resiliency is significantly higher (at 189% for spread and 32% for depth resiliency) for large firms than for small firms.

V. Resiliency Deeper in the Order Book

The results reported thus far are based on liquidity at the best bid and offer prices. However, there is extensive evidence on the additional relevance of liquidity deeper within the order book.[14] Therefore, we extend our analysis to resiliency deeper in the order book. We accordingly compute the relative spread and depth at the best three price ticks (Spread3, Depth3), and at the best five price ticks (Spread5, Depth5); and then estimate resiliency for Spread3, Spread5, Depth3, and Depth 5 using Equation (2).

We find that spread and depth resiliency at different order book levels are highly and positively correlated. In particular, resiliency at Spread1 (at best prices), Spread 3, and Spread 5 are correlated with correlation coefficients of at least 0.70, irrespective of whether we consider cross-sectional or time-series correlations. Correlations for depth resiliency at different levels of the order book are of a similar order of magnitude, consistently exceeding 0.65. We display further summary statistics, our commonality results, and the results of our hypotheses tests for resiliency deeper in the order book in Table VII.

Insert Table VII about here.

Panel A clearly shows that resiliency decreases as we go deeper in the order book. Spread resiliency is 0.53 for Spread3 and 0.47 for Spread 5 (vs. 0.61 for Spread1). Depth resiliency is 0.38 for Depth3 and 0.30 for Depth5 (vs. 0.55 for Depth1). These results are consistent with what one would expect: since investors typically place their new orders at the best quotes, the change in liquidity over any particular interval will be a smaller proportion of the total liquidity when one measures total liquidity deeper in the book. Therefore, liquidity changes deeper in the order book are similar to liquidity changes at best quotes. Liquidity levels, on the other hand, are of a higher order of magnitude (higher spreads / higher depth) deeper in the book, which leads to lower estimates for the mean reversion coefficient.

Panel B documents that commonality in resiliency is higher inside the order book. This is consistent with Kempf and Mayston (2008) who document a higher commonality inside the order book for the price and quantity dimensions of liquidity. Hence, systematic liquidity risk is substantially higher for large traders, who potentially trade deeper in the order book.

To explore the determinants of resiliency deeper in the order book, we again run the most general regression model (0) of Section IV using resiliencies based on Spread3, Spread5, Depth3, and Depth5 as dependent variables. We also compute the explanatory variable market resiliency $MR^{S/D}$ from the appropriate liquidity variable and order book level. The results are presented in Panel C of Table VII. For ease of comparison, we again report the results for resiliency based on Spread1 and Depth1 in this table.

The strong and unequivocal conclusion of Panel C of Table VII is that the factors that determine resiliency deeper in the order book are qualitatively the same as those that determine resiliency at the best bid and offer prices. The adjusted R^2 is also of a similar order of magnitude. The only systematic difference is that the estimated intercept decreases as we go deeper into the order book, which is also consistent with a decreasing average. Overall, our overall bottom-line conclusions are clearly robust to where we measure resiliency in the order book.

VI. Consumption and Replenishment Resiliency

Our model of mean reversion implies that liquidity reverts to its mean at the same speed, irrespective of whether the current liquidity of the order book is above or below the "normal" average level. However, the process of abnormally high liquidity being consumed can arguably differ from the process of abnormally low liquidity being replenished. For example, high information flow makes liquidity provision more risky. Liquidity providers may not only react to this risk by increasing the price they charge for providing liquidity, but also replenish liquidity at a lower speed. On the other hand, consumption of excess liquidity is likely to be quicker in this scenario. Hence, we adjust our model to take this potential asymmetry into account.

We re-estimate our resiliency measures building in different speeds of mean reversion from above and below the mean. In particular, we re-formulate Equation (2) as:

$$(0) \qquad \Delta L_{i,t}^{S/D} = \alpha_{\text{down},i,\text{T}}^{S/D} + \alpha_{\text{up},i,\text{T}}^{S/D} 1_{L_{i,t-1}^{S/D} < \theta_{i,\text{T}}^{S/D}} - \kappa_{\text{down},i,\text{T}}^{S/D} L_{i,t-1}^{S/D} - \kappa_{\text{up},i,\text{T}}^{S/D} L_{i,t-1}^{S/D} 1_{L_{i,t-1}^{S/D} < \theta_{i,\text{T}}^{S/D}} + \sum_{\tau=1}^{5} \gamma_{i,t-\tau}^{S/D} \Delta L_{i,t-\tau}^{S/D} + \varepsilon_{i,t}^{S/D},$$

where $\theta_{i,T}^{S/D}$ denotes the mean liquidity level of stock *i* on trading day *T*, $1_{L_{i,t-1}^{S/D} < \theta_{i,\text{T}}^{S/D}}$ is an indicator function of whether the liquidity level of stock *i* on trading day *T* at time *t-1* is below the mean liquidity level, and the remaining variables are defined as in Equation (2). We estimate the parameters of Equation (0) for each stock and trading day as before, and compare the consumption resiliency $\kappa^{S/D}_{\text{cons},i,\text{T}} = \kappa^{S/D}_{\text{down},i,\text{T}}$ and the replenishment resiliency $\kappa^{S/D}_{\text{replen},i,\text{T}} = \kappa^{S/D}_{\text{up},i,\text{T}} + \kappa^{S/D}_{\text{down},i,\text{T}}$ to explore whether liquidity reverts differently back to its mean level $\theta^{S/D}_{i,T}$.[15] Note that liquidity being replenished means that high spreads decrease and that low depth increases, while liquidity being consumed means that low spreads increase and high depth decreases. We display summary statistics, commonality results, and the results of our hypotheses tests in Table VIII.

Insert Table VIII about here.

Panel A of Table VIII shows that consumption resiliency is higher than replenishment resiliency, but the difference is small and only marginally significant. Panel B of Table VIII shows that commonality is somewhat higher for replenishment resiliency than for consumption resiliency. Overall, these results imply that excess liquidity is consumed slightly more quickly than a shortage of liquidity is replenished; while liquidity is replenished more uniformly than it is consumed.

Panel C of Table VIII shows that the determinants of consumption and replenishment resiliency are qualitatively very similar to what we observed in earlier analyses where a single resiliency parameter was estimated assuming symmetry in the responses for abnormally higher or lower liquidity. In most cases, this similarity exists whether we look at the size of the coefficients, or at their statistical significance. However, information flow and information asymmetry (proxied by intraday volatility and order imbalance) appear to affect replenishment resiliency more strongly than consumption resiliency, consistent with traders replenishing less aggressively in the face of higher risk.

VII. Resiliency in the Financial Crisis

So far, our analysis has been based on our entire observation interval. One interesting feature of our sample period is that it spans the financial crisis of 2008. Figure 3 shows that the cross-sectional average resiliency remained high during the financial crisis sub-period (as we can see in Panels A and B of Figure 3). Hence, even in this phase, liquidity gets drawn back to its (much lower) average level (seen in Panel C of Figure 3) at an only slightly lower speed. In this section, we focus on the financial crisis interval more closely. To do this, we split our entire sample into a financial crisis period (from August 15, 2008 to December 31, 2008, capturing the month leading up to the Lehman bankruptcy until the end of 2008) and a non-crisis period (the remainder of the observation interval).

Our hypotheses about how resiliency differs during the financial crisis relative to the non-crisis period, build on the intuition of the asymmetry analyzed in the previous section. First, consider the bid side of the limit order book (where liquidity providers stand ready to buy). During the financial crisis, we would expect that any excess liquidity on this bid side of the order book should be consumed relatively more quickly than in the non-crisis period, leading to a relatively higher consumption resiliency. Conversely, we would expect liquidity providers to replenish liquidity on the bid side of the order book less aggressively during the financial crisis, leading to a relatively lower replenishment resiliency.

Second, consider the ask side of the limit order book (where liquidity providers stand ready to sell). There, we would expect that any excess liquidity should be consumed more slowly than in the non-crisis period, since buying pressures will be relatively lower.

Conversely, liquidity should be replenished more quickly. These effects will result in relatively lower consumption resiliency and higher replenishment resiliency during the financial crisis. Figure 5 illustrates our hypotheses.

Insert Figure 5 about here.

Since we cannot distinguish between the bid and the ask side of the order book based on spreads, we focus on depth resiliency to see whether the data supports our hypotheses above. We thus estimate Equation (0) separately for depth at the best bid quote and depth at the best ask quote. Table IX displays summary statistics, commonality results, and the impact of our explanatory determinants on consumption resiliency and replenishment resiliency at the bid side and the ask side.

Insert Table IX about here.

Panel A of Table IX clearly supports our hypotheses above. On the bid side, consumption resiliency is larger in the financial crisis (0.72 vs. 0.60 in the non-crisis period), while replenishment resiliency is smaller (0.66 vs. 0.68). On the ask side, consumption resiliency is smaller in the financial crisis (0.60 vs. 0.65 in the non-crisis period), and replenishment resiliency is larger (0.72 vs. 0.69). The estimates also exhibit the hypothesized relation when we focus purely on the financial crisis: on the bid side, consumption resiliency is larger than replenishment resiliency (0.72 vs. 0.66). On the ask side, consumption resiliency is smaller than replenishment resiliency (0.60 vs. 0.72).

Panel B of Table IX displays commonality for resiliency estimates. Commonality in consumption resiliency is similar, irrespective of whether we consider the bid side or the ask side, and irrespective of whether we consider the financial crisis or the non-financial crisis interval. Hence, excess liquidity consumption for a specific stock always depends on market excess liquidity consumption to a similar extent.

Replenishment resiliency, on the other hand, exhibits high commonality in the financial crisis on both the bid and the ask side, but practically no commonality in the non-crisis interval. This suggests that liquidity provision across stocks, once it has been depleted, is highly correlated during the financial crisis, but almost independent of each other in the non-crisis period.

Finally, Panel C of Table IX displays the impact of the determinants of resiliency. For ease of exposition, we only report the relationships for the financial crisis period. Again, we run the most general regression model (0) of Section IV. The results show that the impact of the explanatory factors on resiliency is roughly the same whether we consider crisis or non-crisis periods, bid depth or ask depth, and consumption or replenishment resiliency.

VIII. Conclusions

We empirically investigate resiliency, a hitherto under-researched dimension of liquidity. We define spread and depth resiliency as the rate of mean reversion in the spread and depth respectively. Our results for spread and depth resiliency are similar, and robust with respect to the order-book depth at which liquidity is measured. We document strong resiliency for each and every stock, and for each and every day of the sample period – even during the financial crisis. We show that resiliency provides potentially valuable information that is not subsumed within the information provided by the other two dimensions of liquidity – spread and depth. That said, there is also strong commonality in resiliency across stocks, not dissimilar from commonality documented for the spread and depth dimensions of liquidity, indicating that traders face significant systematic risk in this context.

We find that both spread and depth resiliency increase with the proportion of patient traders, decrease with order arrival rate, and increase with tick size, strongly supporting the theoretical model of Foucault, Kadan, and Kandel (2005) for spread resiliency. Furthermore, we find that, as expected, greater information-related risks in the form of greater information flow or greater information asymmetry lead to significantly lower resiliency. We also find that, consistent with the dominant liquidity-related role of algorithmic traders, greater algorithmic trading is associated with higher resiliency; but the beneficial contribution of algorithmic trading to resiliency is significantly less when volatility is high.

We split resiliency into consumption resiliency and replenishment resiliency, corresponding respectively to the extent to which abnormally high liquidity is consumed or abnormally low liquidity is replenished. On average, we find only marginal differences between the two. However, during the financial crisis period, consistent with what one could expect in a period of stress and uncertainty, we find that consumption resiliency is high (low) and replenishment resiliency is low (high) on the bid (ask) side, i.e., where liquidity providers stand ready to buy (sell).

The reduction in replenishment resiliency during the financial crisis, and the reduced beneficial contribution to resiliency of algorithmic trading in the face of high volatility, points to the need for an intensive examination of the effects of uncertain and stressful conditions on replenishment resiliency: for example, when order imbalances are exceptionally large or prices particularly volatile. Poor replenishment resiliency potentially makes markets fragile, and this is an issue of major concern for traders, stock exchanges and regulators; particularly in limit order book markets where new liquidity provision is entirely voluntary, and there are no 'market-makers' obliged to stand ready to provide liquidity. This should arguably be an important question for further future research.

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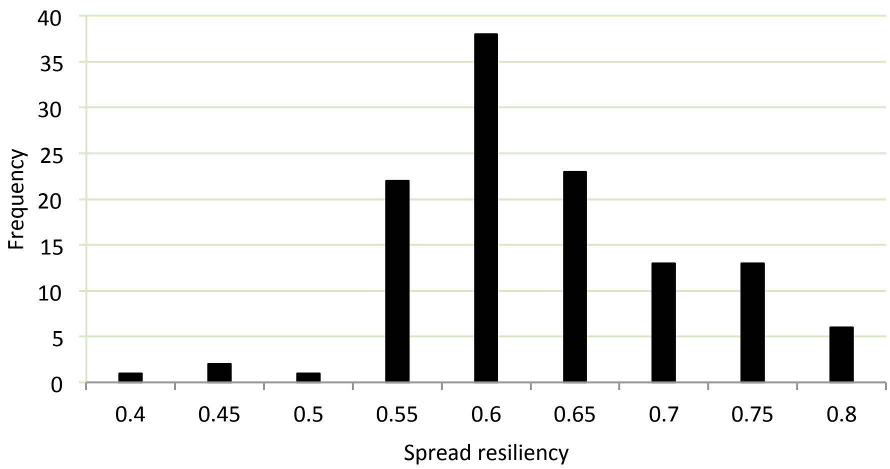
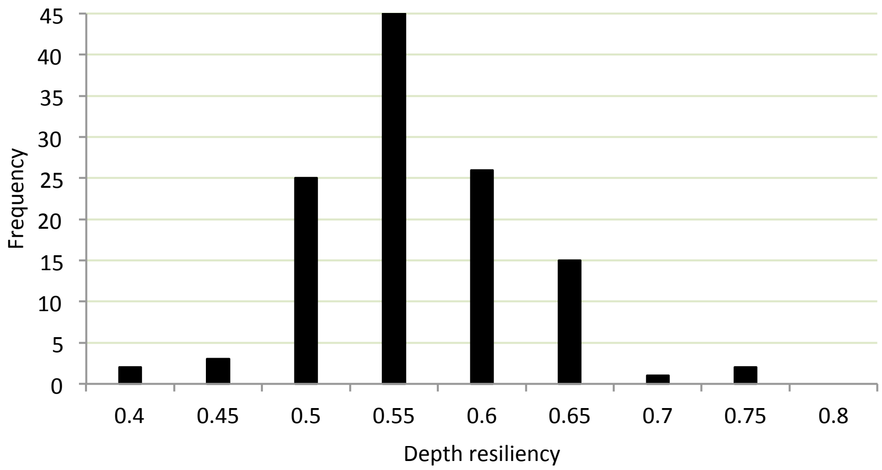
FIGURE 1: Level of resiliency across stocks

Panel A: Spread resiliency



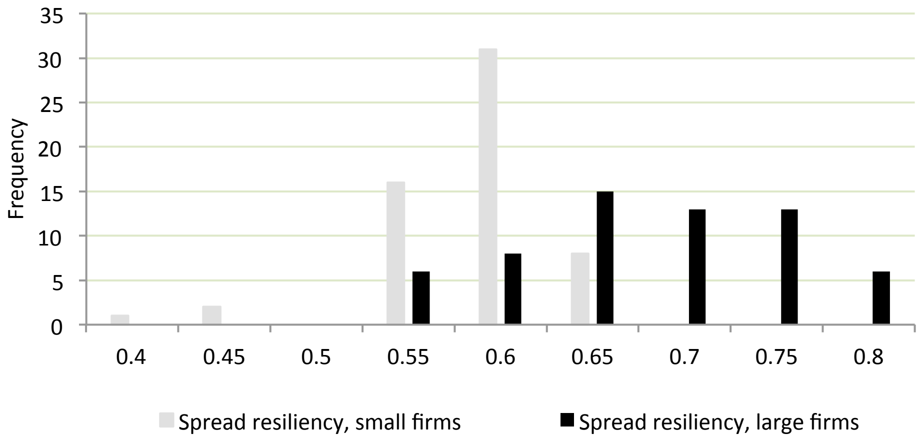
Panel B: Depth resiliency



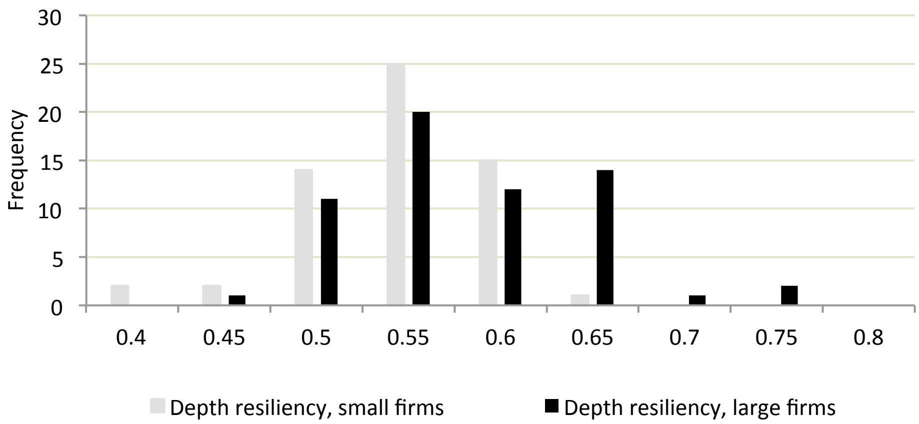
This figure presents the histogram of resiliency estimates for the firms in our sample. We first estimate resiliency coefficients $\hat{\kappa}_{i,T}^{S/D}$ using Equation (0) separately for each stock *i* and trading day *T*. We then calculate the time-series average $\hat{\kappa}_{i}^{S/D}$ of the daily parameters $\hat{\kappa}_{i,T}^{S/D}$. Last, we group the stock-specific resiliency parameters $\hat{\kappa}_{i}^{S/D}$ into size bins of width 0.05, and plot the number of parameters that fall into a given range. The x-axis depicts the upper bin limit, i.e., in Panel A, one estimate of spread resiliency is above 0.35 and does not exceed 0.40.

FIGURE 2: Level of resiliency across stocks for groups sorted by market capitalization

Panel A: Spread resiliency



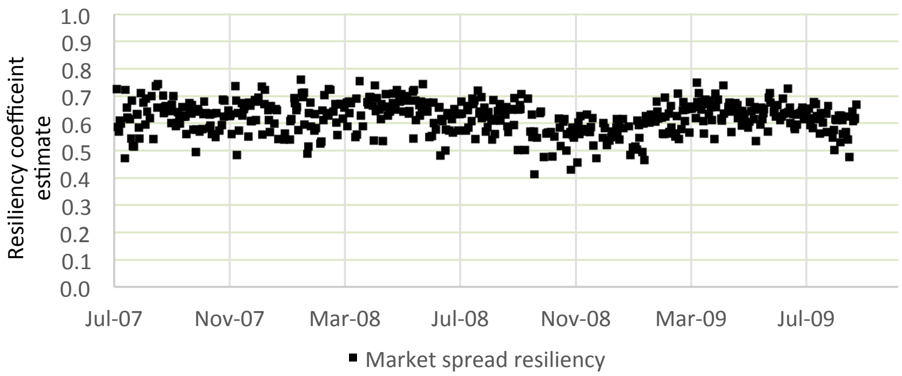
Panel B: Depth resiliency



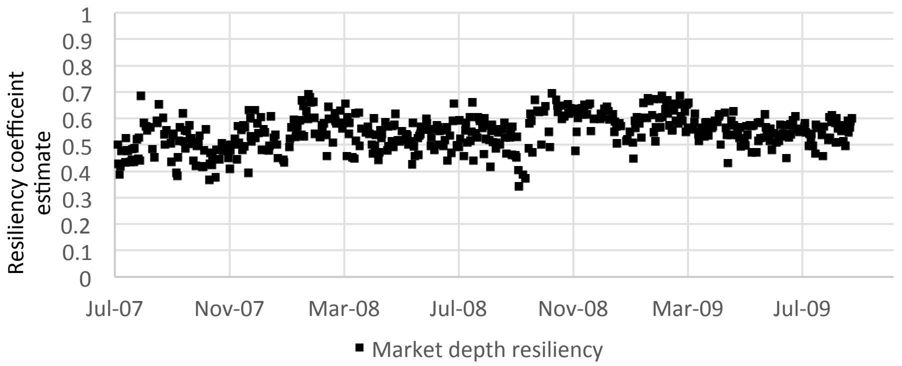
This figure replicates Figure 1, splitting the sample by market capitalization. We first estimate resiliency coefficients $\hat{\kappa}_{i,T}^{S/D}$ using Equation (0) separately for each stock *i* and trading day *T*. We then calculate the time-series average $\hat{\kappa}_{i}^{S/D}$ of the daily parameters $\hat{\kappa}_{i,T}^{S/D}$. Then, we sort the stocks-specific resiliency parameters into two groups, depending on whether the firm's market capitalization is below the median (small firms) or equal to or above the median (large firms). Last, we group the resiliency parameters $\hat{\kappa}_{i}^{S/D}$ into size bins of width 0.05, and plot the number of parameters that fall into a given range. The x-axis depicts the upper bin limit, i.e., in Panel A, one estimate for small firms is above 0.35 and does not exceed 0.40.

FIGURE 3: Liquidity over time

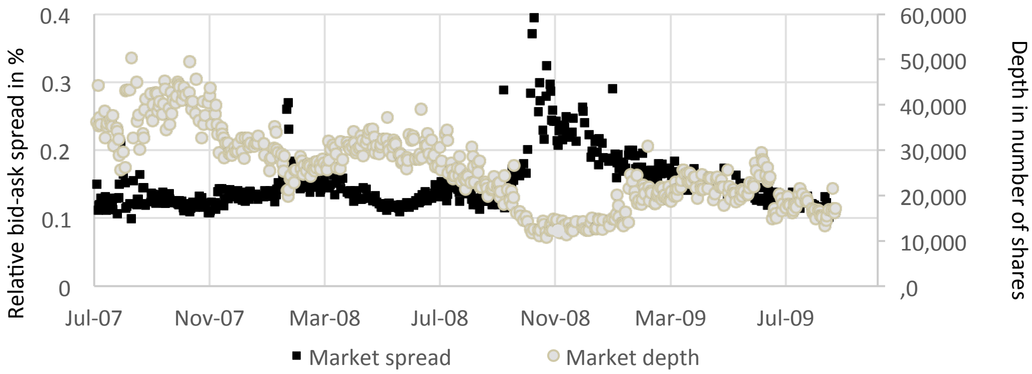
Panel A: Market spread resiliency



Panel B: Market depth resiliency



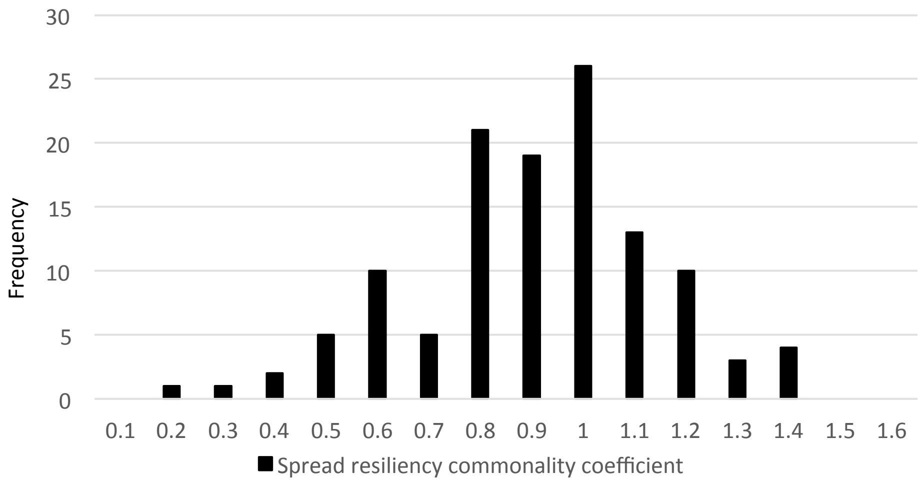
Panel C: Market spread and market depth



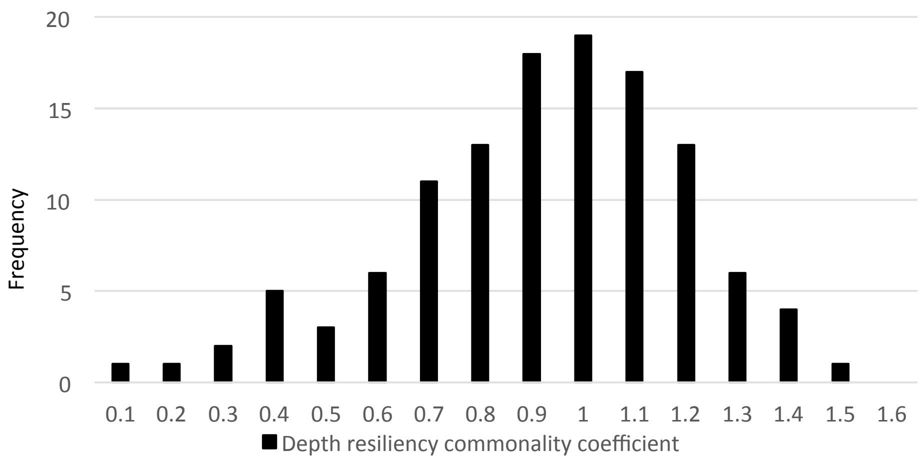
This figure presents the time series of resiliency and liquidity over our sample period. For Panel A and B, we first estimate resiliency coefficients $\hat{\kappa}_{i,T}^{S/D}$ using Equation (0) separately for each stock *i* and trading day *T*. We then calculate the daily market resiliency by taking cross-sectional averages across all parameters $\hat{\kappa}_{i,T}^{S/D}$, and plot the resulting time series. For Panel C, we compute daily averages across all stocks in our sample. The market spread is the daily average across all 5-minute order book snapshots relative bid-ask spread in percentage points. The market depth is the daily average ask depth plus the average bid depth, both measures as number of shares, at the best ask and best bid quote across all 5-minute order book snapshots.

FIGURE 4: Commonality in resiliency across stocks

Panel A: Spread resiliency

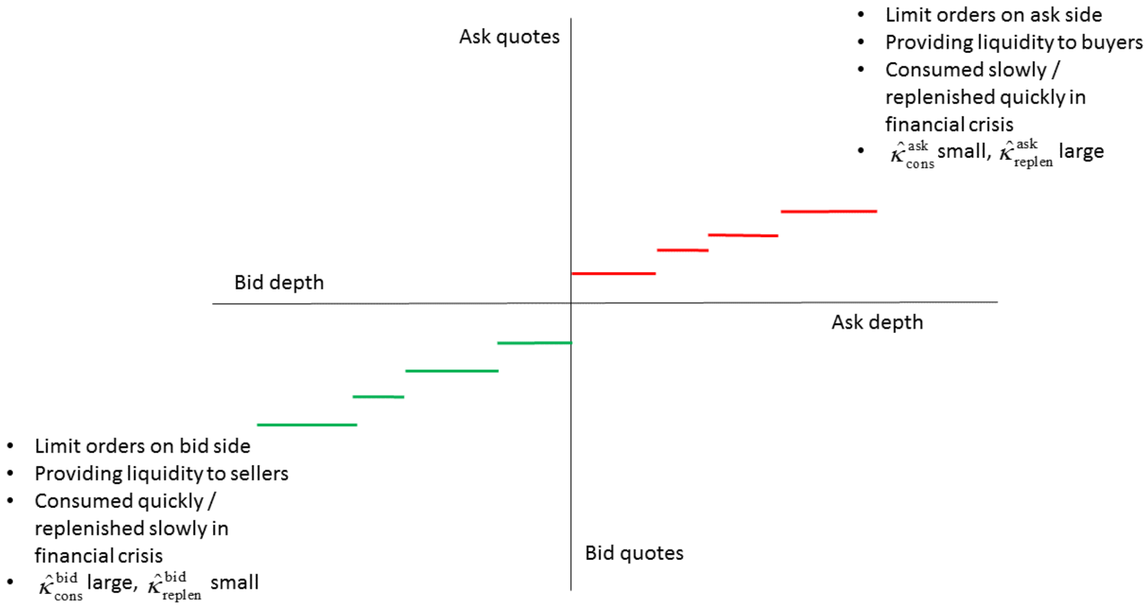


Panel B: Depth resiliency



This figure presents the histogram of the loading on the firm's resiliency parameter on the market average resiliency. We first estimate resiliency coefficients $\hat{\kappa}_{i,T}^{S/D}$ using Equation (0) separately for each stock *i* and trading day *T*. We then calculate the daily market resiliency $MR_T^{S/D}$ by taking cross-sectional averages across all stocks but leave out the resiliency of the specific stock *i*. Next, we regress the stock-specific resiliency $\hat{\kappa}_{i,T}^{S/D}$ on the market resiliency $MR_T^{S/D}$ using Equation (0) to determine the commonality coefficients $\hat{\beta}_i^{S/D}$. Last, we group the commonality coefficients into size bins of width 0.1, and plot the number of average parameters that fall into a given range in Panel A and B. The x-axis depicts the upper limit, i.e., in Panel A, one estimate is above 0.1 and does not exceed 0.2.

FIGURE 5: Consumption and replenishment resiliency on bid and ask side



This figure presents an idealized order book and illustrates our hypotheses of the impact of the financial crises on consumption and replenishment resiliency on the bid side and the ask side of the limit order book. The top right quadrant represents the ask side of the order book, where liquidity is provided by standing ready to sell. The bottom left quadrant represents the bid side of the order book, where liquidity is provided by standing ready to buy. The red graph relates quantities to ask quotes. The green graph relates quantities to bid quotes.

TABLE I: Summary statistics

This table summarizes the main characteristics of the stocks in our data set. Market capitalization is in millions of GBP. Daily aggregate trading volume is the trading volume of the stock aggregated across all 5-minute order book snapshots in millions of GBP. Daily average relative bid-ask spread is the daily average of the relative bid-ask spread in percentage points across all 5-minute order book snapshots. Daily average depth at best prices is the daily average of the ask depth plus the average bid depth at the best ask and best bid quote across all 5-minute order book snapshots. Depth is given in GBP.

	Mean	Min	25%	50%	75%	Max	# Obs.
Market capitalization	11,898	1,279	2,577	3,998	11,892	113,016	120
Daily trading volume	45.90	0.35	15.63	25.34	42.12	312.59	120
Daily average relative bid-ask spread	0.16	0.05	0.12	0.15	0.18	0.69	120
Daily average depth at best prices	102,265	17,421	55,096	75,532	121,964	622,302	120

TABLE II: Resiliency estimates

This table provides summary statistics of the resiliency estimates. We first estimate resiliency coefficients $\hat{\kappa}_{i,T}^{S/D}$ using Equation (0) separately for each stock *i* and trading day *T*, using the relative bid-ask spread as the liquidity measure for spread resiliency $\hat{\kappa}_{i,T}^{S}$ and the depth of the order book in number of shares for depth resiliency $\hat{\kappa}_{i,T}^{D}$. We then calculate the time-series average and the inter-quartile ranges (75% time-series percentile minus 25% time-series percentile) of the daily parameters $\hat{\kappa}_{i,T}^{S/D}$ for each stock *i*. Panel A presents summary statistics on the time-series average, Panel B on inter-quartile ranges of the resiliency estimates.

Panel A: Average resiliency

	Mean	Min	25%	50%	75%	Max	# Obs.
Spread resiliency	0.6033	0.3874	0.5561	0.5951	0.6528	0.7980	120
Depth resiliency	0.5390	0.3561	0.5025	0.5341	0.5644	0.7486	120

Panel B: Inter-quartile range of resiliency

	Mean	Min	25%	50%	75%	Max	# Obs.
Spread resiliency	0.1202	0.0584	0.1091	0.1201	0.1310	0.1793	120
Depth resiliency	0.1267	0.0881	0.1139	0.1246	0.1374	0.1783	120

TABLE III: Commonality in resiliency

This table shows the results for commonality in resiliency based on the market model approach of Chordia, Roll, and Subrahmanyam (2000). The results are obtained in a two-step approach. We first estimate resiliency $\hat{\kappa}_{i,T}^{S/D}$ for each stock *i* and day *T* separately using Equation (0) . We then perform a regression with the resiliency of the stock, $\hat{\kappa}_{i,T}^{S/D}$ as the dependent variable on market resiliency $MR_T^{S/D}$ which is calculated as the average resiliency across all sample stocks but leaving out the resiliency of the specific stock. Panel A is based on the univariate regression in Equation (0). Panel B is based on the multivariate regression in Equation (0). The control variables in Equation (0) are the market resiliency with lag 1 and lead 1, the daily market return (contemporaneous and with lag 1) calculated as the daily average stock return, and the market price range (contemporaneous and with lag 1) calculated as the daily average stock price range. The latter is determined as the difference between the highest and the lowest price of the stock during a day divided by the average stock price during this day. In both panels, we report in the first column the average stock-specific loading $\hat{\beta}_i^{S/D}$ on market resiliency $MR_T^{S/D}$ and the average *t*-statistics in parentheses, the percentage of estimates significant at the 10% level in the second column, and the average adjusted R^2 in percentage points in the third column.

	Panel A: Univariate Analysis			Panel B: Multivariate Analysis		
	$MR^{S/D}$	% Sign.	Adj. R^2	$MR^{S/D}$	% Sign.	Adj. R^2
Spread resiliency	0.8106 (4.99)	95.83	6.63	0.7720 (3.31)	86.67	6.46
Depth resiliency	0.7899 (4.51)	93.33	5.53	0.8434 (4.48)	93.33	8.60

TABLE IV: Foucault, Kadan, and Kandel (2005) hypotheses

This table shows the results of regressions testing the predictions of the model of Foucault, Kadan, and Kandel (2005). The results are obtained in a two-step approach. We first estimate resiliency for each stock and day separately using Equation (0) and then run the pooled regression in Equation (0) using 44,739 observations. The dependent variables in Equation (5) are the spread and depth resiliency $\hat{\kappa}^{S/D}$ estimated from Equation (0). The explanatory variables in Equation (0) are the proportion of patient traders (PPT), the order arrival rate (OAR), and a dummy variable for whether the tick size is at or above, or below, the median tick size (TS). PPT is measured as log of the volume of all new limit orders minus the volume of all canceled limit orders over the day, divided by the volume of all new limit orders minus the volume of all canceled limit orders plus the volume of all new market orders over the day. OAR is measured as log of the volume of all new limit and market orders minus the volume of all cancelled limit orders, divided by the number of outstanding shares. We include firm size (Size) and market resiliency $MR^{S/D}$ as additional explanatory variables. Size is a dummy variable whether the market capitalization of a stock is at or above, or below, the median market capitalization. Market resiliency $MR^{S/D}$ is computed as the average market resiliency, excluding the considered firm. In the table, the estimated coefficients are provided in the first line and *t*-statistics in the second line in parentheses. Standard errors are two-way clustered by trading day and stock. The last column provides the adjusted R^2 in percentage points.

	Constant	*PPT*	*OAR*	*TS*	*Size*	$MR^{S/D}$	Adj. R^2
Spread resiliency	0.2972	0.0796	-0.0491	0.0233	0.1251	0.8766	14.69
	(5.65)	(4.27)	(-6.90)	(2.97)	(13.34)	(29.83)	
Depth resiliency	0.3339	0.0802	-0.0537	0.0180	0.0383	0.9198	9.95
	(11.10)	(5.18)	(-11.45)	(1.92)	(3.94)	(37.68)	

TABLE V: Information and resiliency

This table shows the results of regressions testing the impact of information on resiliency. It extends the regressions underlying Table IV by adding proxies for information. In Panel A, we use the (annualized) intraday-volatility of the log-returns (Vola) as the information proxy and estimate Equation (0). In Panel B, we use the imbalance in executed orders (OI) which is calculated as the absolute value of the buy volume minus the sell volume divided by the buy volume plus the sell volume and estimate Equation (0). The proportion of patient traders (PPT), order arrival rate (OAR), tick size (TS), size, and market resiliency $MR^{S/D}$ are defined as in Table IV. The estimated coefficients are provided in the first line and *t*-statistics in the second line in parentheses. Standard errors are two-way clustered by trading day and stock. The last column provides the adjusted R^2 in percentage point. The number of observations is 44,641.

Panel A: Information proxied by volatility

	Constant	PPT	OAR	TS	Size	Vola	$MR^{S/D}$	Adj. R^2
Spread resiliency	0.2751	0.0763	-0.0472	0.0251	0.1247	-0.0118	0.8919	14.82
	(5.12)	(4.12)	(-6.48)	(3.11)	(13.31)	(-2.82)	(23.00)	
Depth resiliency	0.3389	0.0790	-0.0516	0.0200	0.0380	-0.0169	0.8880	10.28
	(11.06)	(5.14)	(-11.69)	(2.24)	(4.11)	(-2.97)	(30.19)	

Panel B: Information proxied by imbalance in executed orders

	Constant	PPT	OAR	TS	Size	OI	$MR^{S/D}$	Adj. R^2
Spread resiliency	0.3924	0.0716	-0.0358	0.0259	0.1375	-0.0015	-0.0023	12.59
	(4.74)	(2.78)	(-3.11)	(2.66)	(11.51)	(-2.75)	(-1.96)	
Depth resiliency	0.4416	0.0869	-0.0420	0.0149	0.0284	-0.0313	-0.0086	7.07
	(8.64)	(3.16)	(-6.71)	(2.45)	(2.72)	(-4.47)	(-5.59)	

TABLE VI: Algorithmic trading and resiliency

This table shows the results of regressions testing the impact of algorithmic traders on resiliency. It extends the regressions underlying Table V by adding a variable proxying for the presence of algorithmic traders. We define this proxy as the log of the volume of all newly cancelled limit orders, divided by the buy and sell limit and market orders, corrected for the cancelled limit orders. We calculate the Algo proxy for each 5-minute interval separately and then average it over the day. In Panel A, we use the Algo proxy separately and estimate Equation (0). In Panel B, we interact the Algo proxy with intraday volatility and estimate Equation (0). In Panel C, we interact the Algo proxy with intraday volatility and with a size dummy (above/below median) and estimate Equation (0). All other variables are defined as in Table V. The estimated coefficients are provided in the first line and *t*-statistics in the second line in parentheses. Standard errors are two-way clustered by trading day and stock. The last column provides the adjusted R^2 in percentage points. The number of observations is 43,730 in all panels.

Panel A: Algorithmic trading

	Constant	PPT	OAR	TS	Size	Vola	OI	Algo	$MR^{S/D}$	Adj. R^2
Spread resiliency	0.2374	0.0392	-0.0579	0.0217	0.1355	-0.0028	-0.0075	0.0355	0.8883	14.99
	(4.59)	(2.48)	(-7.45)	(2.63)	(14.87)	(-2.23)	(-1.97)	(4.85)	(29.11)	
Depth resiliency	0.3326	0.0150	-0.0717	0.0149	0.0589	-0.0066	-0.0065	0.0609	0.8086	11.36
	(9.78)	(2.50)	(-12.81)	(1.69)	(6.02)	(-2.46)	(-1.96)	(7.75)	(25.62)	

Panel B: Algorithmic trading and volatility

	Constant	PPT	OAR	TS	Size	Vola	OI	Algo	VolaAlgo	$MR^{S/D}$	Adj. R^2
Spread resiliency	0.2350	0.0400	-0.0572	0.0219	0.1358	-0.0014	-0.0073	0.0335	-0.0021	0.8910	15.01
	(4.51)	(2.53)	(-7.28)	(2.64)	(14.83)	(-1.71)	(-1.91)	(4.35)	(-1.67)	(28.61)	
Depth resiliency	0.3412	0.0186	-0.0704	0.0150	0.0600	-0.0032	-0.0061	0.0559	-0.0054	0.7939	11.52
	(10.34)	(1.98)	(-12.95)	(1.64)	(6.25)	(-1.68)	(-1.85)	(7.09)	(-2.84)	(27.08)	

Panel C: Algorithmic trading, volatility, and size

	Constant	PPT	OAR	TS	Size	Vola	OI	Algo	VolaAlgo	SizeAlgo	$MR^{S/D}$	Adj. R^2
Spread resiliency	0.2527	0.0383	-0.0560	0.0221	0.0980	-0.0013	-0.0063	0.0158	-0.0024	0.0299	0.8926	15.13
	(4.95)	(2.35)	(-7.22)	(2.65)	(6.06)	(-1.82)	(-1.80)	(2.20)	(-1.95)	(2.72)	(29.07)	
Depth resiliency	0.3282	0.0198	-0.0713	0.0148	0.0876	-0.0031	-0.0068	0.0688	-0.0052	0.0218	0.7924	11.58
	(14.05)	(2.93)	(-13.31)	(0.70)	(5.21)	(-2.56)	(-3.29)	(10.83)	(-3.29)	(2.22)	(7.91)	

TABLE VII: Determinants of resiliency deeper in the order book

This table proves information about resiliency deeper in the order book. We estimate resiliency from the relative bid-ask spread and depth at tick 3 in the order book (Resiliency based on Spread3, Resiliency based on Depth3) and at tick 5 (Resiliency based on Spread5, Resiliency based on Depth5). To determine these coefficients, we estimate the resiliency for each stock and day separately using Equation (0) for the liquidity measures relative bid-ask spread and depth at tick size 3 and at tick size 5. Panel A replicates Panel A of Table II and presents summary statistics on the time series averages of spread and depth resiliency at the various steps. Panel B presents the results of a commonality analysis like in Panel A of Table III, but now for resiliency at the various steps. Panel C and D show the results of regressions testing the full model from Panel C of Table VI, for resiliency computed from spread and depth deeper in the order book. We run the pooled regression in Equation (0) using 43,730 observations. We display the results for spread resiliency in Panel C and the results for depth resiliency in Panel D. For ease of comparison, we repeat the results on resiliency based on step 1 from earlier tables. All explanatory variables are as in Table VI. In Panel B to D, the estimated coefficients are provided in the first line and *t*-statistics in the second line in parentheses. Standard errors are two-way clustered by trading day and stock. The last column provides the adjusted R^2 in percentage points.

Panel A: Average resiliency

	Mean	Min	25%	50%	75%	Max	# Obs.
				Spread resiliency			
Step 1	0.6033	0.3874	0.5561	0.5951	0.6528	0.7980	120
Step 3	0.5231	0.2943	0.4896	0.5141	0.5590	0.6776	120
Step 5	0.4613	0.2671	0.4374	0.4626	0.4883	0.5853	120
				Depth resiliency			
Step 1	0.5390	0.3561	0.5025	0.5341	0.5644	0.7486	120
Step 3	0.3740	0.2434	0.3313	0.3643	0.4041	0.6151	120
Step 5	0.3004	0.11939	0.2580	0.2909	0.3337	0.5308	120

Panel B: Commonality in resiliency

	Step 1		Step 3		Step 5	
	$MR^{S/D}$	Adj. R^2	$MR^{S/D}$	Adj. R^2	$MR^{S/D}$	Adj. R^2
Spread resiliency	0.8106 (4.99)	6.63	0.8656 (5.39)	7.44	0.8853 (6.10)	9.45
Depth resiliency	0.7899 (4.51)	5.53	0.8496 (5.09)	6.92	0.8981 (6.90)	12.33

Panel C: Spread resiliency

	Constant	PPT	OAR	TS	Size	Vola	OI	Algo	VolaAlgo	SizeAlgo	MR^S	Adj. R^2
Step 1	0.2527 (4.95)	0.0383 (2.35)	-0.0560 (-7.22)	0.0221 (2.65)	0.0980 (6.06)	-0.0013 (-1.82)	-0.0063 (-1.80)	0.0158 (2.20)	-0.0024 (-1.95)	0.0299 (2.72)	0.8926 (29.07)	15.13
Step 3	0.2079 (5.58)	0.0416 (3.33)	-0.0461 (-7.89)	0.0154 (2.29)	0.0856 (6.09)	-0.0009 (-1.86)	-0.0086 (-2.74)	0.0205 (3.03)	-0.0033 (-2.73)	0.0140 (3.62)	0.8883 (32.53)	13.64
Step 5	0.1961 (4.82)	0.0244 (1.73)	-0.0469 (-8.37)	0.0138 (2.29)	0.0711 (5.56)	-0.0012 (-0.93)	-0.0069 (-2.24)	0.0257 (3.74)	-0.0022 (-1.76)	0.0051 (0.61)	0.9030 (30.57)	14.34

Panel D: Depth resiliency

	Constant	PPT	OAR	TS	Size	Vola	OI	Algo	VolaAlgo	SizeAlgo	MR^D	Adj. R^2
Step 1	0.3282	0.0198	-0.0713	0.0148	0.0876	-0.0031	-0.0068	0.0688	-0.0052	0.0218	0.7924	11.58
	(14.05)	(2.93)	(-13.31)	(0.70)	(5.21)	(-2.56)	(-3.29)	(10.83)	(-3.29)	(2.22)	(7.91)	
Step 3	0.2448	0.0077	-0.0635	0.0066	0.0968	-0.0036	-0.0066	0.0721	-0.0043	0.0466	0.7959	11.77
	(7.98)	(2.65)	(-10.43)	(0.65)	(5.73)	(-2.06)	(-1.88)	(9.48)	(-2.66)	(3.95)	(24.35)	
Step 5	0.1582	0.0285	-0.0520	0.0077	0.0792	-0.0029	-0.0026	0.0563	-0.0037	0.0326	0.8925	15.05
	(5.42)	(2.26)	(-8.44)	(0.77)	(5.10)	(-2.22)	(-0.71)	(7.08)	(-2.38)	(-2.66)	(23.23)	

Table VIII: Consumption and replenishment resiliency

This table shows the results for resiliency estimated separately as liquidity reverts to its mean from above or below. We estimate Equation (0) and obtain one resiliency coefficient to measure whether liquidity reverts to is mean from above (downwards resiliency $\kappa^{S/D}_{\text{down},i,\text{T}}$) or from below (upwards resiliency $\kappa^{S/D}_{\text{up},i,\text{T}}$). From these coefficients we calculate consumption liquidity as $\kappa^{S/D}_{\text{cons},i,\text{T}} = \kappa^{S/D}_{\text{down},i,\text{T}}$ and replenishment resiliency as $\kappa^{S/D}_{\text{replen},i,\text{T}} = \kappa^{S/D}_{\text{up},i,\text{T}} + \kappa^{S/D}_{\text{down},i,\text{T}}$. All explanatory variables are as in Table VI. Panel A replicates Panel A of Table II and presents summary statistics on the time series averages of spread and depth resiliency, but now separately for consumption resiliency $\kappa^{S/D}_{\text{cons},i,\text{T}}$ and replenishment resiliency $\kappa^{S/D}_{\text{replen},i,\text{T}}$. In Panel B presents the results of a commonality analysis like in Panel A of Table III, but now separately for consumption resiliency and replenishment resiliency. In Panel C we replicate Panel C of Table VI, but now separately for consumption resiliency and replenishment resiliency. All explanatory variables are as in Table VI. The estimated coefficients are provided in the first line and *t*-statistics in the second line in parentheses. Standard errors are two-way clustered by trading day and stock. The last column provides the adjusted R^2 in percentage points.

Panel A: Average resiliency

	Mean	Min	25%	50%	75%	Max	# Obs.
				Spread resiliency			
Consumption	0.6833	0.0530	0.6258	0.6671	0.7320	0.9583	120
Replenishment	0.6328	0.2358	0.5521	0.6274	0.6903	0.8634	120
				Depth resiliency			
Consumption	0.5524	0.2706	0.5048	0.5452	0.5976	0.8265	120
Replenishment	0.5518	0.3787	0.5105	0.5509	0.5938	0.7436	120

Panel B: Commonality in resiliency

	Spread resiliency		Depth resiliency	
	$MR^{S/D}$	Adj. R^2	$MR^{S/D}$	Adj. R^2
Consumption	0.3510	1.72	0.7535	3.28
	(2.06)		(3.82)	
Replenishment	0.4651	2.16	0.8702	5.45
	(3.11)		(4.00)	

Panel C: Determinants of consumption and replenishment resiliency

	Constant	PPT	OAR	TS	Size	Vola	OI	Algo	VolaAlgo	SizeAlgo	$MR^{S/D}$	Adj. R^2
	Spread resiliency											
Consumption	0.0567	0.0545	-0.0741	0.0069	0.1029	-0.0116	-0.0129	0.0250	-0.0631	0.0363	0.7883	9.59
	(0.79)	(1.95)	(-4.33)	(0.05)	(3.98)	(-2.02)	(-1.92)	(1.87)	(-1.65)	(2.06)	(35.55)	
Replenishment	0.3646	0.0672	-0.0772	0.1536	0.0897	-0.0348	-0.0619	0.0759	-0.1661	0.0250	0.7171	12.43
	(1.14)	(1.81)	(-2.64)	(3.73)	(3.77)	(-2.68)	(-1.74)	(2.81)	(-2.09)	(3.62)	(12.98)	
	Depth resiliency											
Consumption	0.3412	0.0234	-0.0756	0.0189	0.0940	-0.0090	-0.0059	0.0734	-0.0141	0.0241	0.8342	6.50
	(9.50)	(1.64)	(-12.26)	(2.06)	(5.76)	(-2.08)	(-1.63)	(9.89)	(-2.87)	(2.33)	(26.82)	
Replenishment	0.9090	0.1585	-0.1016	0.0178	0.0494	-0.0360	-0.1372	0.0803	-0.0182	0.0570	0.9721	9.39
	(0.99)	(1.80)	(-2.48)	(1.88)	(1.74)	(-2.25)	(-1.92)	(2.93)	(-2.05)	(1.98)	(26.78)	

TABLE IX: Resiliency in the financial crisis

This table replicates Table VIII, but now separately for the financial crisis vs. non-crisis period. Panel A replicates Panel A of Table VIII for depth resiliency, but now separately for the financial crisis and non-crisis period and for the bid and the ask side of the order book. We calculate the time-series average $\hat{\kappa}^{D\ \text{bid/ask}}_{\text{cons/replen},i}$ of the daily parameters $\hat{\kappa}^{D\ \text{bid/ask}}_{\text{cons/replen},i,T}$ at the bid and the ask depth for each stock *i* for the financial crisis period ($T \in$ [August 15, 2008; December 31, 2008]) and for the non-crisis period. Panel B presents the results of a commonality analysis like in Panel B of Table VIII for depth resiliency, but now separately for the financial crisis and non-crisis period and for the bid and the ask side of the order book. Panel C replicates the results of Panel C of Table VIII for the financial crisis period. The resulting number of observations is 7,343 for the financial crisis and 36,387 for the preceding and following time periods. All explanatory variables are as in Table VI. The estimated coefficients are provided in the first line and *t*-statistics in the second line in parentheses. Standard errors are two-way clustered by trading day and stock. The last column provides the adjusted R^2 in percentage points.

Panel A: Average resiliency

		Mean	Min	25%	50%	75%	Max	# Obs.
		Bid depth resiliency						
Consumption	Financial crisis	0.7165	0.3850	0.6334	0.7134	0.7950	0.8341	107
	Non-crisis	0.5987	0.2214	0.5552	0.5935	0.6338	0.8773	119
Replenishment	Financial crisis	0.6567	0.4106	0.5986	0.6570	0.7173	0.8746	107
	Non-crisis	0.6827	0.2794	0.6437	0.6812	0.7208	0.8630	119
		Ask depth resiliency						
Consumption	Financial crisis	0.5995	0.2978	0.5509	0.5984	0.6362	0.8648	107
	Non-crisis	0.6502	0.3861	0.5964	0.6551	0.7080	0.8787	119
Replenishment	Financial crisis	0.7159	0.3250	0.6344	0.7191	0.7904	0.9536	107
	Non-crisis	0.6861	0.4624	0.6303	0.6854	0.7296	0.9556	119

Panel B: Commonality in resiliency

	Bid depth resiliency				Ask depth resiliency			
	Financial crisis		Non-crisis		Financial crisis		Non-crisis	
	$MR^{S/D}$	Adj. R^2	$MR^{S/D}$	Adj. R^2	$MR^{S/D}$	Adj. R^2	$MR^{S/D}$	Adj. R^2
Consumption	0.6935	5.95	0.7734	2.66	0.7585	4.99	0.7317	2.69
	(1.81)		(2.86)		(1.88)		(2.78)	
Replenishment	0.9211	13.76	0.0394	0.06	0.9120	16.19	0.0668	0.12
	(8.95)		(0.08)		(9.79)		(0.20)	

Panel C: Determinants of resiliency in the financial crisis

	Constant	PPT	OAR	TS	Size	Vola	OI	Algo	VolaAlgo	SizeAlgo	$MR^{S/D}$	Adj. R^2
	Bid depth resiliency											
Consumption	0.2239	0.0178	-0.0531	0.0311	0.0835	-0.0059	-0.0221	0.0564	-0.0057	0.0223	0.8160	7.45
	(3.30)	(2.63)	(-6.48)	(2.80)	(3.15)	(-2.35)	(-2.58)	(6.43)	(-1.75)	(2.35)	(17.51)	
Replenishment	-0.6272	0.0061	-0.0522	0.0127	0.0934	-0.0171	-0.0322	0.0325	-0.0096	0.0165	0.9427	14.52
	(-0.98)	(1.98)	(-6.20)	(2.45)	(6.05)	(-1.74)	(-2.41)	(2.83)	(-2.62)	(2.07)	(25.32)	
	Ask depth resiliency											
Consumption	0.2626	0.0169	-0.0578	0.0169	0.0938	-0.0049	-0.0115	0.0590	-0.0037	0.0104	0.8712	9.48
	(3.57)	(1.74)	(-6.54)	(1.75)	(3.88)	(-1.74)	(-1.71)	(5.14)	(-1.72)	(1.95)	(17.85)	
Replenishment	0.4900	0.0102	-0.0286	0.0412	0.0848	-0.0046	-0.0171	0.0228	-0.0106	0.0092	0.9588	13.54
	(2.85)	(2.02)	(-1.88)	(5.05)	(1.92)	(-1.73)	(-1.68)	(3.48)	(-2.04)	(1.00)	(14.29)	

ENDNOTES

[1] On the other hand, while Garbade (1982, page 422) focuses on resiliency in liquidity, the perspective on resiliency in Kyle (1985) and Harris (2003, page 399-402) is that of convergence to pricing efficiency after a liquidity shock.

[2] The literature analyzing the price dimension starts with Glosten and Milgrom (1985) and Stoll (1989). Glosten and Harris (1988) and Hasbrouck (1991) are among the first to examine the quantity dimension. Biais, Hillion, and Spatt (1995), Ahn, Bae, and Chan (2001), Ranaldo (2002), or Bae, Jang and Park (2003) do investigate order submissions, order flows and order aggressiveness; but their focus is not on resiliency, or the refreshment mechanism of the order book.

[3] As per the World Federation of Stock Exchanges 2013 Market Highlights Report (http://www.world-exchanges.org/files/statistics/pdf/2013_WFE_Market_Highlights.pdf), the trading volume in electronic limit order books in 2013 was $54.7 trillion, out of which $25.7 trillion was traded within the US.

[4] See Kirilenko et al. (2014) for an analysis of the flash crash; and see Sornette and von der Becke (2011) for examples of mini flash-crashes.

[5] This decision problem is examined in the optimal execution literature. Almgren and Chriss (2003) and Huberman and Stanzl (2005) assume that trades have permanent and temporary price impacts and impose the restriction that traders wait with their next lot until the temporary price impact has been absorbed by the market. Obizhaeva and Wang (2013) allow traders to choose whether they wait or trade before the temporary impacts have been taken back. In their model, resiliency has a strong impact on the optimal strategy.

[6] A major focus of Degryse et al. (2005) is to extend Biais, Hilliot, and Spatt (1995) to document more extensively the patterns in the order-flow around aggressive orders, and hence, they provide useful results on the timing and frequency of different types of aggressive orders. The focus of this paper is exclusively on resiliency.

[7] Holden, Jacobsen, and Subrahmanyam (2014) provide an excellent review of the empirical literature on liquidity.

[8] We could not find any theoretical models of depth resiliency in extant literature. Foucault, Kadan, and Kandel (2005) is also the only theoretical model we found of spread resiliency.

[9] The tick-sizes were 0.01 pence (p), 0.1p, 0.25p, 0.5p, and 1p, for stocks priced below 10p, between 10p and 199.9p, between 200p and 499.75p, between 500p and 999.5p, and above 1,000p respectively.

[10] The FTSE-100 is rebalanced quarterly, such that the total number of stocks exceeds 100.

[11] See, for example, Ross (1989) and Andersen (1996).

[12] Order imbalances have been extensively used as an information-related proxy in the literature. See, for example, Easley and O'Hara (1997), Chan and Fong (2000), and Chordia, Roll, and Subrahmanyam (2002). Order imbalances are also the basis of the PIN measure, a widely used proxy for information asymmetry.

[13] This finding is also consistent with the Boehmer, Fong, and Wu (2014) who find that algorithmic traders prefer stocks with low volatility.

[14] See, e.g., Irvine, Benston, and Kandel (2000), Kempf and Mayston (2008), and Degryse, de Jong, and van Kervel (2014).

[15] To estimate the parameters of Equation (0), we need to specify a value for the average liquidity level $\theta_{i,T}^{S/D}$. We use the daily mean in the results displayed below, but there are no qualitative differences when we use the daily median. Our inferences are also robust against using an estimate for $\theta_{i,T}^{S/D}$ based on data from day *T-1*.