The Dynamics of Liquidity in a Limit Order Market[1]

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January 15, 2007

[1]I would like to thank Hans Degryse and Frank de Jong for detailed comments on an earlier draft. Very valuable comments from Hans Dewachter, Dirk Heremans, Patrick Van Cayseele and Marno Verbeek are also gratefully acknowledged.

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Abstract

This paper develops a multivariate framework to study liquidity in an order driven market. It allows for analyzing various dimensions of liquidity (prices, depth, and duration) and for capturing the interactions between them. In addition, we investigate resiliency, i.e. how fast best prices, depths and duration recover to their initial, pre-shock level after the market has been hit by a liquidity shock. Our results clearly demonstrate the importance of incorporating different dimensions of liquidity in the analysis. In case of a negative liquidity shock, we find a permanent effect on prices, with returns (in absolute value) ranging from 0.06 to 0.16%, depending on size and tick size of the stock. Also, we find an initial widening of the spread, but it becomes smaller again in subsequent periods. On the other hand, depth at the best prices increases, initially with up to 20%. Symmetric results are obtained for a positive liquidity shock. A second main conclusion is that an analysis of liquidity should also allow for asymmetries in dynamics at bid and ask side of the market, while at the same time accounting for the existence of a relationship between them.

JEL Classification: G10

Keywords: Liquidity, Liquidity Shock, Resiliency, Limit Order Market, Order Aggressiveness

1 Introduction

This paper develops a multivariate framework to study liquidity in an order driven market. It allows for analyzing various dimensions of liquidity and capturing the interactions between them. Models such as Rosu (2006) and Parlour (1998) show that bid and ask side of the market do not evolve independently. Also intuitively, it is for instance clear that the ask price will not move randomly far away from the bid price. Moreover, prices and depths at these prices could interact. If an arriving trader is faced with a long queue of limit orders at the ask, she might prefer to undercut the ask to obtain price priority and probably faster execution. Moreover, an interaction may also exist between prices and depths, and duration. Therefore, the main goal of this paper is to empirically investigate in a *joint* framework the different dimensions of liquidity in a limit order market. The methodology we employ is a vector autoregressive (VAR) model. Prices, depths and duration form the vector of endogenous variables capturing different dimensions of liquidity. The exogenous variables include the degree of aggressiveness of orders, their size and time-of-day dummies. In the literature, liquidity has been extensively analyzed (see Section 2). This paper however differs from and adds to this literature in several aspects. First, in contrast with much of the earlier literature - which focusses on the spread or the midquote - we include both bid and ask prices in our model, following recent papers such as Engle and Patton (2004). These authors however, consider the NYSE, which is a hybrid market, while we study a pure order-driven market without dealers that have an obligation to provide liquidity. Moreover, we add to the literature by simultaneously modeling complementary aspects of liquidity: the depth at the best bid and ask and duration. By explicitly incorporating both bid and ask side of the market in our model, we allow for asymmetries between both sides. These five variables comprise the vector of endogenous variables in the VAR model, specified in error correction form. Kavajecz and Odders-White (2001) have a similar approach but focus on quote setting behavior of specialists and neglect cointegration between bid and ask prices and do not model duration.

Besides allowing for the analysis of prices, depths and duration, our VAR-approach provides a convenient framework for studying resiliency, another aspect of liquidity. Harris (1990) defines this concept as "how quickly prices revert to former levels after they change in response to large order flow imbalances initiated by uninformed traders". We use a slightly different definition and define resiliency as how fast best prices, depths and duration recover to their initial (i.e. pre-shock) level after the market has been hit by a liquidity shock. In the literature, such shock is typically implemented via the innovation process of the VAR-model. For example, Beltran, Durré and Giot (2004) take this approach when studying liquidity in a limit order market. The disadvantage of this is that little is said about the specific origins of such "general" shock. This paper proposes an alternative and novel approach by analyzing a well-defined liquidity shock having a very specific source. We measure a liquidity shock by a very aggressive order, following Biais, Hillion and Spatt (1995) who propose a scheme to classify orders according to their aggressiveness. In addition, we make a distinction between a negative and a positive shock, and between a shock on the ask and bid side of the market. We thus consider four types of shocks which are defined as follows. A negative liquidity shock on the ask (bid) side is a buy (sell) order that consumes all the depth at the best ask (bid) and moves up (down) the best ask (bid). A positive liquidity shock is defined as a buy (or sell) order that improves the best bid (ask), hence it is an order that narrows the bid-ask spread. It is natural to specify a liquidity shock in term of a specific type of orders[1], since in a limit order market, liquidity (and resiliency) is determined by the interaction between limit orders, which supply liquidity, and market orders, which consume it. Ultimately, it is the mix between both types of orders that shapes the liquidity of a limit order market. Also the theoretical model in Foucault, Kadan and Kandel (2005) defines a liquidity shock as a "string of market orders that enlarges the spread". Such string is closely related to our measure of a negative liquidity shock, being an aggressive order. Such order can be interpreted as a string of market orders.

The analysis is applied to a sample of stocks, quoted on Euronext Paris. The remainder of this paper is organized as follows. In Section 2 we relate our work to the existing literature and elaborate on the differences with previous studies. In Section 3, the multivariate econometric model is developed. Also, we explain the simulation methodology for studying resiliency. Section 4 presents the dataset used. In Section 5, the results of the multivariate model are presented. A robustness check of the econometric model and methodology is discussed in Section 6. Section 7 concludes.

2 Related Literature

In empirical market microstructure research, the use of VAR-models has been pioneered by Hasbrouck (1991). He finds that the full impact of a trade innovation is not realized instantaneously but with a lag. Moreover, the impact is higher if the stock is more infrequently traded, if the trade size is large and if there exists a wide spread at the moment of the trade. Since this seminal paper, numerous variants and extensions have been developed. Dufour and Engle (2000) investigate the informational role of market activity and show how the dynamics in prices and trades are affected by the information revealed by the time between transactions. In the model of Easley and O'Hara (1992), the time between trades is an indication whether or not a news event has occurred. Uninformed traders use this signal to revise their beliefs about the arrival of news about which some

[1] Remark that also the definition of Harris (1990) defines resiliency in terms of order flow.

traders might be informed. Dufour and Engle find that both larger quote revisions and stronger positive autocorrelation of trades are linked to a higher trading activity. In this case, prices converge faster to the full information value after an unexpected trade. When combining their results with those of Hasbrouck, they conclude that high trading activity goes together with large spreads, high volume and a high price impact of trades. Active markets are then illiquid in the sense that the price impact of trades is higher. Both Hasbrouck (1991) and Dufour and Engle (2000) include the change in the quote midpoint (and the trade direction) as endogenous variables in their VAR-models. Two recent papers, Engle and Patton (2004) and Escribano and Pascual (2000), include both bid and ask quotes in their model and in this way allow trades to have an asymmetric impact on bid and ask prices. They also correct for cointegration between bid and ask. The motivation of Engle and Patton (2004) for including both bid and ask quotes lies in a study by Jang and Venkatesh (1991). The latter show that the most common response by liquidity suppliers to news is no adjustment, but the second preferred response is that only one of both quotes is changed. After a buy, it is more likely for the ask to be changed than for the bid. This means that the dynamics of ask and bid quotes will be different after a buy order than after a sell order. Our approach captures this by including both ask and bid in the VAR-model, in this way following Engle and Patton (2004), and by looking at aggressive buy and sell orders as a measure for a liquidity shock. Engle and Patton (2004) find evidence for a strong asymmetric impact on bid and ask prices of buyer and seller initiated trades in the short run. Short durations and medium volume trades have the largest impact. The order of magnitude of the effects is in general larger in the lower trade frequency deciles. Also Escribano and Pascual (2000) find that the responses of bid and ask quotes to a trade are not necessarily symmetric. They show that the mean impact of an unexpected buy on the ask quote differs from the mean impact of an unexpected sell on the bid quote. Moreover, the sensitivity of the response of the ask to a trade innovation when market conditions are changed, differs from that of the bid quote. The impact of a buy on the ask quote depends e.g. more on the time since the previous trade than the impact of the corresponding sell on the bid quote. However, symmetry is more likely the more informative trades are. In the context of a dealer market, Kavajecz and Odders-White (2001) investigate the quote revision process of specialists on the NYSE using a VAR-model with quoted bid and ask and quoted depth at these prices. As exogenous variables they include a wide range of market and order flow characteristics. They conclude that specialists revise both quotes prices and depth in response to different events. For instance, quoted depth is revised in response to any transaction, while prices are only revised when the transaction size exceeds quoted depth. However, these changes are not only induced by transactions, but also by other events, such as e.g. changes in prices or depth in the (competing) limit order book.

A study, related to ours, which also addresses the issue of liquidity in a limit order market is Coppejans, Domowitz and Madhavan (2004), although they use 5-minute intervals, instead of tick-time as we do. They use market depth at the buy and sell side as a measure of liquidity and the change in the midquote as a return. With data from the limit order book of the market for Swedish stock index futures, they show that liquidity varies over the trading day. Secondly, by estimating a structural VAR-model, they find that the contemporaneous impact of returns on depth is symmetric and significant. Lagged returns do not have a significant effect on depth. On the other hand, changes in depth have an influence on returns, but with a lag. Thirdly, they analyze the responses of depth and returns to shocks. A liquidity shock on the ask (bid) side of the market lowers (increases) returns. The effects are short-lived since almost all the impact occurs during the 10 minutes following the shock. Moreover, they find evidence of liquidity clustering since if there is an increase in liquidity[2] on one side of the market, this leads to an increase in liquidity at the other side of the market as well.

In our empirical model, we also include the duration between blim updates. The duration between blim updates $t-1$ and t can be interpreted as a measure of trading and order submission activity. The reason is that only type 6 and 12 orders do not generate such an update, all other types cause prices and/or depths to change. Theory shows that the time between trades is informative. In the model of Easley and O'Hara (1992), the lack of trades (or in other words, the duration since the last trade) provides a signal about the existence of new information in the market[3]. As a result, spreads are shown to decrease as the time between trades increases. Foucault, Kadan and Kandel (2005) show that the resiliency of a limit order market is decreasing in the order arrival rate, i.e. a market having a lower order arrival rate, is more resilient than a fast market. The reasoning is that, when the order arrival rate increases, limit order traders become less aggressive in their price improvements. As a consequence, more orders are needed to bring down the spread to its competitive level, implying resiliency declines. Empirically, Engle and Patton (2004) confirm that the impact of a trade is different depending on the time elapsed since the previous trade. They find that short duration and medium volume trades have the largest impacts on quote prices.

Finally, we want to remark that this paper does not aim to explain *why* a trader chooses a certain order type. Ranaldo (2004) discusses the complementary issue of the determinants of the choice of an order type by a trader. We do not model this choice, but take the submission of the order as given and analyze its aftermath. In this sense, Ranaldo focusses on the period *before* the submission of an order while we investigate the period *thereafter*. In this way, we shed some light on the consequences of the order choices and how the market responds to them. Note however that we do correct in the regression models for past order flow.

[2] They measure a liquidity shock as a shock to market depth, defined as total depth 6 ticks away from the quote midpoint

[3] Trades themselves then reveal information about the direction of the information event.

3 Econometric Methodology

3.1 Modeling Prices, Depths and Duration

As argued in the introduction, prices and depth at the bid and ask side of the market may not move independently, but rather interact with each other. The same holds for prices and duration between updates of the limit order book. Therefore, we develop in this section an empirical model which is able to capture these elements. In empirical research, vector autoregressive (VAR) models are a popular and convenient methodology for analyzing the interaction between variables of interest and their behavior around shocks. In our study, which makes use of a VAR-model, the variables of interest are the best bid and ask prices in the limit order book, the depth at these best prices and duration.

By explicitly modeling both sides of the market, we allow for asymmetries between them. This approach is also in line with recent work by e.g. Engle and Patton (2004) and Escribano and Pascual (2000) who consider both bid and ask prices. When analyzing a limit order market, also depth at the best prices needs to be incorporated in the model. Parlour (1998) shows that in an order driven market the choice between limit and market orders depends on the depth at both sides of the book. Recall that it is precisely the mix between market and limit orders which determines liquidity in a limit order market, since they determine respectively liquidity demand and supply. We include also duration in our model. Theory shows that the time between trades is informative. In the model of Easley and O'Hara (1992), the lack of trades (or in other words, the duration since the last trade) provides a signal about the existence of new information in the market[4]. As a result, spreads are shown to decrease as the time between trades increases. Foucault, Kadan and Kandel (2005) show that the resiliency of a limit order market is decreasing in the order arrival rate, i.e. a market having a lower order arrival rate, is more resilient than a fast market. The reasoning is that, when the order arrival rate increases, limit order traders become less aggressive in their price improvements. As a consequence, more orders are needed to bring down the spread to its competitive level, implying resiliency declines. Empirically, Engle and Patton (2004) confirm that the impact of a trade is different depending on the time elapsed since the previous trade. They find that short duration and medium volume trades have the largest impacts on quote prices.

Hence, we define the vector of endogenous variables y_t as follows:

$$y_t = \{\Delta \ln A_t, \Delta \ln B_t, AD_t, BD_t, \ln(d_t)\}$$

with A_t (B_t) the best ask (bid) price at time t, AD_t (BD_t) the depth at the best ask (bid) at time t and $\ln(d_t)$ the natural logarithm of the duration since the previous blim

[4] Trades themselves then reveal information about the direction of the information event.

update[5]. In the remainder of this paper, when we refer to bid or ask prices, this should be interpreted as referring to the log price. We thus also follow Harris (1990) who considers prices and depth as two separate aspects of liquidity. In the above definition, we take first differences of the price series because the null hypothesis of a unit root in both best bid and ask series cannot be rejected. These first difference of log prices can be interpreted as the return on the best bid (or ask). The time index t refers to a best limit or *blim update*. We record a blim update each time when at least one of the following endogenous variables changes: best bid, best ask, depth at best bid or depth at best ask. This means that the VAR model is specified in event time (as opposed to calendar time). If there are multiple blim updates in the same second, we take the values after the last update. Kavajecz and Odders-White (2001) use a similar y_t vector, but within the context of quote setting behavior of specialists in the NYSE. Moreover, they do not include duration.

When analyzing prices, depths and duration, we account for the characteristics of the order flow. Order flow is modelled by including three sets of exogenous variables. The first set describes the degree of *aggressiveness* of the submitted orders and consists of the *number* of orders of type $i = 1, ..., 12$ that has been submitted since the last blim update, which we denote by $O01_t, ..., O12_t$. For a definition of the different aggressiveness types, we refer to Appendix A. In general, only $O06_t$ and $O12_t$ can have a value larger than one, since these are the only order types that do not cause a change in best prices or depth. In addition, only one of the ten other variables will have a value equal to one, while the others are zero. The only exception is when multiple orders are recorded within the same second. It is e.g. possible that an order of type 1 and two orders of type 3 are submitted at the same time (meaning within the same second). In this case $O01_t = 1$ and $O03_t = 2$. We already mention here that $O01_t$ and $O07_t$, will be used to simulate a negative liquidity shock, and $O04_t$ and $O10_t$ to simulate a positive liquidity shock; we return to this issue in the description of the simulation procedure in the next section.

The second set of order flow variables is related to *order size*. On average, orders with a higher degree of aggressiveness have a larger order size (as can be expected from definition), see Table 1. By including both the degree of aggressiveness and size, we are able to disentangle both effects. Moreover, Easley and O'Hara (1987) show that order size is important in determining price impacts. Hence, $OSize01_t$ represents the cumulative order size of all type 1 orders that have been submitted since the last blim update. For the other eleven order types, similar order size variables $OSize02_t, ..., OSize12_t$ are defined.

Thirdly, to account for possible intraday patterns in returns and depth[6], we include *time of day* dummies. We take a separate dummy for the first and last half hour of trading because of the more pronounced trading activity during these intervals. Hence,

[5]Using the natural logarithm of duration is in line with the literature, see e.g. Dufour and Engle (2000).

[6]This effect might e.g. be due to the U-shaped pattern of trading activity during the day (see Biais, Hillion and Spatt (1995) for an illustration of this phenomenon on the Paris Bourse).

$T01_t$ ($T08_t$) equals 1 if the blim update takes place between 10h and 10h30 (16h30 and 17h). The remainder of the trading day is divided in intervals of 1 hour: $T02_t$ is 1 if the order is between 10h30 and 11h30, ... , $T07_t$ is 1 if the order is between 15h30 and 16h30 and zero otherwise.

Summarizing, we define the vector of exogenous variables x_t as:

$$x_t = \{O01_t, ..., O12_t, OSize01_t, ..., OSize12_t, T01_t, ...T07_t\}$$

where we left out the dummy for the last interval of the trading day to avoid perfect multicollinearity in estimation.

A final point concerns the econometric properties of the series used. Best ask and bid prices not only have a unit root, but can also be expected to be *cointegrated*. Engle and Patton (2004) find empirical evidence of the presence of cointegration. In our model, the cointegrating term has a simple interpretation, being the log spread, hence: $Spread_t = \ln(A_t) - \ln(B_t)$. This means that the VAR-model is specified in error correction form. We do not impose other cointegrating relations since only bid and ask prices are found to be integrated of order 1 or $I(1)$. Depths and (log) duration are $I(0)$.

Bringing all of the above together, our VAR-model is specified as follows:

$$y_t = A_0 + \sum_{l=1}^{L} A_l y_{t-l} + \sum_{m=0}^{M} B_m x_{t-m} + \Phi Spread_{t-1} + u_t \tag{1}$$

with u_t the error term which is assumed to be white noise and A_0, A_l, B_m and Φ the coefficient matrices to be estimated. Remark that for the endogenous variables, only lags are included, while for the vector of exogenous variables, also the contemporaneous values are considered.

3.2 Resiliency

Resiliency, another aspect of liquidity next to prices, depths and duration, refers to the ability of a trading system to cope with shocks hitting the market. Earlier, we defined resiliency as "the speed of recovery to their initial (pre-shock) levels of different measures of liquidity (i.e. prices, depths and duration) after a liquidity shock hits the market". It then remains to be specified what comprises such liquidity shock. Most of the market microstructure literature uses a "general" shock, implemented via the error terms in a VAR-model (in our case this would be u_t in equation (1)). In contrast, this paper proposes an alternative and novel approach by using a clearly identifiable and concrete event. More specifically, we measure a negative liquidity shock on the ask (bid) side as a type 1 (type 7) order. From Appendix A, it is clear that such orders are the most aggressive buy (sell) orders. Such shock widens the bid-ask spread and consumes all the depth at the best prices and some of the depth behind. Note that a distinction is made between a shock on the buy and sell side of the market. This measure is also in line with the one in the model of Foucault, Kadan and Kandel (2005), who specify a liquidity shock as a string of market orders, which widens the spread. Next to a negative shock, we also investigate the impact of a positive liquidity shock and how long the beneficial effect remains in the market. Such shock is measured by a type 4 order for a shock on the bid side and a type 10 order for the ask side of the market. These are orders that improve one of the best prices hence narrow the bid-ask spread.

Using these concepts, the resiliency of the market can then be investigated by simulating a liquidity shock. This simulation is performed using the VAR-model in equation (1). More specifically, we start from an order of type i, $i = 1, 7, 4$ or 10, and compute the evolution of prices (returns), depths and duration during a period of $h = 1..25$ blim updates after the submission. In the simulation procedure, which is inspired by Escribano and Pascual (2000), it is assumed that an aggressive order of type i is submitted in interval 4 (this is between 12h30 and 13h30). After having estimated the VAR model in (1), the simulation procedure proceeds through the following steps:

1. As stated, a liquidity shock will be measured by an order of type i in interval 4 of the day. This is simulated by setting the relevant order type and time of day dummies equal to one. So, $T04_t = 1$, and either $O01_t, O07_t, O04_t$ or $O10_t = 1$, depending on whether $i = 1, 7, 4$ or 10. The other variables in the x_t vector (order sizes) are set equal to their unconditional mean.

2. In a second step, we need to compute the initial values for the lags of the endogenous variables ($y_{t-l}, l = 1..L$), as well as the lags of the exogenous variables (x_{t-m}, $m = 1..M$)[7]. They are equated to their unconditional mean. The reasoning is that in this way the system starts from a "stationary" or "steady-state" situation, after which a shock arrives.

3. For each of the *exogenous* variables, a predicted value needs to be computed for $h = 1..25$ periods[8] after the order. For predicting the *order type* and *order size* variables, we calculate the average value of each of these variables in period $t + h, h = 1..25$, conditional upon the submission of a type i order in interval 4 which is indexed by t. Finally, we need predicted values for the last group of exogenous variables, being the *time of day* dummies. For them, we assume that the 25 blim updates following an aggressive order, fall entirely in the fourth interval of the day (i.e. between 12u30 and 13u30), such that $T04_{t+h} = 1, h = 1..25$. This is however not a restrictive

[7] The values for x_0 are those of the initial shock and are determined in step 1.

[8] Recall that a period refers to the next blim update.

assumption since, as will turn out later, the coefficients of the time of day dummies often are not significant, neither econometrically, nor from an economic point of view.

4. On the basis of the VAR in (1) and the necessary data computed in the previous three steps, we are able to compute the impulse response functions for bid and ask returns and depth at best bid and ask for each period $h = 1, ..., 25$ after the liquidity shock, i.e. the submission of the order of type i. Note that for each period h, the value of $Spread$ is updated in the following way: $Spread_{t+h} = Spread_{t+h-1} + \Delta \ln A_{t+h} - \Delta \ln B_{t+h}$.

4 Data

4.1 Sample

Our sample consists of a random selection of twenty stocks (see Table 1 for a list of the stocks) quoted on Euronext Paris. We divide the selected stocks into four groups, based on the size and tick size of the stock. Group 1 contains five small stocks with small tick size (more specifically stocks with a tick size of 0.1 French Francs (FF)), while group 2 is composed of small stocks with large tick size (i.e. stocks with a minimum price variation of 1 FF). Groups 3 and 4 contain large stocks with tick size 0.1 FF and 1 FF respectively. The distinction between large and small stocks, or frequently and less frequently traded stocks as there is a high correlation between both concepts, is motivated by papers such as Spierdijk et al. (2002), who show that considerable differences exist between the price impact of trades for frequently and infrequently traded stocks. The motivation for creating separate groups based on the minimum price variation is rooted in Foucault, Kadan and Kandel (2005). They show that there exists a link between the resiliency of a limit order market and tick size. More specifically, a smaller tick size may reduce resiliency. The reasoning is that when the tick size is larger, traders need to improve prices by more than they would with a smaller tick size in order to obtain price priority. This spread improvement effect causes the bid-ask spread to narrow faster between transactions, making the market more resilient.

Our sample period ranges from 23 February 1998 until 24 August 1998, which are 123 trading days. We assured that during this sample period the tick size of a given stock is constant, because a varying tick size, i.e. a tick size that changes from 0.1 FF to 1 FF or the other way around, might make it difficult to precisely determine the effect of tick size on our results. The data are taken from the SBF database of the Paris Bourse. For the selected stocks, we use the order file of this database, which contains data on all incoming orders, and the best limit file, which keeps track of all best bid and ask prices in the limit order book, as well as the depth at these prices. We eliminated all pre-opening orders from our data set because the trading mechanism during this period, which is a batch auction, differs from the continuous auction setting during the day. The fact that the data do not allow for the observation of order modifications and cancellations does not hamper our order classification methodology, as we take the state of the order book just before the arriving order into account.

4.2 Descriptive Statistics

In Table 1, we present the composition of the four groups of stocks as well as some descriptive statistics of the data. Panel A and B show the statistics for small and large stocks respectively. Within each panel, the left part contains the stocks with a small tick size (group 1 in Panel A, group 3 in Panel B), the right part those with a large tick size (groups 2 and 4). In the first block of the table, we show the number of best limit updates, as well as the market capitalization (in million FF) at the end of 1998 and the average daily turnover (in million FF) in 1998. For the latter two, we also give the rank of the stock in the top 100 of the Paris Bourse. These three variables clearly show that the stocks in our sample are indeed different in trading frequency and size.

In the second block of each panel, some descriptive statistics on the different variables in our VAR-model are presented[9]. First, we show the average *return* on the best ask and bid prices in the limit order book as well as the standard deviation (second row). For all stocks, this return is very small on average. This is due to the fact that for a majority of the best limit updates only the depth at the best prices changes. Best prices themselves do not change, hence the return is zero for these observations. Subsequently, the *depths* at the best bid and ask (in number of shares) and their standard deviations are shown. Remarkable is that in almost all cases the average depth at the best ask is larger than average depth at the best bid. Next, the frequency (in %) of occurring of the different *order types* are shown. The results reveal that aggressive buy and sell orders (type 1 and 7) have the smallest frequency of occurring across order types. Types 4 and 10, which are orders that narrow the spread, are submitted around twice as often. For all four orders types just discussed, the frequency is smaller for large tick stocks. In other words, relatively fewer aggressive orders (types 1 and 7) are submitted for stocks with a large tick size. The least aggressive buy and sell orders (types 6 and 12) are the most frequent. These frequencies are in line with the findings of Biais, Hillion and Spatt (1995) for the Paris Bourse and of Griffiths et al. (2000) for the Toronto stock exchange. The next group of variables shows the average *order size* of the different order types. Type

[9] We did not use the symbols that are used in equation 1 since their definition is sometimes slightly different. In the VAR, depths are expressed in 1000 shares, in Table 1 in number of shares. Moreover, order sizes in the VAR are the cumulative order size of all orders of a given type that have been submitted since the last blim update (in 1000 shares). In Table 1, they are the mean of an order of a given type (in shares)

1 and 7 are the largest orders on average. At first sight, this might be expected from their definition since these are the most aggressive orders, consuming all depth at the best prices. However, a priori it could also be true that orders are classified as aggressive because they are submitted at times when depths are small. The fact that the average order size of aggressive orders is large and moreover considerably larger than the average depth shows that this is not the case. *Duration* (in seconds) between best limit updates is comparable across groups of stocks of a given size (compare 1 with 2 and 3 with 4). Stocks that are part of the CAC40 stock index are more frequently traded than smaller stocks, which is reflected in the smaller duration. Finally, also the average *spread* (in French Francs) is larger for stocks with a large tick size. Taking tick size as given, it is also larger for smaller stocks (compare group 1 with 3 and 2 with 4).

5 Empirical Results

5.1 Model Specification

Before estimating the model, we verified the econometric properties of the series. Augmented Dickey-Fuller tests (not-reported) reveal that log ask and bid prices contain a unit root, while depth at the best ask and bid and log duration between blim-updates are stationary. As stated in Section 3, we took this into account in the model specification. During the estimation of the model in equation (1), we included five lags of the endogenous variables ($L = 5$) and one lag of the exogenous variables ($M = 1$). The AIC criterion points to this choice and it is also in line with the literature, see e.g. Engle and Patton (2004). Recall that we also include the contemporaneous values of the exogenous variables. A final note concerns the units of the variables. Returns are expressed in percentages. Depth at the best prices and order sizes are measured in 1000 shares. Duration is measured in seconds. F-tests show that the model is highly significant.

The results reported in Table 2 below, are robust to alternative specifications of the VAR-model (1). Adding more lags of endogenous and exogenous variables do not alter our results discussed below. Leaving out certain exogenous variables also does not change the main conclusions obtained.

5.2 Prices, Depths and Duration

The first aspects of liquidity that will be analyzed are the best prices in the limit order book, the depth at these prices and the duration between blim updates. As explained earlier, the basis for this analysis is the VAR-model in equation (1). The results of the estimation are presented in Table 2, in Panel A for small stocks and Panel B for large stocks. Each panel is further divided in two parts. The left part contains stocks having

Table 1: **Descriptive Statistics**

Note: This table presents the descriptive statistics of the sample. The first block shows the average number of best limit updates (where a best limit update is defined as the case where or best prices or depths change), the market capitalization (in million FF), and the daily turnover (in million FF). For the latter two, we also give the rank of the stock in the respective top 100 of Euronext Paris. In the second block, average returns on the best ask and bid ($\Delta \ln A$ and $\Delta \ln B$) as well as the average depth at these best prices in number of shares (*Askdepth* and *Biddepth*) are presented, together with their standard deviation (*S.d.*). Next, the frequency of occurring, in % of the total number of orders, of the different order types in our sample are given (% type i) and the average order size of each order type. Furthermore, the average duration (in seconds) between blim updates and the average spread (in FF) are shown.

	Group 1: Small Stocks, Small Tick Size					Group 2: Small Stocks, Large Tick Size				
	Moulinex	Nord Est	Pernod Ricard	SCOR	Sidel	Christian Dior	Imetal	Pathe	SEB	Technip
# Blim Updates	40516	10198	47833	35275	45037	33840	22097	16892	22098	28782
Market Cap	2 926	2 112	20 468	13 269	15 963	27 882	8 971	11 992	7 168	8 791
Rank	> 100	> 100	51	64	56	43	77	66	91	79
Daily Turnover	27	7	43	40	30	44	19	32	18	31
Rank	> 100	> 100	46	47	55	45	61	51	64	53
Δ ln A	-0.00097	-0.00086	-0.00058	-0.00011	-0.00033	-0.00025	-0.00239	0.00044	-0.00096	-0.00139
S.d.	0.1967	0.2941	0.1022	0.1648	0.1192	0.1537	0.1534	0.2124	0.1732	0.1772
Δ ln B	-0.00042	-0.00265	-0.00020	0.00058	-0.00063	0.00013	-0.00175	0.00236	-0.00062	-0.00138
S.d.	0.1937	0.2745	0.0962	0.1586	0.1125	0.1472	0.1588	0.1878	0.1857	0.1816
Askdepth	808	465	468	625	391	367	299	137	240	352
S.d.	1226	614	684	829	526	444	304	195	275	394
Biddepth	637	508	414	579	331	374	241	160	230	295
S.d.	1139	726	654	727	481	457	304	272	379	362
% type 1	4.84	3.43	3.70	4.02	3.23	2.50	2.68	2.87	2.81	2.90
% type 2	6.14	4.61	5.73	6.28	5.73	5.90	5.85	5.14	5.55	6.39
% type 3	11.13	8.63	10.94	8.27	12.36	7.55	14.71	6.90	11.24	11.51
% type 4	8.20	8.30	8.68	10.65	6.87	6.25	7.02	7.70	7.64	7.23
% type 5	5.58	5.29	6.15	7.35	5.23	7.17	7.31	6.26	7.68	7.61
% type 6	18.70	15.62	19.36	15.05	17.77	14.51	17.37	13.60	17.81	17.33
% type 7	3.86	4.28	3.61	3.31	3.74	2.63	3.05	3.00	3.34	3.10
% type 8	5.00	6.06	5.26	5.37	5.36	7.56	6.12	6.61	6.60	5.81
% type 9	5.96	10.32	7.75	5.81	9.17	11.09	7.05	10.87	7.96	7.22
% type 10	6.46	7.89	6.44	8.55	6.09	7.66	5.79	7.57	6.27	6.43
% type 11	6.23	5.48	5.72	8.44	6.06	7.97	7.37	6.90	6.80	7.92
% type 12	17.91	20.08	16.67	16.89	18.40	19.21	15.67	22.57	16.30	16.56
Order size type 1	1722	1294	1016	1742	743	2695	537	634	513	790
Order size type 2	1575	1031	771	1461	492	1663	406	631	425	588
Order size type 3	253	192	140	265	111	160	67	64	74	116
Order size type 4	1378	991	814	1494	624	1686	404	456	452	543
Order size type 5	1672	1798	990	1777	821	2324	522	592	594	656
Order size type 6	862	777	493	1189	372	1605	227	261	306	397
Order size type 7	3111	1169	1290	1974	836	717	709	444	595	746
Order size type 8	2472	745	893	1743	530	717	742	366	565	657
Order size type 9	326	195	158	307	113	117	108	65	100	138
Order size type 10	2235	902	1119	2017	704	583	705	437	516	716
Order size type 11	2739	1760	1607	2978	958	699	977	517	612	914
Order size type 12	1596	593	892	1988	475	430	526	238	387	625
Duration	76.15	297.81	64.26	87.10	68.34	90.94	137.40	180.78	138.42	106.67
Spread	0.99	1.08	1.38	1.96	1.66	3.66	3.93	7.17	4.98	4.19

Table 1 (continued)

	Group 3: Large Stocks, Small Tick Size					Group 4: Large Stocks, Large Tick Size				
	Lagardere	Michelin B	Renault	Rhone Poulenc	Thomson CSF	Danone	Elf Acquitaine	LVMH	Paribas	Total
# Blim Updates	101634	140156	142392	217454	81820	124282	186553	137407	157430	151878
Market Cap	28 486	30 767	60 189	106 964	40 256	117 881	177 850	98 402	77 853	138 299
Rank	41	38	23	12	32	11	5	15	18	8
Daily Turnover	92	173	162	393	62	397	636	259	440	531
Rank	36	24	27	12	40	10	5	16	9	6
Δ ln A	-0.00018	-0.00038	0.00033	-0.00014	-0.00028	0.00025	-0.00004	0.00004	-0.00026	-0.00013
S.d.	0.0973	0.0656	0.0916	0.0545	0.1060	0.0738	0.0633	0.0742	0.0672	0.0769
Δ ln B	0.00004	-0.00031	0.00035	-0.00010	-0.00005	0.00039	0.00002	0.00013	-0.00019	-0.00005
S.d.	0.0954	0.0657	0.0873	0.0525	0.1065	0.0675	0.0617	0.0725	0.0690	0.0774
Askdepth	807	879	993	1341	829	475	2061	410	2089	1720
S.d.	1174	1395	1434	1825	1127	6039	2338	531	2330	1798
Biddepth	760	781	887	1216	771	419	1946	413	1853	1624
S.d.	1227	1342	1075	1865	930	471	1994	447	1881	1721
% type 1	3.42	3.26	3.31	3.52	3.31	2.84	1.22	2.64	1.09	1.42
% type 2	5.42	5.36	5.36	6.43	5.40	6.14	5.58	5.56	6.80	6.25
% type 3	9.56	12.22	7.89	12.74	9.44	9.84	10.12	9.79	13.64	12.98
% type 4	9.69	7.65	9.30	6.11	11.15	6.60	2.85	5.47	2.57	3.71
% type 5	6.65	5.81	6.55	5.51	7.66	7.51	8.79	6.66	9.72	9.83
% type 6	15.51	19.05	13.83	17.41	14.31	13.56	12.89	15.66	14.70	17.07
% type 7	3.67	3.51	3.40	3.04	3.18	2.65	1.20	2.64	1.16	1.46
% type 8	5.75	5.40	6.66	6.33	5.63	7.08	8.12	7.09	7.80	6.80
% type 9	8.53	8.56	14.68	12.95	7.69	13.90	20.05	12.69	14.68	12.06
% type 10	8.93	6.98	7.78	5.21	10.38	6.41	2.80	5.48	2.32	3.54
% type 11	6.62	5.68	5.85	4.87	7.18	7.21	8.46	6.88	9.32	9.40
% type 12	16.26	16.53	15.39	15.88	14.68	16.25	17.91	19.44	16.18	15.48
Order size type 1	2156	1960	2169	2647	2316	874	2354	914	2172	2360
Order size type 2	2015	1427	1851	2161	1863	1035	2571	857	2247	2209
Order size type 3	273	222	379	341	325	166	519	131	408	395
Order size type 4	1582	1584	1840	2023	1625	715	2022	656	1694	1880
Order size type 5	1713	1735	1863	2177	1823	888	1830	710	1566	1473
Order size type 6	1325	957	1584	1277	1492	612	1309	461	1078	960
Order size type 7	2007	2444	2402	4344	2923	825	2270	801	2345	2157
Order size type 8	1337	1751	1334	2088	2060	849	1596	547	1852	1857
Order size type 9	307	286	195	248	348	111	267	122	329	421
Order size type 10	1654	1822	2121	2831	1850	704	2005	604	1936	2010
Order size type 11	2212	2307	2757	3693	2378	906	1907	650	2050	1780
Order size type 12	1361	1387	1699	2080	1836	480	919	381	1199	1160
Duration	30.22	21.99	21.67	14.17	37.33	24.79	16.54	22.42	19.58	20.31
Spread	0.78	0.77	0.89	0.52	0.81	2.93	1.50	2.67	1.37	1.60

a small tick size, the right part large tick stocks. Within each part, the column headers give the endogenous variables (return on best ask and bid, depth at best ask and bid and the natural logarithm of the duration between blim updates), while the rows show the right hand side variables in the VAR-model. The model is estimated for each stock separately, the table shows the unweighted averages across stocks in a group. Significant coefficients at the 5% level, determined on basis of the (not reported) average t-statistics, are indicated in bold. In the discussion of the table, we first focus on the lags of the endogenous variables. Subsequently, the different exogenous variables are reviewed. This section concludes by pointing to some striking differences between stocks.

Table 2 clearly provides evidence for the existence of a number of relationships between the *endogenous variables*. These hold in particular for the large stocks (groups 3 and 4). First, the estimates show a relation between both sides of the market. Ask returns are significant in the bid return equation and the other way around, in both cases with a negative sign. Also, depth at the ask (bid) side of the market is positively related to depth at the bid (ask) side, especially for large stocks. This result is in line with the theory in Parlour (1998) who shows that traders look at both sides of the market when determining their order choice between market and limit orders (and this choice determines liquidity in a limit order market). Secondly, our results also demonstrate a clear interaction between the dimensions of liquidity, as argued by Harris (1990). This can be seen by noting that depth has a significant impact on returns, though in general only the first or second lag. AD has a negative sign in the ask- and bidreturn-equations, while BD has a positive sign. The intuition is as follows. Suppose depth at the best ask is high and a seller arrives. Since the execution probability of an additional sell limit order joining the queue at the best ask is small, she will not submit such order. She will either improve the best ask (implying a negative return on the ask) or submit a market order. If in the latter case all depth at the best bid is consumed, this implies a negative return on the bid. Similarly, if depth at the best bid is higher, ceteris paribus, a buyer will either submit a market order (increasing the best ask if all depth at the best ask in consumed), or improve the best bid, implying a positive return on the best bid.

Furthermore, we find significant coefficients of returns in the equations for depth, positive for the ask return, negative for the bid return. The intuition is that an undercutting of the best ask by a limit order, implying a negative return on the best ask, will lower depth at the best ask (since the size of the order becomes the new depth and this is most likely smaller than the depth that was present before the order). This in turn leads to a positive correlation between $\Delta \ln A$ and AD.

Moreover, we also find a relation between duration on the one hand and prices and depths on the other hand. From the ask (bid) return equation, we find a negative (positive) correlation between lagged duration and the returns on the best ask (bid). This means that the spread narrows when there is a best limit update after a longer time. However, the depth declines, as can be seen from the negative coefficient of duration in the depth equations. Yet, although significant from an econometric point of view, economically the impact of duration on prices and depth is rather small since the magnitude of the coefficients is small. This is in line with Engle and Patton (2004) and the predictions in Easley and O'Hara (1992) that long durations do not reveal information. Turning to the duration equation, both ask and bid depth have a negative sign in this equation, while ask return and bid return have a positive and negative sign, respectively. In general only for large stocks (groups 3 and 4), these coefficients are significant.

Finally, in line with the literature, all endogenous variables are autocorrelated, since the coefficients of their own five lags are significant. However, their magnitude quickly decreases. For returns the autocorrelations are negative, while for depths and duration they are positive.

The signs of the *order type variables* in the *return* equations are as can be expected from their definition. Type 1 orders have a positive sign in the ask return equation, while type 7 orders have a negative sign in the bid equation. Remarkable is however that the coefficients of these two order types are also significant in the return equation on the other side of the market, although the magnitude is much smaller. The effect on the other side of the market partly offsets the effect on the own side. More specifically, a type 1 order is associated with a negative return on the best ask (implying a widening of the spread), but also with a small positive return on the best bid (which means that the spread becomes smaller). A symmetric reasoning holds for a type 7 order. This result is in line with the predictions of the model of Rosu (2006). Type 4 orders imply a positive return on the best bid meaning that the spread narrows. This effect is amplified by the fact that type 4 orders entail also a negative return on the best ask, meaning a further narrowing of the spread. Symmetric results are found for a type 10 order which has a negative sign in the ask returns equation and a positive one on the bid return equation. At first sight, the results for type 2 and 8 orders might be surprising and may require a brief discussion. Type 2 orders have a positive impact on both bid and ask returns. Recall that, according to their definition, these orders consume all the depth at the best ask, causing the ask to increase. This implies a positive return on the ask. Moreover, these orders are not allowed to walk up the limit order book and their remaining part is converted into a limit order, meaning that also the bid rises. A similar, symmetric reasoning holds for type 8 orders. The effects of order types are not only significant, but also important from an economic point of view. Especially for small stocks (groups 1 and 2), the most aggressive order types (1 and 7) are associated with rather large returns on the best prices (ask and bid respectively) Also an improvement of the best bid (ask) by an order of type 4 (10) is related to substantial returns.

Now turning the effect of different order types on the *depth* at the best prices, we find that type 1 orders have a positive sign in the askdepth equation, while type 7 orders have a positive sign in the biddepth equation. This can be interpreted as evidence that the limit order book behind the best quotes is rather deep. For both order types, there is a small negative effect on the depth at the other side of the market. The depth at the best bid after a type 4 order decreases. Such order improves the best bid but also implies that the depth at the new best bid becomes equal to the order size of the type 4 order. This order size is likely to be smaller than the depth that was available when the order was submitted. A symmetric conclusion is obtained for type 10 orders.

Finally, the type of the order also has an impact on the duration. In general, less aggressive order types are associated with higher durations between blim updates, as can be seen from the increasing positive coefficient of order types of decreasing aggressiveness.

The second group of endogenous variables in the VAR-model are the *order sizes*. Their estimated coefficients in Table 2 show that, next to the degree of aggressiveness of an order, also the size of an order of a given aggressiveness type matters. The order size coefficients are in general significant, both in the return and depth equations. For type 1 and 7 orders, their signs in the return equations are the same as those of the corresponding order aggressiveness coefficients. In other words, order size amplifies the effect of aggressiveness and a larger order size implies a larger return (positive on the ask for buy orders, negative on the bid for sell orders).

For depth, results are mixed. We find that for type 1 orders, a larger order size is associated with an increase in depth at the best ask for large stocks. Since a type 1 order with larger order size walks farther in the limit order book, this finding can be explained by the fact that the book farther behind the best quotes is deeper than just beyond the best quotes. In contrast, for smaller stocks, the signs are negative, meaning that a larger order decreases subsequent depth at the best ask. Secondly, an aggressive sell order of type 7 decreases the depth at the best bid. In case of a type 4 order, order size has a positive effect on the bid depth, since it is precisely the size of the type 4 order that becomes the new depth at the best bid. The same holds for the ask side after a type 10 order.

In general order size thus has a significant effect on returns on the best prices and depth, even when correcting for the order type. Economically, the effect of the order type matters much more, the additional effect of order size is smaller but not negligible.

Order size hardly has an impact on duration. In the duration equation, a considerable number of order size coefficients are not significant. When being significant in an econometric sense, their economic impact is small. In other words, the main impact of an order on duration comes from its aggressiveness, its size explains little more in addition to the order type.

Thirdly, *time of day* dummies were included in the VAR. We do not find evidence of significant time of day effects for returns and depths since very little of the coefficients in all equations are significant. Engle and Patton (2004) find, using piecewise linear splines, that time of day effects are not an important source of variation in quote prices. Only at the beginning of the trading day, they find evidence for a significant deterministic component. We do find significant coefficients in the duration equation. Compared to the case with 2 subsequent orders in the eighth interval of the trading day, the first interval has a log duration which is slightly higher[10]. Repeating this computation for the other time of day dummies, we find a inverted U-shaped pattern, i.e. the duration between blim updates is highest in interval 4. This corresponds to the well known U-shaped patters for trading activity. In general, activity is found to be higher at the beginning and end of the trading day, see e.g. Admati and Pfleiderer (1988).

Finally, as in Engle and Patton (2004), we find evidence of *cointegrating* behavior, since the lagged (log) spread is significant in the return equations. Its sign is as expected. If the spread after the previous period was large, the ask can be expected to decrease and/or the bid to increase at the next blim update. This causes the spread to become narrower and return to its equilibrium value. Also, if the spread is larger, it is easier to undercut the best prices in the limit order book. Our results confirm this intuition since the lagged spread has a negative sign in the ask return equation and a positive sign in the bid return. The magnitude of the coefficients is slightly larger for large tick stocks. In the duration equation, the spread has a negative sign, meaning that when the lagged spread was larger, the duration between blim updates will become smaller.

To conclude the analysis, the results in Table 2 are compared across stocks with different characteristics. Although the main conclusions discussed above are valid among all groups, some notable differences emerge from the table, especially on the order of magnitude of the effects. First, we hold the tick size of a stock constant and compare across different sizes (i.e. compare group 1 with 3 and 2 with 4). For smaller stocks, the autocorrelations of returns on the best prices and of duration are larger, while these of depths at the best prices are smaller. Moreover, the interaction between returns (prices) and depth is weaker. This comes forward from less significant coefficients of depth in the return equations and returns in the depth equations. The same holds for the relation between duration, and prices and depths. The effect of aggressive orders on returns is larger for smaller stocks while the impact of an order of type 1 and 7 on depths is smaller. The latter is likely a consequence of the lower depth at the best prices for smaller stocks. Furthermore, order size still plays a role in addition to order type, but its additional effect is often weaker than for large stocks.

Secondly, we take the size of the stock as given and compare across stocks with different tick sizes (i.e. group 1 versus 2 and 3 versus 4). It can be seen that the autocorrelation coefficients of returns depths and duration are in general larger for small tick stocks. Also,

[10] E.g. for group 3 it is $-6.3854 + 6.3950 = 0.0096$.

the impact of the most aggressive orders (type 1 and 7) on returns at the own side of the market (ask for type 1, bid for type 7) is larger for stocks with a large tick size. For returns at the opposite side, in general the reverse holds. Moreover, for small tick stocks, aggressive buy orders have (in absolute value) a larger influence on the ask return than aggressive sell orders on the bid return (although group 4 contains some exceptions). This shows that shocks to the buy and sell side of the market may have asymmetric impacts. Also, focussing on large stocks (groups 3 and 4), the effect of a type 1 (7) order on the depth at the best ask (bid) is much larger for large tick stocks. For small stocks (groups 1 and 2), the patterns are less clear. The combination of the results for returns and depth might imply that the larger tick size in group 4 is a binding constraint. The reasoning is that, since these are heavily traded stocks, more traders arrive, and they would like to undercut the best prices if a long queue at their side of the market exists. However, a too high minimum price variation might prevent this. For smaller stocks, the queues are less long (see also the smaller depth at the best prices in the table of descriptive statistics), which makes the problem of a minimum price variation less severe.

5.3 Resiliency

After having discussed prices, depth and duration, we now turn to resiliency. As explained in Section 3.2, this dimension of liquidity is analyzed by simulating the paths of prices and depths after a liquidity shock. This simulation is performed on basis of the estimated VAR-model in equation (1). In the discussion, we make a distinction between a shock occurring on the ask side of the market and one occurring on the bid side. Moreover, we distinguish between a "negative" and a "positive" liquidity shock. The former is defined as an order that consumes all the depth at the best price and some of the depth behind. Hence, it widens the bid-ask spread. Such shock is measured by a type 1 order on the ask side and a type 7 order on the bid side. A positive liquidity shock is a buy (or sell) order that improves the best bid (or ask) price and thus narrows the spread. This is modelled by a type 4 (or 10) order. Again, a distinction between the four groups of stocks will be made.

5.3.1 Negative Liquidity Shock

The results of the simulation of a *negative liquidity shock* are presented in Figures 1 and 2. The three rows show the findings for returns on the best prices, depths and duration, respectively. The paths of the respective variables are drawn in a period of 25 blim updates after the shock. The four columns within each graph plot them for the four groups of stocks. Full lines represent the ask side of the market, dashed lines the bid side. Unweighted averages across the stocks in each group are drawn. An important caveat in interpreting the figure is however that the period of time of 25 blim updates is much

Table 2: **Estimation Results VAR-model**

Note: This table present the estimation results of equation (1) for the different groups of stocks. Estimations are performed per stock; unweighted average values across stocks in a group are shown. Significant coefficients at the 5% level are indicated in bold. The definitions of the endogenous and exogenous variables can be found in Section 3.1.

Panel A: Small Stocks

	Group 1: Small Stocks, Small Tick Size					Group 2: Small Stocks, Large Tick Size				
	$\Delta \ln A_t$	$\Delta \ln B_t$	AD_t	BD_t	$\ln(d_t)$	$\Delta \ln A_t$	$\Delta \ln B_t$	AD_t	BD_t	$\ln(d_t)$
$\Delta \ln A_{t-1}$	**-0.2585**	-0.0077	-0.0063	0.0038	0.1052	**-0.2374**	0.0010	0.0173	0.0021	0.0835
$\Delta \ln A_{t-2}$	**-0.1024**	0.0056	0.0134	-0.0069	0.0396	**-0.0922**	-0.0033	0.0102	0.0007	0.0026
$\Delta \ln A_{t-3}$	**-0.0841**	**0.0113**	0.0116	0.0068	0.0654	**-0.0555**	0.0109	0.0099	0.0027	-0.0134
$\Delta \ln A_{t-4}$	**-0.0452**	0.0081	0.0119	0.0191	-0.0016	**-0.0308**	0.0103	0.0090	-0.0052	-0.0048
$\Delta \ln A_{t-5}$	**-0.0334**	-0.0006	-0.0076	-0.0053	0.0412	**-0.0234**	0.0008	-0.0055	0.0077	0.0116
$\Delta \ln B_{t-1}$	-0.0109	**-0.2428**	-0.0431	-0.0318	-0.0486	0.0118	**-0.2226**	-0.0096	-0.0205	-0.0040
$\Delta \ln B_{t-2}$	-0.0022	**-0.1054**	-0.0164	-0.0278	-0.1058	-0.0020	**-0.0893**	-0.0079	-0.0104	-0.0058
$\Delta \ln B_{t-3}$	0.0013	**-0.0655**	-0.0277	-0.0092	**-0.1152**	0.0071	**-0.0438**	-0.0058	-0.0076	-0.0450
$\Delta \ln B_{t-4}$	-0.0004	**-0.0403**	-0.0116	-0.0080	-0.0915	0.0014	**-0.0324**	-0.0095	0.0043	-0.0401
$\Delta \ln B_{t-5}$	-0.0007	**-0.0281**	0.0102	-0.0044	-0.0693	0.0029	-0.0084	-0.0029	0.0030	-0.0251
AD_{t-1}	-0.0040	**-0.0051**	**0.6824**	0.0102	-0.0115	-0.0086	-0.0040	**0.6370**	0.0064	-0.0311
AD_{t-2}	-0.0007	0.0019	**0.0890**	-0.0017	0.0147	-0.0109	-0.0049	**0.0899**	0.0010	-0.0081
AD_{t-3}	-0.0016	-0.0008	0.0118	0.0071	-0.0075	-0.0024	-0.0046	**0.0372**	0.0041	-0.0023
AD_{t-4}	-0.0009	0.0002	**0.0261**	-0.0058	-0.0015	-0.0055	0.0032	**0.0261**	0.0048	-0.0216
AD_{t-5}	-0.0007	0.0003	**0.0248**	0.0075	-0.0184	0.0034	0.0011	**0.0365**	0.0021	-0.0414
BD_{t-1}	**0.0048**	0.0000	0.0084	**0.6717**	**-0.0568**	**0.0146**	0.0084	0.0039	**0.6027**	-0.0388
BD_{t-2}	0.0004	0.0019	-0.0033	**0.0590**	0.0170	-0.0002	0.0070	0.0084	**0.1040**	0.0400
BD_{t-3}	0.0007	0.0010	0.0018	**0.0274**	-0.0061	-0.0028	0.0010	0.0022	**0.0406**	-0.0248
BD_{t-4}	-0.0014	0.0010	0.0077	**0.0257**	0.0203	0.0026	0.0006	0.0015	**0.0257**	-0.0258
BD_{t-5}	-0.0007	0.0013	0.0000	**0.0223**	-0.0083	-0.0016	0.0016	0.0007	**0.0313**	-0.0028
$\ln(d_{t-1})$	**-0.0019**	**0.0018**	-0.0031	-0.0039	**0.1856**	**-0.0025**	**0.0018**	-0.0016	-0.0012	**0.1967**
$\ln(d_{t-2})$	-0.0009	**0.0016**	-0.0022	-0.0034	**0.0924**	-0.0009	0.0007	-0.0008	-0.0008	**0.0902**
$\ln(d_{t-3})$	-0.0001	0.0000	-0.0030	-0.0016	**0.0693**	-0.0001	0.0011	-0.0001	-0.0001	**0.0649**
$\ln(d_{t-4})$	-0.0003	0.0000	-0.0001	-0.0020	**0.0577**	-0.0002	0.0002	-0.0008	-0.0013	**0.0573**
$\ln(d_{t-5})$	-0.0002	-0.0003	-0.0003	-0.0016	**0.0590**	-0.0001	0.0000	-0.0005	-0.0007	**0.0545**
C	**0.0546**	**-0.0484**	**0.1640**	**0.1829**	**1.4393**	**0.0413**	**-0.0488**	**0.0727**	**0.0965**	**1.5084**
$O01_t$	**0.0871**	**0.0419**	**0.1518**	**-0.0341**	**0.2153**	**0.1454**	**0.0451**	**0.0950**	**-0.0238**	**0.2406**
$O01_{t-1}$	**0.0136**	0.0018	0.0230	0.0073	**-0.2324**	**0.0230**	-0.0090	0.0090	0.0080	**-0.2903**
$O02_t$	**0.0589**	**0.0854**	0.0146	**-0.0764**	**0.3110**	**0.0735**	**0.0826**	**0.0217**	**-0.0448**	**0.3056**
$O02_{t-1}$	0.0059	-0.0051	-0.0056	0.0064	**-0.1758**	**0.0092**	**-0.0105**	0.0006	0.0006	**-0.2513**
$O03_t$	**-0.0087**	**0.0240**	0.0164	**-0.0383**	**0.3689**	0.0037	**0.0208**	**0.0117**	**-0.0205**	**0.3744**
$O03_{t-1}$	-0.0029	0.0052	0.0002	-0.0101	-0.0407	-0.0008	0.0056	0.0005	-0.0037	**-0.0697**
$O04_t$	**-0.0098**	**0.1514**	-0.0119	**-0.2739**	**0.3656**	-0.0024	**0.1956**	0.0008	**-0.1672**	**0.3999**
$O04_{t-1}$	**-0.0104**	**0.0143**	0.0002	0.0106	**-0.1083**	-0.0056	**0.0168**	0.0018	0.0002	**-0.1344**
$O05_t$	**-0.0157**	**0.0213**	-0.0213	**0.2182**	**0.3036**	**-0.0098**	**0.0231**	-0.0058	**0.0815**	**0.2856**
$O05_{t-1}$	-0.0081	**0.0095**	-0.0108	0.0082	-0.0297	-0.0044	**0.0095**	0.0008	0.0103	-0.0498
$O06_t$	-0.0008	0.0000	-0.0048	-0.0029	**0.4844**	**-0.0031**	-0.0025	-0.0006	-0.0018	**0.4357**
$O06_{t-1}$	-0.0019	0.0004	-0.0026	-0.0007	**-0.0593**	-0.0003	-0.0001	-0.0001	0.0001	**-0.0626**

Table 2 (continued)

	Group 1: Small Stocks, Small Tick Size					Group 2: Small Stocks, Large Tick Size				
	$\Delta \ln A_t$	$\Delta \ln B_t$	AD_t	BD_t	$\ln(d_t)$	$\Delta \ln A_t$	$\Delta \ln B_t$	AD_t	BD_t	$\ln(d_t)$
$O07_t$	**-0.0335**	**-0.1080**	**-0.0372**	**0.1597**	**0.3157**	**-0.0332**	**-0.1502**	-0.0105	**0.0538**	**0.2436**
$O07_{t-1}$	0.0052	**-0.0156**	0.0012	0.0193	**-0.2320**	0.0064	**-0.0242**	0.0030	0.0031	**-0.3011**
$O08_t$	**-0.0972**	**-0.0607**	**-0.0819**	0.0106	**0.3084**	**-0.0850**	**-0.0700**	**-0.0397**	0.0050	**0.3661**
$O08_{t-1}$	**0.0094**	-0.0077	-0.0076	-0.0091	**-0.0763**	**0.0118**	-0.0063	0.0034	-0.0068	**-0.1903**
$O09_t$	**-0.0183**	**0.0076**	-0.0183	-0.0033	**0.3854**	**-0.0139**	0.0024	-0.0080	-0.0054	**0.4098**
$O09_{t-1}$	-0.0073	0.0007	-0.0158	0.0049	0.0175	-0.0017	0.0032	-0.0024	-0.0001	-0.0200
$O10_t$	**-0.1530**	**0.0138**	**-0.3067**	-0.0135	**0.3501**	**-0.1870**	**0.0094**	**-0.1591**	-0.0111	**0.3993**
$O10_{t-1}$	**-0.0132**	0.0064	0.0073	-0.0029	**-0.0869**	**-0.0164**	**0.0087**	0.0009	-0.0068	**-0.0944**
$O11_t$	**-0.0207**	**0.0194**	**0.2362**	**-0.0330**	**0.3189**	**-0.0147**	**0.0165**	**0.1065**	**-0.0142**	**0.3016**
$O11_{t-1}$	**-0.0107**	0.0031	0.0002	-0.0067	0.0257	**-0.0091**	0.0044	0.0093	0.0005	-0.0341
$O12_t$	**0.0022**	**0.0022**	-0.0029	-0.0020	**0.3691**	0.0022	0.0016	0.0013	-0.0026	**0.4398**
$O12_{t-1}$	0.0005	-0.0003	0.0005	-0.0002	**-0.0502**	0.0007	-0.0001	-0.0005	-0.0018	**-0.0613**
$Osize01_t$	**0.0240**	**0.0093**	-0.0011	0.0056	0.0013	**0.0493**	**0.0217**	**-0.0180**	0.0040	0.0191
$Osize01_{t-1}$	0.0019	-0.0028	0.0042	0.0057	**-0.0596**	0.0051	0.0030	0.0001	-0.0064	**-0.1214**
$Osize02_t$	**0.0103**	**-0.0039**	**-0.0366**	**0.0110**	**-0.0274**	**0.0190**	**0.0083**	**-0.0335**	0.0062	-0.0226
$Osize02_{t-1}$	**0.0057**	-0.0001	0.0023	-0.0032	**-0.0427**	**0.0069**	**0.0057**	0.0007	-0.0038	-0.0207
$Osize03_t$	**0.0224**	0.0024	**-0.5138**	0.0094	**-0.2006**	**0.0551**	0.0013	**-0.4844**	0.0037	**-0.4397**
$Osize03_{t-1}$	0.0029	-0.0019	**-0.0610**	0.0103	**-0.1467**	0.0246	-0.0013	-0.0260	0.0101	-0.2108
$Osize04_t$	0.0014	**-0.0039**	**-0.0156**	**0.0474**	0.0007	**0.0065**	**-0.0061**	**-0.0089**	**0.0777**	-0.0097
$Osize04_{t-1}$	**0.0037**	**0.0025**	0.0023	0.0001	-0.0068	**0.0053**	0.0036	0.0008	**-0.0127**	-0.0105
$Osize05_t$	**0.0031**	**0.0025**	-0.0018	**0.0401**	0.0114	**0.0044**	0.0034	0.0016	**0.0758**	0.0277
$Osize05_{t-1}$	0.0010	0.0016	0.0028	-0.0030	0.0134	0.0019	0.0023	0.0020	-0.0001	0.0287
$Osize06_t$	-0.0007	**-0.0023**	0.0004	-0.0008	**-0.0315**	-0.0009	**-0.0089**	-0.0010	-0.0020	-0.0206
$Osize06_{t-1}$	0.0011	**-0.0025**	0.0004	0.0009	-0.0016	0.0006	-0.0004	0.0005	0.0058	-0.0041
$Osize07_t$	**-0.0160**	**-0.0205**	0.0023	-0.0046	**-0.0584**	**-0.0333**	**-0.0284**	-0.0001	-0.0015	-0.0007
$Osize07_{t-1}$	-0.0011	**-0.0055**	-0.0041	0.0007	**-0.0539**	0.0044	-0.0050	0.0014	0.0054	**-0.1133**
$Osize08_t$	**-0.0064**	**-0.0101**	0.0075	**-0.0397**	-0.0071	**-0.0077**	**-0.0124**	0.0030	**-0.0316**	**-0.0461**
$Osize08_{t-1}$	0.0012	-0.0025	-0.0008	0.0039	**-0.0567**	-0.0005	**-0.0055**	-0.0037	-0.0008	**-0.0506**
$Osize09_t$	-0.0011	**-0.0150**	-0.0206	**-0.5161**	**-0.1734**	**-0.0180**	**-0.0300**	-0.0067	**-0.5287**	**-0.3736**
$Osize09_{t-1}$	0.0023	-0.0077	-0.0045	**-0.0422**	**-0.1750**	0.0004	-0.0105	-0.0074	**-0.0614**	-0.1391
$Osize10_t$	0.0023	-0.0006	**0.0413**	**-0.0209**	-0.0113	**0.0053**	**-0.0065**	**0.0378**	**-0.0188**	-0.0196
$Osize10_{t-1}$	**-0.0034**	-0.0022	-0.0031	0.0006	0.0000	**-0.0050**	**-0.0054**	-0.0010	0.0047	-0.0225
$Osize11_t$	-0.0018	**-0.0019**	**0.0232**	-0.0012	**0.0158**	-0.0031	**-0.0041**	**0.0391**	-0.0010	0.0274
$Osize11_{t-1}$	-0.0002	-0.0005	0.0002	0.0012	-0.0009	-0.0031	-0.0025	-0.0007	0.0025	0.0151
$Osize12_t$	0.0005	-0.0003	-0.0013	-0.0014	0.0068	**0.0061**	0.0008	0.0007	-0.0003	-0.0150
$Osize12_{t-1}$	**0.0018**	0.0008	0.0005	0.0016	-0.0021	-0.0002	-0.0003	0.0011	0.0049	0.0035
$T01_t$	0.0105	-0.0344	0.0546	0.0417	**-7.8932**	0.0514	-0.0512	0.0225	-0.0153	**-8.5348**
$T01_{t-1}$	-0.0097	0.0266	-0.0777	-0.0722	**7.7348**	-0.0449	0.0429	-0.0300	-0.0028	**8.3900**
$T02_t$	0.0071	-0.0333	0.0536	0.0493	**-6.8587**	0.0426	-0.0397	0.0101	-0.0104	**-7.3972**
$T02_{t-1}$	-0.0094	0.0284	-0.0739	-0.0741	**6.8504**	-0.0404	0.0319	-0.0209	-0.0027	**7.4488**
$T03_t$	0.0002	-0.0292	0.0761	0.0679	**-5.9884**	0.0424	-0.0333	0.0161	0.0031	**-6.4745**
$T03_{t-1}$	-0.0039	0.0261	-0.0892	-0.0881	**6.1147**	-0.0388	0.0285	-0.0248	-0.0124	**6.6575**
$T04_t$	0.0079	-0.0204	0.0600	0.0531	**-4.7754**	0.0388	-0.0319	0.0270	-0.0009	**-5.1196**
$T04_{t-1}$	-0.0074	0.0157	-0.0686	-0.0738	**5.0965**	-0.0296	0.0228	-0.0299	-0.0092	**5.4818**
$T05_t$	-0.0031	-0.0198	0.0334	0.0552	**-3.3969**	0.0402	-0.0252	0.0225	0.0040	**-3.7328**
$T05_{t-1}$	0.0011	0.0154	-0.0432	-0.0767	**3.6768**	-0.0311	0.0167	-0.0266	-0.0154	**4.0372**
$T06_t$	0.0015	-0.0134	0.0217	0.0390	**-2.3162**	0.0317	-0.0208	0.0037	0.0169	**-2.5543**
$T06_{t-1}$	-0.0012	0.0117	-0.0290	-0.0657	**2.4939**	-0.0265	0.0122	-0.0056	-0.0216	**2.7407**
$T07_t$	-0.0021	-0.0132	0.0010	0.0468	**-1.1897**	0.0168	-0.0094	-0.0085	0.0136	**-1.2310**
$T07_{t-1}$	0.0010	0.0087	-0.0041	-0.0541	**1.3112**	-0.0105	0.0034	0.0052	-0.0165	**1.3990**
$Spread_{t-1}$	**-2.2084**	**1.9509**	-0.9806	0.8586	**-6.1875**	**-1.7558**	**2.0094**	-0.6077	-0.6484	-1.9747
$Adj\ R^2$	0.2758	0.2926	0.5956	0.5623	0.3006	0.3192	0.3254	0.5670	0.4979	0.2884

Table 2 (continued)

Panel B: Large Stocks

	Group 3: Large Stocks, Small Tick Size					Group 4: Large Stocks, Large Tick Size				
	$\Delta \ln A_t$	$\Delta \ln B_t$	AD_t	BD_t	$\ln(d_t)$	$\Delta \ln A_t$	$\Delta \ln B_t$	AD_t	BD_t	$\ln(d_t)$
$\Delta \ln A_{t-1}$	**-0.1570**	**0.0209**	0.0562	0.0197	**0.1124**	**-0.1194**	0.0039	**0.3907**	0.0315	**0.1236**
$\Delta \ln A_{t-2}$	**-0.0844**	0.0049	**0.1186**	0.0323	0.0101	**-0.0463**	0.0010	**0.3137**	**0.1026**	0.0291
$\Delta \ln A_{t-3}$	**-0.0490**	**0.0074**	**0.0896**	0.0069	0.0445	**-0.0397**	-0.0002	**0.2117**	**0.0836**	0.0571
$\Delta \ln A_{t-4}$	**-0.0304**	0.0027	**0.0937**	0.0153	0.0623	**-0.0262**	0.0010	**0.1861**	0.0205	0.0500
$\Delta \ln A_{t-5}$	**-0.0164**	0.0009	-0.0135	0.0198	0.0384	**-0.0151**	-0.0025	-0.0097	0.0423	0.0497
$\Delta \ln B_{t-1}$	**0.0114**	**-0.1686**	-0.0167	-0.0210	**-0.1070**	0.0002	**-0.1079**	0.0273	**-0.3811**	-0.0808
$\Delta \ln B_{t-2}$	0.0036	**-0.0816**	0.0088	-0.0567	-0.0375	0.0016	**-0.0504**	**-0.0930**	**-0.1834**	-0.0189
$\Delta \ln B_{t-3}$	0.0033	**-0.0576**	-0.0216	-0.0458	**-0.1001**	**0.0243**	**-0.0302**	-0.0758	**-0.1550**	-0.0631
$\Delta \ln B_{t-4}$	0.0005	**-0.0336**	-0.0464	0.0070	-0.0616	**0.0114**	**-0.0235**	-0.0565	**-0.0988**	**-0.1196**
$\Delta \ln B_{t-5}$	0.0020	**-0.0219**	0.0212	-0.0529	-0.0708	0.0040	**-0.0140**	-0.0527	-0.0096	**-0.0911**
AD_{t-1}	**-0.0012**	**-0.0007**	**0.7442**	0.0050	**-0.0125**	**-0.0011**	**-0.0009**	**0.6143**	0.0036	**-0.0178**
AD_{t-2}	-0.0004	-0.0002	**0.0080**	0.0032	0.0039	**-0.0008**	-0.0003	**0.0259**	**0.0057**	0.0063
AD_{t-3}	-0.0001	-0.0001	**0.0478**	0.0000	-0.0005	0.0000	0.0000	**0.0357**	-0.0004	-0.0007
AD_{t-4}	-0.0001	0.0004	**0.0150**	-0.0034	-0.0053	-0.0002	0.0001	0.0042	**0.0056**	-0.0002
AD_{t-5}	-0.0002	-0.0001	**0.0297**	**0.0055**	-0.0069	0.0000	0.0002	**0.0342**	0.0024	**-0.0073**
BD_{t-1}	**0.0010**	**0.0009**	**0.0111**	**0.6855**	**-0.0225**	**0.0025**	**0.0026**	**0.0312**	**0.7152**	**-0.0363**
BD_{t-2}	0.0002	**0.0007**	0.0025	**0.0534**	0.0056	0.0007	**0.0015**	**-0.0126**	**0.0602**	**0.0196**
BD_{t-3}	-0.0001	0.0002	-0.0061	**0.0419**	-0.0018	0.0001	-0.0002	0.0013	**0.0212**	-0.0068
BD_{t-4}	0.0002	0.0002	0.0025	**0.0217**	-0.0014	**-0.0008**	0.0000	0.0055	**0.0222**	-0.0030
BD_{t-5}	-0.0004	-0.0001	0.0012	**0.0217**	-0.0056	-0.0005	0.0003	**0.0099**	**0.0308**	-0.0011
$\ln(d_{t-1})$	**-0.0006**	**0.0006**	-0.0028	**-0.0050**	**0.1552**	**-0.0005**	**0.0007**	-0.0036	-0.0030	**0.1479**
$\ln(d_{t-2})$	-0.0003	0.0003	-0.0019	-0.0031	**0.0977**	**-0.0004**	**0.0006**	-0.0032	-0.0029	**0.0917**
$\ln(d_{t-3})$	**-0.0004**	0.0000	-0.0033	-0.0025	**0.0740**	-0.0002	0.0002	-0.0024	-0.0010	**0.0717**
$\ln(d_{t-4})$	-0.0001	0.0000	-0.0038	-0.0028	**0.0635**	-0.0002	0.0001	-0.0037	-0.0017	**0.0588**
$\ln(d_{t-5})$	0.0000	0.0001	-0.0031	-0.0015	**0.0593**	-0.0001	0.0001	-0.0028	-0.0030	**0.0552**
C	**0.0238**	**-0.0188**	**0.2438**	**0.2108**	**1.0586**	**0.0177**	**-0.0218**	**0.3075**	**0.2129**	**1.0804**
$O01_t$	**0.0474**	**0.0157**	**0.2747**	**-0.0434**	0.0118	**0.0782**	**0.0116**	**0.4939**	**-0.0375**	-0.0198
$O01_{t-1}$	0.0002	**-0.0034**	0.0046	-0.0065	**-0.1681**	**0.0046**	0.0002	-0.0045	0.0083	**-0.1678**
$O02_t$	**0.0293**	**0.0433**	**0.0478**	**-0.0967**	**0.0634**	**0.0406**	**0.0535**	**0.3202**	**-0.3006**	**0.1128**
$O02_{t-1}$	0.0006	**-0.0049**	-0.0003	0.0066	**-0.0827**	-0.0009	**-0.0047**	**-0.0221**	**0.0277**	**-0.0817**
$O03_t$	**-0.0082**	**0.0090**	**0.0148**	**-0.0161**	**0.0290**	**-0.0053**	**0.0095**	**-0.0206**	-0.0085	**0.0926**
$O03_{t-1}$	**-0.0017**	**0.0015**	0.0037	0.0026	**-0.0529**	-0.0003	**0.0011**	-0.0058	0.0004	**-0.0583**
$O04_t$	**-0.0082**	**0.0687**	-0.0112	**-0.3729**	**0.1789**	-0.0008	**0.1213**	**0.0375**	**-0.9852**	**0.1528**
$O04_{t-1}$	**-0.0034**	**0.0053**	0.0020	0.0072	**-0.0309**	**-0.0031**	**-0.0040**	**-0.0413**	**0.1066**	**-0.0544**
$O05_t$	**-0.0099**	**0.0089**	**-0.0190**	**0.4371**	**0.1176**	**-0.0090**	**0.0093**	**0.1148**	**0.3933**	**0.1406**
$O05_{t-1}$	-0.0011	**0.0045**	-0.0001	**-0.0212**	-0.0203	0.0006	**0.0043**	**0.1134**	0.0084	**-0.0262**
$O06_t$	**-0.0011**	**-0.0029**	-0.0048	**-0.0097**	**0.4380**	-0.0004	**-0.0013**	**-0.0101**	**-0.0093**	**0.4547**
$O06_{t-1}$	0.0000	-0.0001	0.0012	0.0034	**-0.0617**	0.0001	-0.0003	-0.0035	-0.0023	**-0.0573**

Table 2 (continued)

	Group 3: Large Stocks, Small Tick Size					Group 4: Large Stocks, Large Tick Size				
	$\Delta \ln A_t$	$\Delta \ln B_t$	AD_t	BD_t	$\ln(d_t)$	$\Delta \ln A_t$	$\Delta \ln B_t$	AD_t	BD_t	$\ln(d_t)$
$O07_t$	**-0.0234**	**-0.0648**	**-0.0759**	**0.2729**	-0.0009	**-0.0088**	**-0.0632**	**-0.0640**	**0.4356**	**-0.1170**
$O07_{t-1}$	0.0002	**-0.0034**	0.0003	0.0227	**-0.2066**	0.0012	-0.0007	0.0216	0.0007	**-0.0925**
$O08_t$	**-0.0481**	**-0.0281**	**-0.1550**	**0.0574**	**0.0802**	**-0.0448**	**-0.0305**	**-0.4218**	**0.2472**	**0.0852**
$O08_{t-1}$	**0.0068**	0.0011	0.0127	-0.0043	**-0.0656**	**0.0038**	**0.0012**	**-0.0425**	**-0.0215**	**-0.0585**
$O09_t$	**-0.0099**	**0.0070**	**-0.0289**	0.0053	**0.0581**	**-0.0082**	**0.0080**	**-0.0317**	-0.0033	**0.0675**
$O09_{t-1}$	-0.0008	**0.0017**	0.0067	0.0046	**-0.0440**	**-0.0012**	0.0004	0.0046	0.0034	**-0.0385**
$O10_t$	**-0.0718**	**0.0056**	**-0.3885**	**0.0254**	**0.1641**	**-0.1212**	**0.0029**	**-1.0075**	**0.1364**	**0.1486**
$O10_{t-1}$	**-0.0034**	**0.0038**	**0.0241**	0.0000	-0.0143	**0.0020**	**0.0034**	**0.0533**	**-0.0767**	**-0.0323**
$O11_t$	**-0.0106**	**0.0091**	**0.4505**	-0.0076	**0.1445**	**-0.0069**	**0.0112**	**0.3683**	**-0.0141**	**0.1161**
$O11_{t-1}$	**-0.0042**	**0.0016**	**-0.0349**	0.0032	-0.0124	**-0.0038**	0.0003	0.0136	0.0096	**-0.0199**
$O12_t$	**0.0026**	0.0007	-0.0030	-0.0031	**0.4602**	**0.0011**	**0.0010**	**-0.0130**	**-0.0064**	**0.4336**
$O12_{t-1}$	-0.0001	-0.0003	0.0012	0.0013	**-0.0549**	0.0002	0.0002	-0.0009	-0.0007	**-0.0573**
$Osize01_t$	**0.0082**	**0.0045**	**0.0092**	**0.0106**	-0.0027	**0.0135**	**0.0101**	**0.0165**	0.0016	**-0.0158**
$Osize01_{t-1}$	**0.0012**	**0.0008**	0.0032	**0.0077**	-0.0039	-0.0002	**-0.0006**	-0.0060	0.0045	0.0004
$Osize02_t$	**0.0026**	**0.0013**	**-0.0358**	**0.0103**	0.0034	**0.0039**	**0.0028**	**-0.0478**	-0.0003	**-0.0077**
$Osize02_{t-1}$	**0.0007**	0.0003	-0.0007	0.0005	**-0.0060**	**0.0010**	**0.0007**	-0.0019	-0.0023	**-0.0090**
$Osize03_t$	**0.0053**	0.0014	**-0.5769**	0.0045	0.0115	**0.0075**	0.0013	**-0.4402**	-0.0132	-0.0245
$Osize03_{t-1}$	**0.0033**	0.0007	**0.0174**	0.0099	**-0.0231**	**0.0022**	0.0006	**0.0399**	-0.0008	**-0.0655**
$Osize04_t$	**0.0006**	-0.0002	**-0.0146**	**0.0412**	0.0019	0.0000	-0.0004	**-0.0431**	**0.1136**	-0.0012
$Osize04_{t-1}$	**0.0009**	**0.0007**	**0.0040**	**-0.0036**	-0.0012	**0.0020**	**0.0020**	-0.0014	**-0.0363**	-0.0003
$Osize05_t$	**0.0010**	**0.0012**	**-0.0068**	**0.0425**	**0.0078**	**0.0028**	**0.0031**	**-0.1956**	**0.0409**	**0.0047**
$Osize05_{t-1}$	0.0003	**0.0005**	-0.0008	-0.0006	0.0009	0.0001	**0.0003**	**-0.1608**	**-0.0046**	0.0014
$Osize06_t$	0.0001	**-0.0006**	0.0014	0.0018	-0.0020	0.0000	**-0.0013**	**0.0063**	0.0020	**-0.0077**
$Osize06_{t-1}$	0.0001	-0.0001	0.0001	0.0015	-0.0011	0.0001	0.0000	**0.0071**	0.0012	-0.0046
$Osize07_t$	**-0.0041**	**-0.0051**	**0.0180**	**0.0041**	0.0030	**-0.0118**	**-0.0142**	-0.0041	**-0.0105**	-0.0010
$Osize07_{t-1}$	0.0001	**-0.0008**	0.0020	0.0031	-0.0026	0.0001	-0.0006	0.0071	-0.0053	**-0.0193**
$Osize08_t$	**-0.0015**	**-0.0028**	**0.0198**	**-0.0328**	0.0005	**-0.0032**	**-0.0042**	**0.2055**	**-0.0356**	0.0008
$Osize08_{t-1}$	-0.0003	**-0.0006**	0.0022	-0.0004	-0.0031	-0.0002	**-0.0004**	**0.1609**	**0.0040**	**-0.0052**
$Osize09_t$	-0.0011	**-0.0058**	-0.0107	**-0.5265**	-0.0123	-0.0014	**-0.0093**	-0.0028	**-0.5763**	0.0033
$Osize09_{t-1}$	-0.0005	**-0.0022**	0.0060	**-0.0450**	**-0.0328**	-0.0006	**-0.0041**	0.0063	-0.0132	**-0.0774**
$Osize10_t$	-0.0002	**-0.0002**	**0.0189**	**-0.0295**	0.0002	**0.0011**	**-0.0008**	**0.0541**	**-0.0999**	0.0062
$Osize10_{t-1}$	**-0.0008**	**-0.0007**	**-0.0040**	**0.0030**	0.0010	**-0.0020**	**-0.0020**	0.0017	**0.0334**	0.0001
$Osize11_t$	**-0.0012**	**-0.0008**	**0.0325**	**-0.0044**	**0.0041**	**-0.0039**	**-0.0030**	**0.0480**	0.0011	**0.0104**
$Osize11_{t-1}$	**-0.0003**	-0.0002	0.0018	0.0006	0.0026	**-0.0010**	**-0.0007**	0.0018	0.0023	**0.0093**
$Osize12_t$	**0.0008**	0.0001	0.0006	0.0002	**-0.0031**	**0.0012**	0.0000	0.0006	0.0002	**0.0076**
$Osize12_{t-1}$	0.0000	0.0000	0.0012	0.0009	-0.0009	0.0001	-0.0002	0.0025	0.0019	-0.0054
$T01_t$	0.0137	0.0001	0.0351	-0.1250	**-6.3854**	0.0098	-0.0180	-0.0338	0.1734	**-6.1978**
$T01_{t-1}$	-0.0123	-0.0054	-0.0711	0.0907	**6.3950**	-0.0071	0.0140	-0.0547	-0.2244	**6.2165**
$T02_t$	0.0113	0.0030	-0.0068	-0.1192	**-5.5385**	0.0087	-0.0111	0.0351	0.1401	**-5.3420**
$T02_{t-1}$	-0.0124	-0.0063	-0.0477	0.0759	**5.6184**	-0.0076	0.0090	-0.1052	-0.1914	**5.4382**
$T03_t$	0.0122	-0.0016	0.0182	-0.1377	**-4.8173**	0.0070	-0.0062	-0.0002	0.1303	**-4.6510**
$T03_{t-1}$	-0.0124	-0.0009	-0.0649	0.1043	**5.0065**	-0.0067	0.0037	-0.0588	-0.1594	**4.8594**
$T04_t$	0.0132	-0.0056	-0.0004	-0.1586	**-3.6980**	0.0064	-0.0084	0.0185	0.0959	**-3.6240**
$T04_{t-1}$	-0.0117	0.0013	-0.0331	0.1378	**4.0907**	-0.0051	0.0045	-0.0785	-0.1078	**4.0416**
$T05_t$	0.0120	-0.0060	-0.0157	-0.0984	**-2.6039**	0.0052	-0.0075	-0.0206	0.0602	**-2.5066**
$T05_{t-1}$	-0.0115	0.0026	-0.0236	0.0728	**2.9660**	-0.0040	0.0041	-0.0376	-0.0822	**2.8897**
$T06_t$	0.0032	-0.0015	-0.0194	-0.0604	**-1.8185**	0.0032	-0.0081	-0.0718	0.0409	**-1.7619**
$T06_{t-1}$	-0.0039	-0.0016	-0.0221	0.0354	**2.0311**	-0.0021	0.0056	0.0198	-0.0660	**1.9656**
$T07_t$	-0.0012	-0.0039	-0.0114	-0.0552	**-0.9131**	-0.0006	-0.0072	-0.0036	-0.0063	**-0.9110**
$T07_{t-1}$	0.0001	0.0009	-0.0197	0.0377	**1.0106**	0.0008	0.0049	-0.0381	-0.0068	**1.0101**
$Spread_{t-1}$	**-1.6612**	**1.9983**	-2.4028	**2.6568**	**-17.8598**	**-1.8036**	**2.0597**	3.4896	-0.4217	**-39.0367**
$Adj\ R^2$	0.2375	0.2553	0.6242	0.5862	0.2502	0.3835	0.3787	0.7509	0.6510	0.2378

larger for smaller stocks, when expressed in seconds. The reasoning is that the duration between blim updates is much larger for groups 1 and 2 (see the table with descriptive statistics). In particular, on average the duration between blim updates in group 1 or 2 is about 3 to 5 times as large as between updates in groups 3 and 4.

The return graphs demonstrate that a negative liquidity shock has a permanent effect on the best *prices* in the book. This effect is however realized quickly. More specifically, after a type 1 order, there is a positive return on the best ask, after a type 7 order a negative return on the best bid. But in both cases, in the periods after this initial impact of the aggressive order, there is a small reversal after which returns remain close to zero. In other words, the price impact of an aggressive order is realized almost instantaneously, as is predicted by efficient markets, see e.g. Glosten and Milgrom (1985). One interpretation for this finding is the presence in the market of informed traders that are trading on perishable information. We find also an impact at the other side of the market than where the shock occurred. There is a small positive return on the best bid following a type 1 order. After an aggressive sell order (type 7) a small negative return on the best ask is found. These small effects disappear after some periods. They offset part of the effect on the own side of the market on the spread[11]. The effect on the other side of the market is in line with the predictions of the model of Rosu (2005).

The impact of a negative liquidity shock on *depths* is found at the side of the market at which the shock occurs. More specifically, depth increases at this side of the market. Two interpretations can be given to this result. The first is that the limit order book behind the best quotes is deep. A second explanation for our finding is that new liquidity (in the form of additional depth) is provided to the market after it has been consumed by the aggressive order. At the other side of the market, depth remains more flat and the impact of the shock is small.

The results clearly demonstrate the interaction and complementarity between different dimensions of liquidity. After the shock, there is a permanent effect on prices and the spread increases, such that one aspect of liquidity (spread) deteriorates. However, at the same time depth increases which implies an improvement of another dimension of liquidity.

The last row in Figures 1 and 2 show that the duration between blim updates increases in the periods immediately after the shock. However, within around 10 blim updates, duration stabilizes at a new value.

Again, the results discussed above are valid for the different groups of stocks. Nonetheless, a comparison of the graphs for the different groups reveals some interesting differences

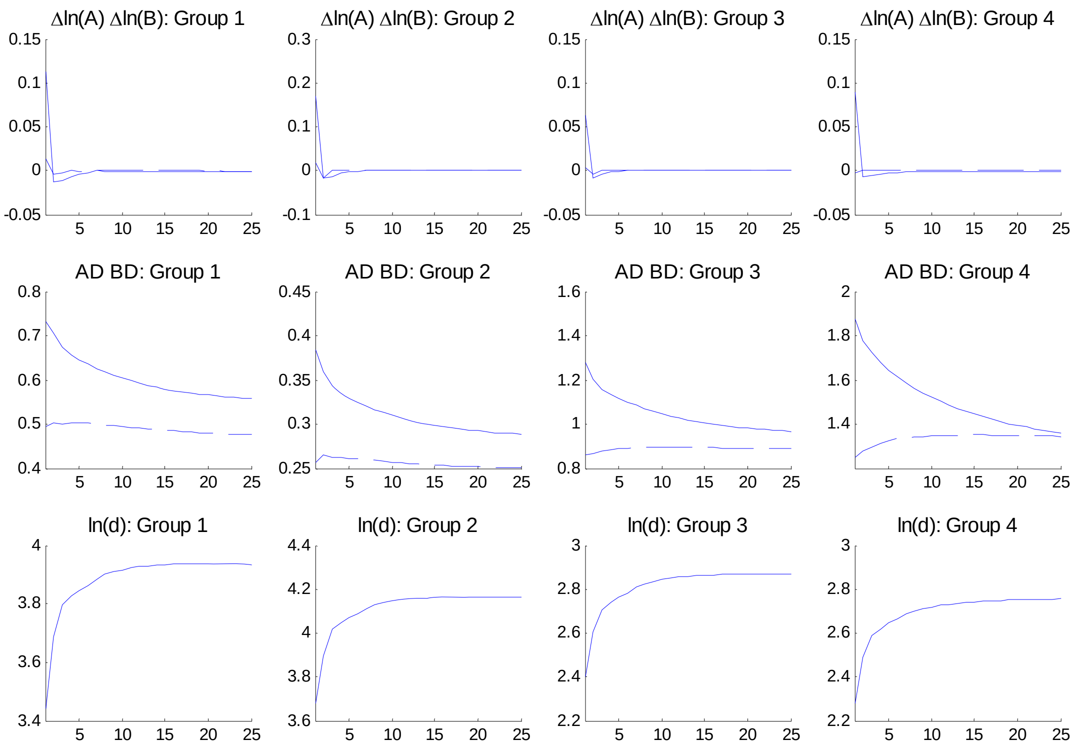
[11] A *negative* return on the ask means an improvement of the best ask. On the other hand, a *positive* return on the bid points to an improvement of the best bid. Both imply a narrower spread.

between stocks. First, we take the size of a stock as given and compare our results across small and large tick stocks. The impact of an aggressive order on returns is found to be much larger for large tick stocks, taking size as given. This finding holds both at the side of the market at which the shock occurred as at the opposite side. Secondly, the impact of aggressive orders on depth is larger for stocks in groups 2 and 4. This is the case both at the side of the market at which the aggressive order was submitted as on the other side. This comparison between both groups for returns and depth seems to suggest that the larger tick size is a binding constraint for these stocks. These results are in line with the literature that investigates tick size. When faced with a smaller tick size, traders use more intermediate prices, but the depth at these prices is lower. As a final point, we investigate whether shocks on the ask and bid side of the market have different effects. Our results reveal that the differences are rather small. For groups 1 and 3 there is a larger effect of an aggressive sell order, while the inverse holds for group 2. For depth, patterns are similar.

Next, we take the minimum price variation of a stock as given and investigate differences across small and large stocks. The impact of a shock on returns is larger for smaller stocks, but still realized quickly. The impact on depth however is smaller. One explanation for these findings might be as follows. For large stocks, the second best price in the book and those beyond might be close to the best one, while for smaller stocks, the difference between the subsequent prices in the book is larger. Furthermore, depth may be more evenly distributed in the book for small stocks than for large stocks. In particular, if the depth at the second best price and beyond is of the same order of magnitude as depth at the best prices, little effect of a liquidity shock will be found. Unfortunately, since we have only data on the best prices, we cannot test these hypotheses. Recall however that the period of time of 25 blim updates is much larger for these small stocks, since the duration between blim updates is much larger. Hence, while the recovery of depth for instance, occurs in the same number of blim updates, this takes much more time (expressed in seconds) than in the case of large stocks.

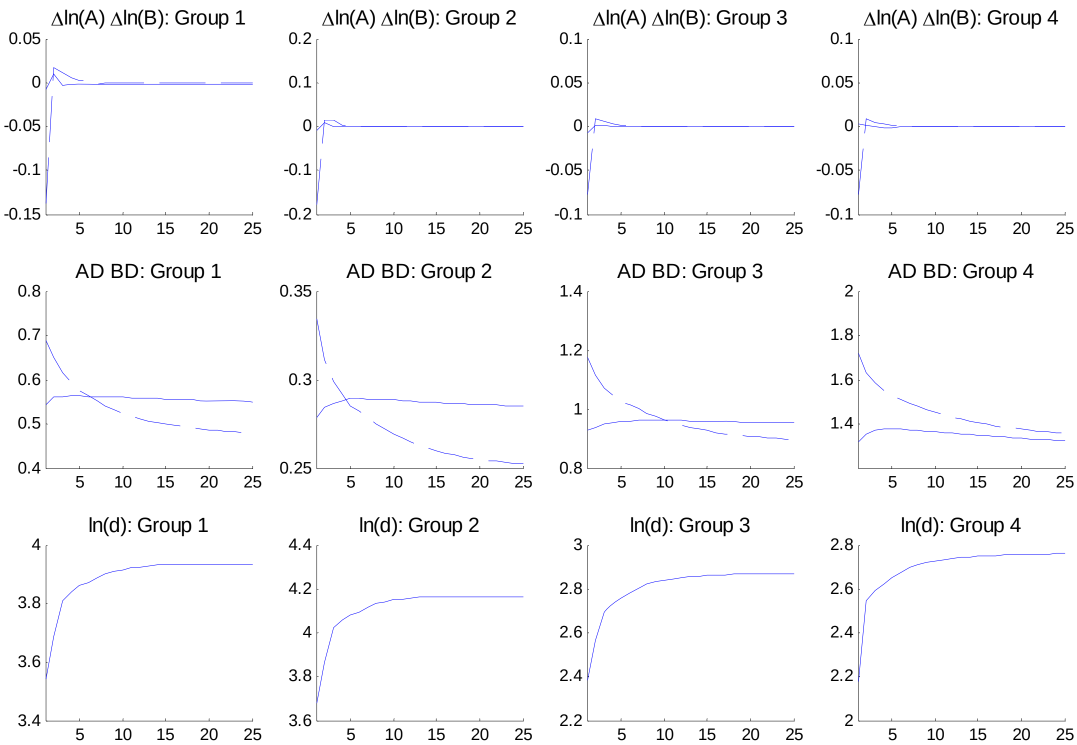
For duration, results across stocks are mixed. In general, the impact of a shock is larger for small stocks, but there is no single conclusion for stocks with different tick sizes.

To conclude the discussion of the impact of a negative liquidity shock, the results obtained in the current section are compared with those reported in Coppejans, Domowitz and Madhavan (2004). They also analyze resiliency, but employ an event study instead of a simulation based on a VAR-model. The results of their are similar to the ones obtained in Figures 1 and 2 in the current paper. The impact of an aggressive order on prices (or returns) is almost instantaneous. The effect of a shock on depths is mainly found at the side of the market at which the shock occurred, depth at the other side of the market changes much less. The duration between blim updates sharply increases just after the order, but stabilizes relatively soon (i.e. within around 10 blim updates) after the order. The event study approach used in their paper has the important advantage of looking directly at what happens in the limit order book around aggressive orders. However, it might be subject to a classic problem in event studies: the issue of confounding events. This means that in the time span around an order of a given type, another order of the same type might occur. Furthermore, their descriptive approach does not allow for disentangling the effects of order type and order size. Therefore, our paper complement the event study in Degryse, de Jong, van Ravenswaaij and Wuyts (2005) by developing a formal econometric analysis of liquidity, allowing for the accommodation of some drawbacks of the descriptive approach. We are able to correct for the problem of confounding events and can account for the state of the limit order book around aggressive orders. Moreover, we can separate the impact of an aggressive order in itself from other elements such as order size or market environment. Also interactions between dimensions of liquidity can be captured in our econometric model.



Note: This figure presents the evolution of a number of variables after a negative liquidity shock on the ask side of the market in a period of 25 blim updates (x-axis) after the shock. This shock is measured by an order of type 1. The first row in the figure draws the impact of such shock on the return on the best ask (solid line) and bid prices (dashed line), the second row on the depth at the best ask (solid line) and bid prices (dashed line) and the third row on the duration between blim updates. The columns in the figure show the results for the different groups of stocks. Unweighted averages across the stocks in each group are drawn.

Figure 1: **Impulse Responses after a Negative Liquidity Shock on the Ask Side**



Note: This figure presents the evolution of a number of variables after a negative liquidity shock on the bid side of the market in a period of 25 blim updates (x-axis) after the shock. This shock is measured by an order of type 7. The first row in the figure draws the impact of such shock on the return on the best ask (solid line) and bid prices (dashed line), the second row on the depth at the best ask (solid line) and bid prices (dashed line) and the third row on the duration between blim updates. The columns in the figure show the results for the different groups of stocks. Unweighted averages across the stocks in each group are drawn.

Figure 2: **Impulse Responses after a Negative Liquidity Shock on the Bid Side**

5.3.2 Positive Liquidity Shock

In the second part of this section, we investigate the effect of a positive liquidity shock, i.e. a shock that narrows the bid-ask spread. Such shock is measured by a type 4 and 10 order. The results for the simulations of such shock are presented in Figures 3 and 4. In each figure, the three rows show the findings for returns on the best prices, depths and duration, respectively, while the four columns plot them for the four groups of stocks. The graphs plot the evolution in an interval of 25 blim updates after the shock. Full lines depict the ask side, dashed lines the bid side. The plots show the unweighted averages across the stocks in each group.

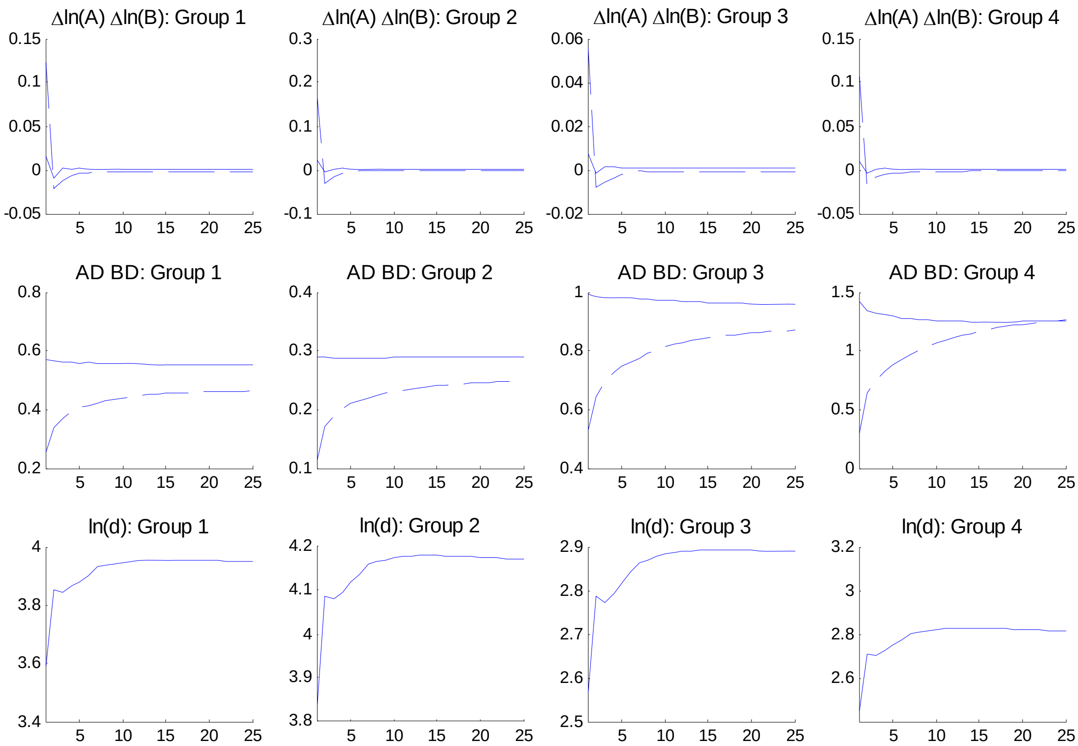
After a type 4 (10) we find a negative return on the best (bid) ask. The graphs show that the price impact is realized quickly and is permanents, since after the initial impact, we observe a small reversal after which returns are close to zero. Compared to the case of a negative liquidity shock, there is a smaller effect on returns at the other side of the market, where returns are near zero during the whole period. Depth at the best bid (ask) decreases immediately after a type 4 (10) order. This is as expected, since, as argued in the previous section, the order size of a type 4 or 10 order becomes the new depth at the best quotes. After this initial decline, the book at the best bid (ask) is refilled quickly as the depth can be seen to increase. Duration increases just after the shock, but then converges to a new value within around ten blim updates. These results point again to the fact that different aspect of liquidity can be seen as substitutes.

A comparison between the groups of stocks reveals that the impact of a positive returns and depth is much larger for large tick stocks, than for small tick stocks. Again, this is an indication that the larger tick size is binding. Furthermore, type 4 and 10 orders do not have an impact on the depth at the other side of the market for small tick stocks. On the other hand, for stocks with a large tick size, depth at the opposite side slightly declines in the periods just after the shock. Furthermore, comparing the effects of a shock at the ask and bid side of the market, we find that the impacts of both are comparable. Finally, the impact of a shock on duration is larger for small stocks. When comparing stocks with different tick sizes (taking size as given), results are mixed.

6 Robustness: Spread-model

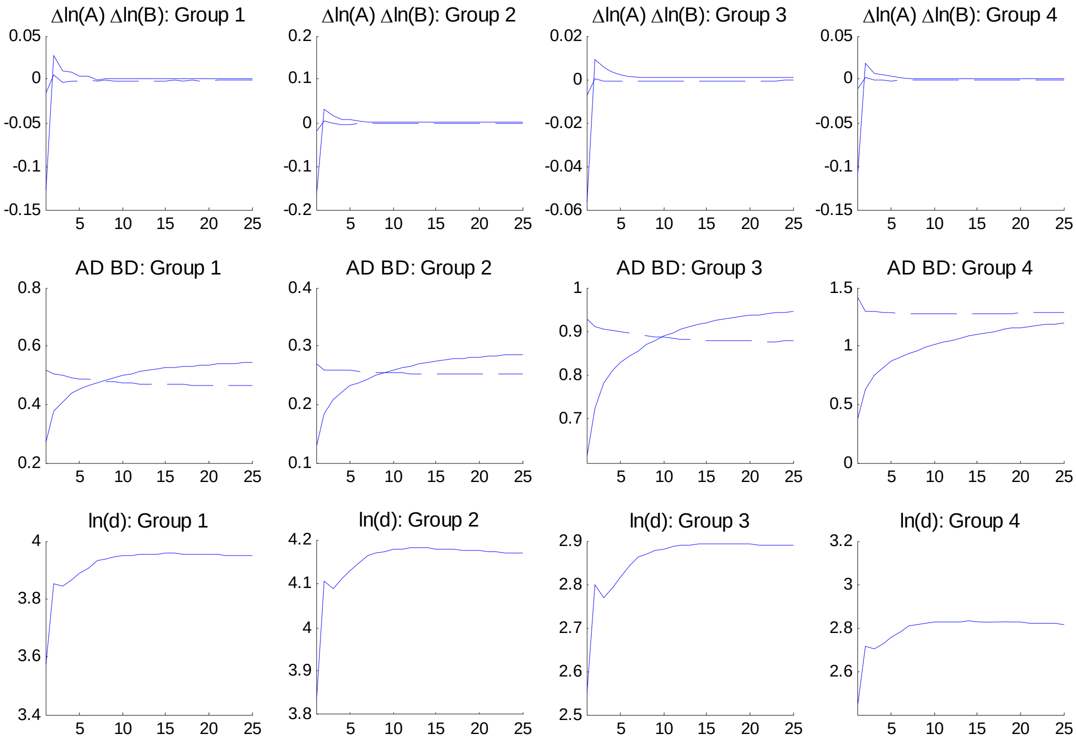
6.1 Specification of the model

So far, we used a model with bid and ask returns, depths and duration. As a robustness check, we now estimate a slightly different specification with the bid-ask spread as endogenous variable instead of ask and bid prices. The new specification also allow to depict the dynamic pattern of the spread after a liquidity shock. We change the specification from



Note: This figure presents the evolution of a number of variables after a positive liquidity shock on the bid side of the market in a period of 25 blim updates (x-axis) after the shock. This shock is measured by an order of type 4. The first row in the figure draws the impact of such shock on the return on the best ask (solid line) and bid prices (dashed line), the second row on the depth at the best ask (solid line) and bid prices (dashed line) and the third row on the duration between blim updates. The columns in the figure show the results for the different groups of stocks. Unweighted averages across the stocks in each group are drawn.

Figure 3: **Impulse Responses after a Positive Liquidity Shock on the Bid Side**



Note: This figure presents the evolution of a number of variables after a positive liquidity shock on the ask side of the market in a period of 25 blim updates (x-axis) after the shock. This shock is measured by an order of type 10. The first row in the figure draws the impact of such shock on the return on the best ask (solid line) and bid prices (dashed line), the second row on the depth at the best ask (solid line) and bid prices (dashed line) and the third row on the duration between blim updates. The columns in the figure show the results for the different groups of stocks. Unweighted averages across the stocks in each group are drawn.

Figure 4: **Impulse Responses after a Positive Liquidity Shock on the Ask Side**

Section 3.1 as follows. We define the new vector of endogenous variables of the spread model y_t^S as:

$$y_t^S = \{Spread_t, AD_t, BD_t, \ln(d_t)\}$$

with $Spread_t$ the bid-ask spread (in FF) at time t, AD_t (BD_t) the depth at the best ask (bid) at time t and $\ln(d_t)$ the natural logarithm of the duration since the previous blim update. The vector of endogenous variables remains equal to:

$$x_t = \{O01_t, ..., O12_t, OSize01_t, ..., OSize12_t, T01_t, ...T07_t\}$$

In the model, all variables are $I(0)$ such that it is not necessary to account for cointegration. The model thus becomes:

$$y_t^S = A_0^S + \sum_{l=1}^{L} A_l^S y_{t-l}^S + \sum_{m=0}^{M} B_m^S x_{t-m} + u_t^S \tag{2}$$

with u_t^S the error term which is assumed to be white noise and A_0^S, A_l^S and B_m^S the coefficient matrices to be estimated.

Finally, the methodology for analyzing resiliency is identical to Section 3.2.

6.2 Estimation Results

The results of the estimations of the new model are presented in Table 3. The interpretation of the table is identical to Table 2. The results for the AD, BD, and $\ln(d_t)$ equations are virtually identical to the ones obtained in Table 2. This means that our earlier results are robust to a new model specification. We therefore do not discuss them further, but focus on the spread, the new variable in the current specification.

First, the spread is positively autocorrelated, but this autocorrelation decreases fast in magnitude. Secondly, only for some stocks, we find significant coefficients of the lagged spread in the AD, BD, and $\ln(d_t)$ equations. On the other hand, lagged AD and BD are not significant in the spread equation. Furthermore, we find a negative relation between lagged durations and the spread, but economically, the magnitude of the coefficients of lagged durations in the spread equation is rather small. Finally, the coefficients of order types and sizes in the spread equation are as can be expected from their definitions. For the intuition, we refer to the discussion of their effect on ask and bid prices in Table 2.

6.3 Resiliency

6.3.1 Negative Liquidity Shock

The results of the simulation of a *negative liquidity shock* are presented in Figures 5 and 6. Their interpretation is the same as in Figures 1 and 2. The results for depths and

Table 3: **Estimation Results VAR-model with Spread**

Note: This table present the estimation results of equation (2) for the different groups of stocks. Estimations are performed per stock; unweighted average values across stocks in a group are shown. Significant coefficients at the 5% level are indicated in bold. The definitions of the endogenous and exogenous variables can be found in Section 3.1.

Panel A: Small Stocks

	Group 1: Small Stocks, Small Tick Size				Group 2: Small Stocks, Large Tick Size			
	$Spread_t$	AD_t	BD_t	$ln(d_t)$	$Spread_t$	AD_t	BD_t	$ln(d_t)$
$Spread_{t-1}$	**0.7160**	0.0040	0.0102	0.0019	**0.7264**	0.0010	0.0006	0.0024
$Spread_{t-2}$	**0.1411**	0.0009	-0.0010	0.0046	**0.1488**	-0.0006	-0.0008	-0.0059
$Spread_{t-3}$	**0.0231**	0.0043	0.0000	0.0012	**0.0310**	-0.0002	0.0001	0.0017
$Spread_{t-4}$	**0.0380**	-0.0048	0.0007	-0.0213	**0.0231**	0.0003	-0.0014	-0.0001
$Spread_{t-5}$	**0.0367**	-0.0076	-0.0035	-0.0125	**0.0313**	-0.0013	0.0008	-0.0022
AD_{t-1}	-0.0011	**0.6793**	0.0093	-0.0109	-0.0453	**0.6373**	0.0055	-0.0280
AD_{t-2}	-0.0025	**0.0929**	-0.0017	0.0106	-0.0558	**0.0897**	0.0016	-0.0119
AD_{t-3}	-0.0017	0.0101	0.0082	-0.0066	0.0056	**0.0375**	0.0040	-0.0083
AD_{t-4}	-0.0036	**0.0276**	-0.0056	-0.0007	-0.0750	**0.0256**	0.0057	-0.0203
AD_{t-5}	-0.0032	**0.0242**	0.0069	-0.0162	0.0290	**0.0362**	0.0018	-0.0376
BD_{t-1}	0.0121	0.0092	**0.6722**	**-0.0571**	0.0597	0.0035	**0.6034**	-0.0419
BD_{t-2}	-0.0057	-0.0039	**0.0591**	0.0207	-0.0644	0.0087	**0.1038**	0.0450
BD_{t-3}	-0.0009	0.0019	**0.0266**	-0.0073	-0.0278	0.0020	**0.0405**	-0.0228
BD_{t-4}	-0.0051	0.0066	**0.0256**	0.0203	0.0120	0.0016	**0.0254**	-0.0258
BD_{t-5}	-0.0062	0.0007	**0.0226**	-0.0106	-0.0358	0.0008	**0.0311**	-0.0054
$ln(d_{t-1})$	**-0.0093**	-0.0032	-0.0040	**0.1858**	**-0.0385**	-0.0016	-0.0011	**0.1970**
$ln(d_{t-2})$	**-0.0056**	-0.0021	-0.0034	**0.0925**	-0.0134	-0.0008	-0.0008	**0.0902**
$ln(d_{t-3})$	-0.0019	-0.0030	-0.0016	**0.0693**	-0.0110	-0.0001	-0.0001	**0.0649**
$ln(d_{t-4})$	-0.0013	-0.0001	-0.0020	**0.0574**	-0.0016	-0.0008	-0.0013	**0.0574**
$ln(d_{t-5})$	0.0011	-0.0002	-0.0016	**0.0588**	0.0001	-0.0005	-0.0008	**0.0544**
C	**0.2599**	**0.1648**	**0.1831**	**1.4401**	**0.8020**	**0.0730**	**0.0965**	**1.5111**
$O01_t$	**0.1297**	**0.1529**	**-0.0338**	**0.2133**	**0.8827**	**0.0949**	**-0.0238**	**0.2389**
$O01_{t-1}$	0.0264	0.0216	0.0047	**-0.2316**	**0.2824**	0.0095	0.0063	**-0.2855**
$O02_t$	**-0.0615**	0.0153	**-0.0757**	**0.3101**	-0.0758	**0.0216**	**-0.0446**	**0.3035**
$O02_{t-1}$	**0.0264**	-0.0072	0.0034	**-0.1725**	**0.1781**	0.0012	-0.0007	**-0.2442**
$O03_t$	**-0.0796**	0.0160	**-0.0383**	**0.3678**	**-0.1405**	**0.0117**	**-0.0206**	**0.3732**
$O03_{t-1}$	**-0.0275**	0.0005	-0.0105	-0.0411	-0.0555	0.0005	-0.0040	**-0.0690**
$O04_t$	**-0.4049**	-0.0118	**-0.2737**	**0.3658**	**-1.6994**	0.0009	**-0.1671**	**0.4011**
$O04_{t-1}$	**-0.0677**	-0.0019	0.0079	**-0.1036**	**-0.2042**	0.0027	-0.0014	**-0.1251**
$O05_t$	**-0.0923**	-0.0211	**0.2180**	**0.3034**	**-0.2946**	-0.0057	**0.0814**	**0.2859**
$O05_{t-1}$	**-0.0437**	-0.0112	0.0080	-0.0303	**-0.1236**	0.0010	0.0102	-0.0491
$O06_t$	-0.0028	-0.0046	-0.0030	**0.4845**	-0.0066	-0.0006	-0.0019	**0.4359**
$O06_{t-1}$	-0.0043	-0.0027	-0.0007	**-0.0601**	-0.0003	-0.0002	0.0001	**-0.0634**

Table 3 (continued)

	Group 1: Small Stocks, Small Tick Size				Group 2: Small Stocks, Large Tick Size			
	$Spread_t$	*AD_t*	*BD_t*	*$ln(d_t)$*	*$Spread_t$*	*AD_t*	*BD_t*	*$ln(d_t)$*
$O07_t$	**0.2032**	**-0.0372**	**0.1596**	**0.3166**	**0.9949**	-0.0106	**0.0539**	**0.2446**
$O07_{t-1}$	**0.0529**	0.0043	0.0223	**-0.2356**	**0.2727**	0.0022	0.0046	**-0.3075**
$O08_t$	**-0.0820**	**-0.0828**	0.0098	**0.3090**	**-0.1466**	**-0.0396**	0.0048	**0.3675**
$O08_{t-1}$	**0.0460**	-0.0053	-0.0059	**-0.0822**	**0.1590**	0.0027	-0.0055	**-0.1957**
$O09_t$	**-0.0630**	-0.0185	-0.0033	**0.3854**	**-0.1569**	-0.0081	-0.0054	**0.4108**
$O09_{t-1}$	**-0.0216**	-0.0153	0.0055	0.0176	-0.0360	-0.0024	0.0000	-0.0204
$O10_t$	**-0.4290**	**-0.3069**	-0.0138	**0.3503**	**-1.7378**	**-0.1590**	-0.0111	**0.4021**
$O10_{t-1}$	**-0.0540**	0.0091	0.0000	**-0.0888**	**-0.2135**	0.0005	-0.0051	**-0.0973**
$O11_t$	**-0.0947**	**0.2361**	**-0.0327**	**0.3189**	**-0.2769**	**0.1065**	**-0.0142**	**0.3019**
$O11_{t-1}$	**-0.0340**	0.0015	-0.0061	0.0269	**-0.1127**	0.0092	0.0008	-0.0334
$O12_t$	0.0011	-0.0029	-0.0019	**0.3690**	0.0029	0.0013	-0.0025	**0.4395**
$O12_{t-1}$	0.0009	0.0003	-0.0002	**-0.0499**	0.0083	-0.0004	-0.0019	**-0.0611**
$Osize01_t$	**0.0391**	-0.0019	0.0055	0.0008	**0.2671**	**-0.0179**	0.0039	0.0193
$Osize01_{t-1}$	0.0097	0.0041	0.0049	**-0.0596**	0.0027	0.0004	-0.0069	**-0.1181**
$Osize02_t$	**0.0336**	**-0.0365**	**0.0112**	**-0.0276**	**0.1084**	**-0.0334**	0.0062	-0.0226
$Osize02_{t-1}$	**0.0117**	0.0020	-0.0034	**-0.0420**	0.0056	0.0008	-0.0040	-0.0192
$Osize03_t$	**0.0447**	**-0.5109**	0.0102	**-0.2030**	**0.5020**	**-0.4847**	0.0044	**-0.4420**
$Osize03_{t-1}$	0.0159	**-0.0644**	0.0100	**-0.1459**	0.2518	-0.0257	0.0095	-0.2053
$Osize04_t$	**0.0182**	**-0.0156**	**0.0473**	0.0006	**0.1006**	**-0.0089**	**0.0777**	-0.0104
$Osize04_{t-1}$	0.0044	0.0023	0.0001	-0.0070	0.0135	0.0009	**-0.0126**	-0.0100
$Osize05_t$	0.0023	-0.0018	**0.0401**	0.0113	0.0112	0.0016	**0.0759**	0.0277
$Osize05_{t-1}$	-0.0025	0.0027	-0.0031	0.0136	-0.0032	0.0021	-0.0001	0.0290
$Osize06_t$	0.0059	0.0001	-0.0009	**-0.0315**	**0.0730**	-0.0010	-0.0020	-0.0199
$Osize06_{t-1}$	**0.0070**	0.0005	0.0009	-0.0020	0.0106	0.0005	0.0058	-0.0047
$Osize07_t$	0.0085	0.0022	-0.0044	**-0.0580**	-0.0762	-0.0001	-0.0016	-0.0009
$Osize07_{t-1}$	0.0097	-0.0036	0.0019	**-0.0539**	**0.1074**	0.0010	0.0058	**-0.1172**
$Osize08_t$	**0.0117**	0.0076	**-0.0398**	-0.0071	0.0428	0.0030	**-0.0316**	**-0.0461**
$Osize08_{t-1}$	**0.0093**	-0.0005	0.0043	**-0.0570**	0.0498	-0.0038	-0.0007	**-0.0524**
$Osize09_t$	0.0323	-0.0216	**-0.5170**	**-0.1718**	0.0900	-0.0062	**-0.5292**	**-0.3714**
$Osize09_{t-1}$	0.0257	-0.0037	**-0.0425**	**-0.1781**	0.0926	-0.0079	**-0.0610**	-0.1444
$Osize10_t$	**0.0092**	**0.0413**	**-0.0211**	-0.0110	**0.1180**	**0.0378**	**-0.0188**	-0.0198
$Osize10_{t-1}$	-0.0030	-0.0031	0.0006	0.0001	0.0121	-0.0011	0.0047	-0.0230
$Osize11_t$	-0.0017	**0.0231**	-0.0013	**0.0160**	0.0090	**0.0391**	-0.0010	0.0274
$Osize11_{t-1}$	-0.0001	0.0002	0.0013	-0.0011	-0.0043	-0.0008	0.0026	0.0144
$Osize12_t$	0.0038	-0.0013	-0.0013	0.0068	**0.0514**	0.0007	-0.0003	-0.0152
$Osize12_{t-1}$	0.0021	0.0005	0.0016	-0.0017	0.0003	0.0012	0.0049	0.0038
$T01_t$	0.1459	0.0550	0.0411	**-7.8934**	**0.9533**	0.0231	-0.0155	**-8.5335**
$T01_{t-1}$	-0.1177	-0.0784	-0.0711	**7.7330**	**-0.8137**	-0.0306	-0.0026	**8.3901**
$T02_t$	0.1057	0.0538	0.0492	**-6.8563**	**0.7544**	0.0105	-0.0103	**-7.3968**
$T02_{t-1}$	-0.0926	-0.0740	-0.0736	**6.8480**	-0.6617	-0.0213	-0.0026	**7.4493**
$T03_t$	0.0873	0.0753	0.0678	**-5.9871**	**0.6913**	0.0163	0.0031	**-6.4757**
$T03_{t-1}$	-0.0800	-0.0884	-0.0878	**6.1135**	-0.6179	-0.0250	-0.0124	**6.6582**
$T04_t$	0.0842	0.0599	0.0528	**-4.7747**	**0.6613**	0.0273	-0.0008	**-5.1201**
$T04_{t-1}$	-0.0604	-0.0686	-0.0734	**5.0957**	-0.4975	-0.0303	-0.0093	**5.4823**
$T05_t$	0.0469	0.0324	0.0554	**-3.3971**	**0.6086**	0.0227	0.0044	**-3.7333**
$T05_{t-1}$	-0.0291	-0.0423	-0.0766	**3.6774**	-0.4451	-0.0268	-0.0157	**4.0368**
$T06_t$	0.0299	0.0213	0.0391	**-2.3165**	**0.4815**	0.0036	0.0172	**-2.5539**
$T06_{t-1}$	-0.0193	-0.0284	-0.0657	**2.4942**	-0.3611	-0.0056	-0.0218	**2.7397**
$T07_t$	0.0187	0.0005	0.0473	**-1.1907**	0.2347	-0.0086	0.0135	**-1.2300**
$T07_{t-1}$	-0.0026	-0.0037	-0.0542	**1.3126**	-0.1189	0.0053	-0.0164	**1.3977**
Adj R^2	0.8021	0.5949	0.5622	0.3004	0.7986	0.5670	0.4979	0.2882

Table 3 (continued)

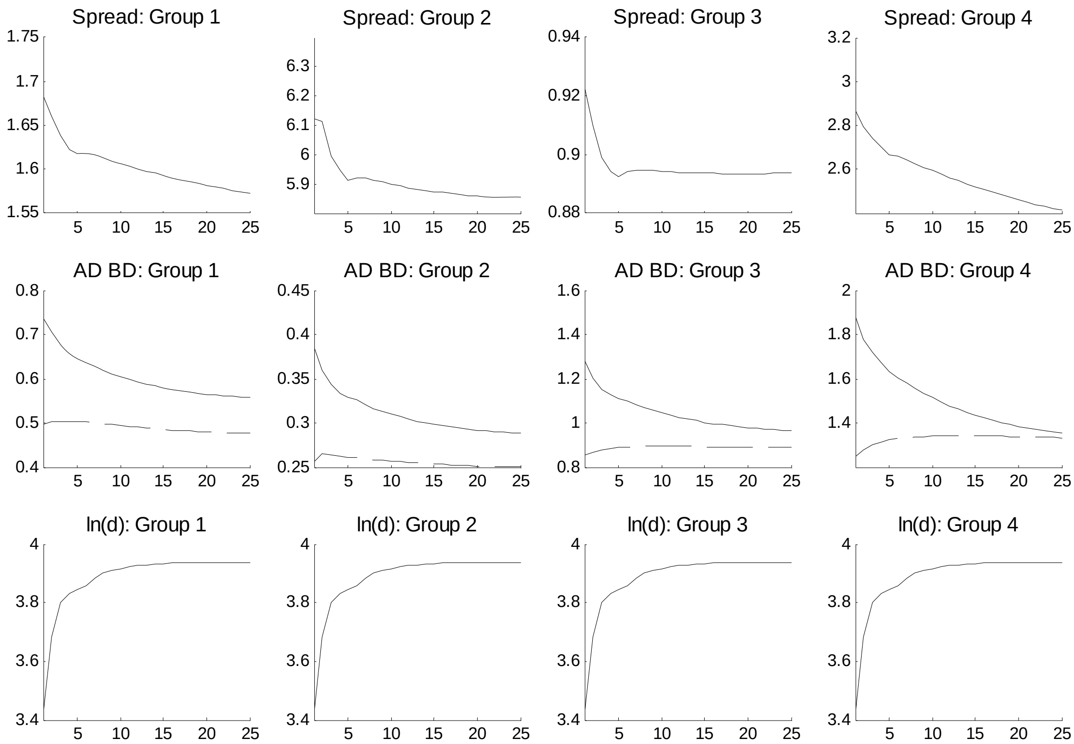
Panel B: Large Stocks

	Group 3: Large Stocks, Small Tick Size				Group 4: Large Stocks, Large Tick Size			
	$Spread_t$	AD_t	BD_t	$ln(d_t)$	$Spread_t$	AD_t	BD_t	$ln(d_t)$
$Spread_{t-1}$	**0.7848**	0.0030	0.0159	-0.0246	**0.8430**	**0.0303**	**0.0271**	**-0.0369**
$Spread_{t-2}$	**0.0940**	0.0064	0.0085	**-0.0318**	**0.0712**	-0.0021	-0.0103	-0.0083
$Spread_{t-3}$	**0.0293**	0.0010	-0.0090	0.0164	**0.0069**	-0.0087	-0.0029	0.0047
$Spread_{t-4}$	**0.0259**	0.0041	-0.0076	-0.0048	**0.0143**	-0.0039	-0.0087	0.0030
$Spread_{t-5}$	**0.0283**	**-0.0246**	0.0003	-0.0147	**0.0244**	**-0.0154**	**-0.0085**	-0.0073
AD_{t-1}	-0.0012	**0.7445**	0.0048	**-0.0126**	-0.0045	**0.6175**	-0.0001	**-0.0170**
AD_{t-2}	-0.0007	**0.0085**	0.0031	0.0037	-0.0035	**0.0253**	**0.0081**	0.0056
AD_{t-3}	0.0001	**0.0473**	0.0000	-0.0007	0.0014	**0.0352**	-0.0003	-0.0013
AD_{t-4}	-0.0012	**0.0150**	-0.0029	-0.0049	-0.0037	0.0039	**0.0057**	-0.0010
AD_{t-5}	-0.0006	**0.0292**	**0.0052**	-0.0071	-0.0016	**0.0325**	**0.0036**	-0.0060
BD_{t-1}	0.0003	**0.0109**	**0.6856**	**-0.0227**	0.0026	**0.0249**	**0.7189**	**-0.0374**
BD_{t-2}	-0.0012	0.0020	**0.0536**	0.0058	**-0.0141**	**-0.0095**	**0.0577**	**0.0204**
BD_{t-3}	-0.0010	-0.0057	**0.0419**	-0.0016	-0.0015	0.0029	**0.0211**	-0.0065
BD_{t-4}	-0.0002	0.0026	**0.0213**	-0.0019	-0.0046	0.0055	**0.0225**	-0.0020
BD_{t-5}	-0.0006	0.0016	**0.0219**	-0.0057	**-0.0078**	**0.0125**	**0.0291**	-0.0024
$ln(d_{t-1})$	**-0.0033**	-0.0028	**-0.0050**	**0.1552**	**-0.0115**	-0.0036	-0.0031	**0.1479**
$ln(d_{t-2})$	**-0.0017**	-0.0019	-0.0031	**0.0977**	**-0.0093**	-0.0032	-0.0030	**0.0917**
$ln(d_{t-3})$	**-0.0012**	-0.0033	-0.0026	**0.0739**	**-0.0045**	-0.0024	-0.0011	**0.0717**
$ln(d_{t-4})$	-0.0002	-0.0038	-0.0029	**0.0634**	-0.0024	-0.0038	-0.0018	**0.0587**
$ln(d_{t-5})$	-0.0002	-0.0032	-0.0015	**0.0593**	**-0.0029**	-0.0029	-0.0031	**0.0553**
C	**0.1192**	**0.2451**	**0.2116**	**1.0577**	**0.3977**	**0.3093**	**0.2186**	**1.0786**
$O01_t$	**0.0916**	**0.2753**	**-0.0440**	0.0113	**0.5960**	**0.4929**	**-0.0356**	-0.0203
$O01_{t-1}$	**0.0103**	0.0063	-0.0077	**-0.1680**	**0.0437**	0.0122	-0.0053	**-0.1658**
$O02_t$	**-0.0379**	**0.0477**	**-0.0968**	**0.0632**	**-0.1296**	**0.3185**	**-0.2993**	**0.1126**
$O02_{t-1}$	**0.0154**	0.0013	0.0055	**-0.0826**	**0.0355**	-0.0054	0.0134	**-0.0800**
$O03_t$	**-0.0475**	**0.0148**	**-0.0162**	**0.0288**	**-0.1506**	**-0.0206**	-0.0085	**0.0923**
$O03_{t-1}$	**-0.0091**	0.0037	0.0025	**-0.0529**	**-0.0129**	-0.0045	-0.0008	**-0.0583**
$O04_t$	**-0.2160**	-0.0107	**-0.3727**	**0.1790**	**-1.0962**	**0.0388**	**-0.9833**	**0.1526**
$O04_{t-1}$	**-0.0242**	0.0036	0.0071	**-0.0306**	-0.0138	-0.0183	**0.0913**	**-0.0525**
$O05_t$	**-0.0519**	**-0.0185**	**0.4369**	**0.1173**	**-0.1841**	**0.1158**	**0.3931**	**0.1406**
$O05_{t-1}$	**-0.0155**	0.0007	**-0.0214**	-0.0204	**-0.0375**	**0.1173**	0.0071	**-0.0258**
$O06_t$	**0.0052**	-0.0046	**-0.0098**	**0.4378**	**0.0097**	**-0.0094**	**-0.0100**	**0.4546**
$O06_{t-1}$	0.0001	0.0016	0.0035	**-0.0620**	0.0054	-0.0034	-0.0021	**-0.0576**

Table 3 (continued)

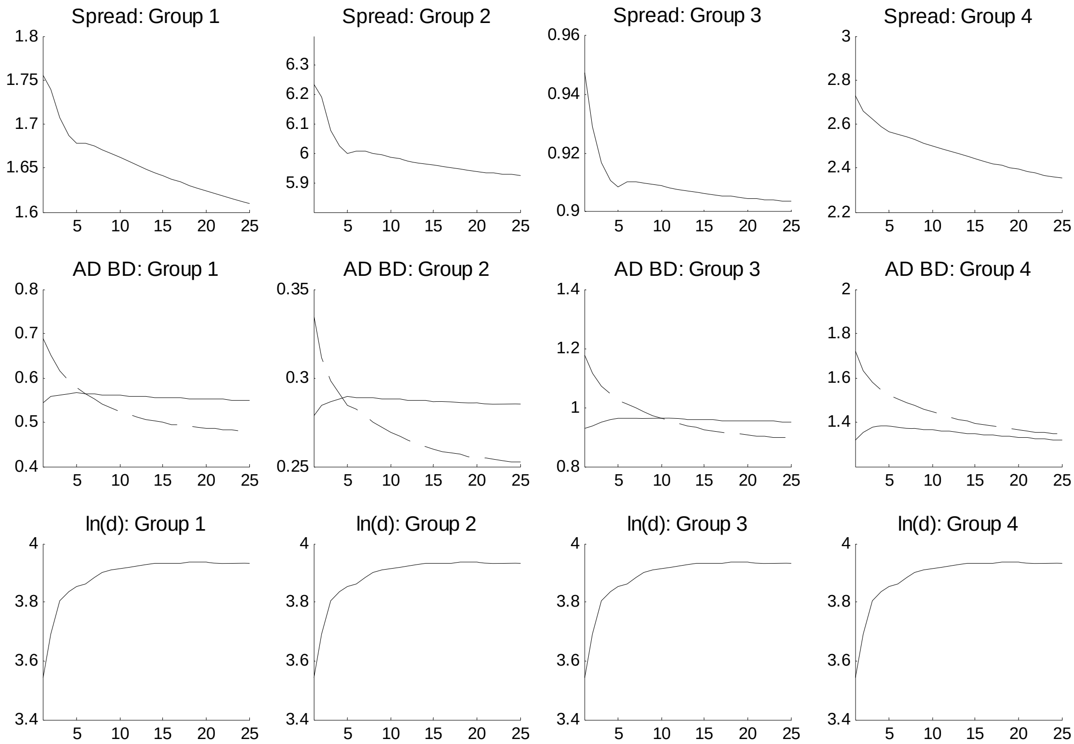
	Group 3: Large Stocks, Small Tick Size				Group 4: Large Stocks, Large Tick Size			
	$Spread_t$	AD_t	BD_t	$ln(d_t)$	$Spread_t$	AD_t	BD_t	$ln(d_t)$
$O07_t$	**0.1168**	**-0.0768**	**0.2732**	-0.0005	**0.4582**	**-0.0626**	**0.4340**	**-0.1169**
$O07_{t-1}$	**0.0095**	-0.0023	**0.0234**	**-0.2064**	**0.0236**	0.0067	0.0092	**-0.0935**
$O08_t$	**-0.0550**	**-0.1550**	**0.0572**	**0.0803**	**-0.1563**	**-0.4204**	**0.2460**	**0.0856**
$O08_{t-1}$	**0.0151**	0.0110	-0.0035	**-0.0651**	**0.0321**	**-0.0565**	-0.0118	**-0.0595**
$O09_t$	**-0.0471**	**-0.0290**	0.0053	**0.0582**	**-0.1658**	**-0.0317**	-0.0035	**0.0678**
$O09_{t-1}$	**-0.0072**	0.0064	0.0047	**-0.0437**	**-0.0174**	0.0044	0.0033	**-0.0381**
$O10_t$	**-0.2197**	**-0.3882**	**0.0257**	**0.1646**	**-1.1282**	**-1.0063**	**0.1387**	**0.1490**
$O10_{t-1}$	**-0.0208**	**0.0228**	0.0007	-0.0141	**-0.0223**	**0.0352**	**-0.0568**	**-0.0336**
$O11_t$	**-0.0539**	**0.4501**	-0.0074	**0.1449**	**-0.1818**	**0.3679**	**-0.0136**	**0.1164**
$O11_{t-1}$	**-0.0162**	**-0.0357**	0.0036	-0.0118	**-0.0424**	0.0124	0.0110	**-0.0195**
$O12_t$	**0.0055**	-0.0033	-0.0030	**0.4604**	0.0016	**-0.0138**	-0.0060	**0.4336**
$O12_{t-1}$	0.0008	0.0008	0.0013	**-0.0546**	-0.0004	-0.0008	-0.0009	**-0.0571**
$Osize01_t$	**0.0104**	**0.0093**	**0.0106**	-0.0028	**0.0475**	**0.0167**	0.0015	**-0.0159**
$Osize01_{t-1}$	0.0011	0.0035	**0.0076**	-0.0039	0.0044	-0.0019	0.0011	0.0010
$Osize02_t$	**0.0037**	**-0.0358**	**0.0103**	0.0034	**0.0129**	**-0.0477**	-0.0003	**-0.0078**
$Osize02_{t-1}$	**0.0012**	-0.0006	0.0004	**-0.0060**	0.0024	-0.0006	**-0.0036**	**-0.0087**
$Osize03_t$	**0.0110**	**-0.5770**	0.0046	0.0116	**0.0715**	**-0.4402**	-0.0129	-0.0251
$Osize03_{t-1}$	**0.0077**	**0.0175**	0.0097	**-0.0232**	0.0147	**0.0432**	-0.0043	**-0.0650**
$Osize04_t$	**0.0023**	**-0.0146**	**0.0412**	0.0019	0.0044	**-0.0432**	**0.1136**	-0.0012
$Osize04_{t-1}$	0.0006	**0.0040**	**-0.0036**	-0.0012	-0.0004	-0.0009	**-0.0372**	-0.0002
$Osize05_t$	-0.0005	**-0.0068**	**0.0425**	**0.0078**	-0.0005	**-0.1956**	**0.0410**	**0.0047**
$Osize05_{t-1}$	-0.0005	-0.0008	-0.0006	0.0009	-0.0018	**-0.1596**	**-0.0061**	0.0016
$Osize06_t$	**0.0021**	0.0015	0.0018	-0.0020	**0.0149**	**0.0066**	0.0019	**-0.0077**
$Osize06_{t-1}$	0.0007	0.0002	0.0014	-0.0011	0.0013	**0.0071**	0.0012	-0.0047
$Osize07_t$	**0.0031**	**0.0180**	**0.0042**	0.0030	**0.0345**	-0.0042	**-0.0103**	-0.0010
$Osize07_{t-1}$	**0.0026**	0.0018	0.0034	-0.0026	**0.0125**	0.0016	-0.0018	**-0.0200**
$Osize08_t$	**0.0033**	**0.0199**	**-0.0329**	0.0005	**0.0087**	**0.2056**	**-0.0357**	0.0008
$Osize08_{t-1}$	0.0009	0.0022	-0.0004	-0.0032	0.0032	**0.1595**	**0.0056**	**-0.0055**
$Osize09_t$	**0.0129**	-0.0106	**-0.5265**	-0.0124	**0.0843**	-0.0016	**-0.5768**	0.0034
$Osize09_{t-1}$	0.0051	0.0060	**-0.0451**	**-0.0332**	**0.0427**	0.0003	-0.0099	**-0.0786**
$Osize10_t$	0.0003	**0.0189**	**-0.0295**	0.0001	**0.0201**	**0.0542**	**-0.0999**	0.0062
$Osize10_{t-1}$	-0.0003	**-0.0040**	**0.0030**	0.0010	0.0000	0.0011	**0.0343**	0.0000
$Osize11_t$	**-0.0010**	**0.0325**	**-0.0044**	**0.0041**	**-0.0100**	**0.0479**	0.0011	**0.0104**
$Osize11_{t-1}$	-0.0004	0.0018	0.0006	0.0026	-0.0021	0.0004	**0.0036**	**0.0090**
$Osize12_t$	**0.0019**	0.0005	0.0002	**-0.0031**	**0.0144**	0.0003	0.0004	**0.0076**
$Osize12_{t-1}$	0.0001	0.0011	0.0009	-0.0009	0.0039	0.0025	0.0018	-0.0054
$T01_t$	0.0347	0.0343	-0.1243	**-6.3844**	0.2830	-0.0322	0.1740	**-6.1981**
$T01_{t-1}$	-0.0156	-0.0697	0.0903	**6.3938**	-0.2102	-0.0558	-0.2239	**6.2165**
$T02_t$	0.0186	-0.0075	-0.1194	**-5.5379**	0.1993	0.0368	0.1397	**-5.3424**
$T02_{t-1}$	-0.0129	-0.0471	0.0764	**5.6181**	-0.1677	-0.1069	-0.1906	**5.4381**
$T03_t$	0.0351	0.0172	-0.1382	**-4.8167**	0.1272	0.0018	0.1296	**-4.6512**
$T03_{t-1}$	-0.0296	-0.0641	0.1050	**5.0063**	-0.1002	-0.0613	-0.1584	**4.8593**
$T04_t$	0.0501	-0.0016	-0.1588	**-3.6974**	0.1434	0.0194	0.0955	**-3.6241**
$T04_{t-1}$	-0.0345	-0.0321	0.1381	**4.0903**	-0.0933	-0.0799	-0.1068	**4.0410**
$T05_t$	0.0473	-0.0168	-0.0984	**-2.6038**	0.1136	-0.0213	0.0610	**-2.5070**
$T05_{t-1}$	-0.0371	-0.0226	0.0728	**2.9662**	-0.0695	-0.0371	-0.0824	**2.8895**
$T06_t$	0.0101	-0.0203	-0.0604	**-1.8184**	0.1106	-0.0721	0.0417	**-1.7617**
$T06_{t-1}$	-0.0038	-0.0213	0.0355	**2.0310**	-0.0775	0.0197	-0.0665	**1.9649**
$T07_t$	0.0058	-0.0120	-0.0543	**-0.9128**	0.0623	-0.0037	-0.0067	**-0.9108**
$T07_{t-1}$	-0.0010	-0.0195	0.0370	**1.0104**	-0.0390	-0.0388	-0.0061	**1.0094**
	0.8391	0.6241	0.5861	0.2502	0.7869	0.7508	0.6508	0.2378

duration are in line with these earlier result, which are thus robust to the new model specification. We therefore focus again only on the spread. An increase in the spread can be observed immediately after the shock, but it starts decreasing again very soon. In general, it takes some time before the spread converges to its new level, i.e. it only converges after more than 25 blim updates (which is outside the scale of the figures). The level to which it converges is close to the last observation in the figure. This is a similar result as in Degryse, de Jong, van Ravenswaaij and Wuyts (2005). The event study there also showed that spreads converge rather slowly. Finally, note that the impact on the spread (in FF) is much larger for large tick stocks (groups 2 and 4) than for stocks having a small ticks size (groups 1 and 3). The effect of shock at the bid side (type 7 order) is somewhat larger than the one of a shock on the ask side (type 1).



Note: This figure presents the evolution of a number of variables after a negative liquidity shock on the ask side of the market in a period of 25 blim updates (x-axis) after the shock. This shock is measured by an order of type 1. The first row in the figure draws the impact of such shock on the bid-ask spread, the second row on the depth at the best ask (solid line) and bid prices (dashed line) and the third row on the duration between blim updates. The columns in the figure show the results for the different groups of stocks. Unweighted averages across the stocks in each group are drawn.

Figure 5: **Spread Model: Impulse Responses after a Negative Liquidity Shock on the Ask Side**



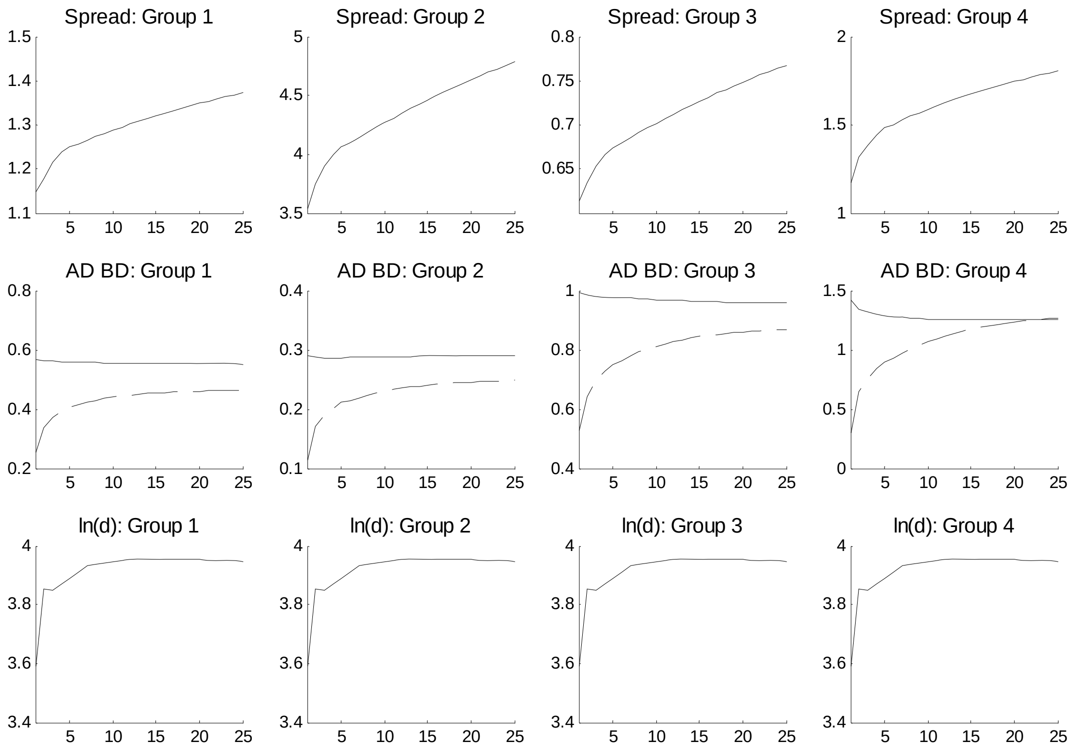
Note: This figure presents the evolution of a number of variables after a negative liquidity shock on the bid side of the market in a period of 25 blim updates (x-axis) after the shock. This shock is measured by an order of type 7. The first row in the figure draws the impact of such shock on the bid-ask spread, the second row on the depth at the best ask (solid line) and bid prices (dashed line) and the third row on the duration between blim updates. The columns in the figure show the results for the different groups of stocks. Unweighted averages across the stocks in each group are drawn.

Figure 6: **Spread Model: Impulse Responses after a Negative Liquidity Shock on the Bid Side**

6.3.2 Positive Liquidity Shock

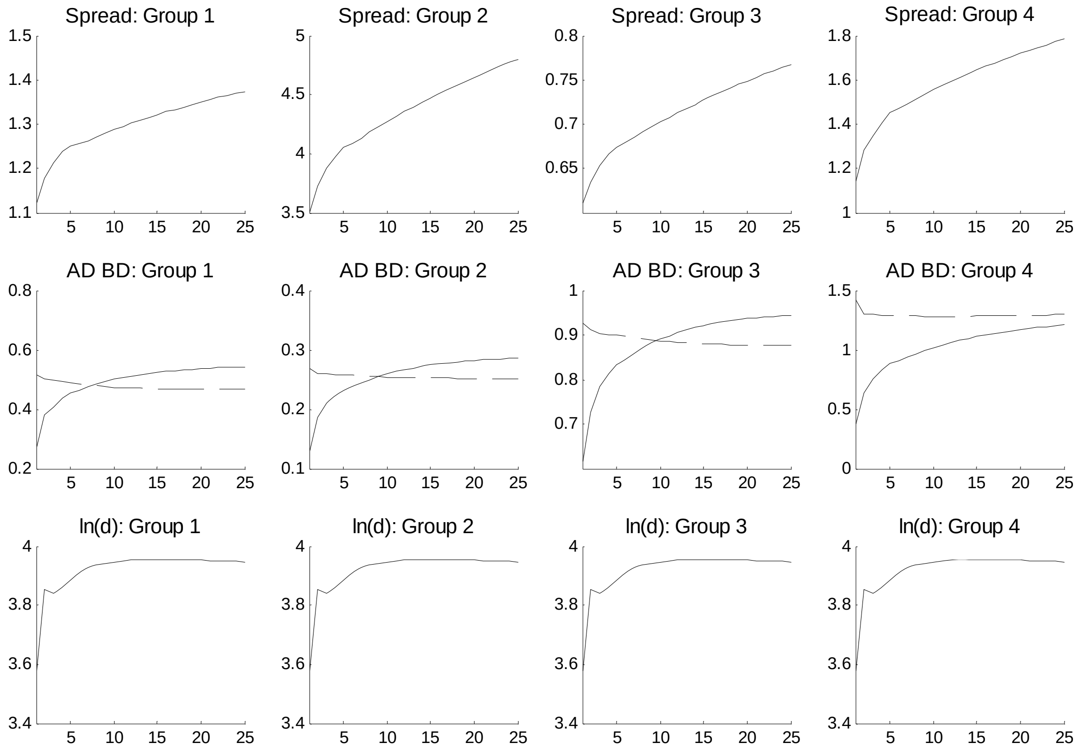
In the second part of this section, we investigate the effect of a positive liquidity shock, i.e. a shock that narrows the bid-ask spread. Such shock is measured by a type 4 and 10 order. The results for the simulations of such shock are presented in Figures 7 and 8. Their interpretation is again the same as before, i.e. Figures 3 and 4.

As before, the results for depths and duration are in line with those found in the earlier model specification. For the spread, we find that after the decrease, caused by the positive shock, it starts increasing again just after the shock. Again, convergence to its new value occurs just outside the scale of the figure and takes 30 - 35 blim updates, and the level to which it converges is close to the last observation in the figure.



Note: This figure presents the evolution of a number of variables after a positive liquidity shock on the bid side of the market in a period of 25 blim updates (x-axis) after the shock. This shock is measured by an order of type 4. The first row in the figure draws the impact of such shock on the bid-ask spread, the second row on the depth at the best ask (solid line) and bid prices (dashed line) and the third row on the duration between blim updates. The columns in the figure show the results for the different groups of stocks. Unweighted averages across the stocks in each group are drawn.

Figure 7: **Spread Model: Impulse Responses after a Positive Liquidity Shock on the Bid Side**



Note: This figure presents the evolution of a number of variables after a positive liquidity shock on the ask side of the market in a period of 25 blim updates (x-axis) after the shock. This shock is measured by an order of type 10. The first row in the figure draws the impact of such shock on the bid-ask spread, the second row on the depth at the best ask (solid line) and bid prices (dashed line) and the third row on the duration between blim updates. The columns in the figure show the results for the different groups of stocks. Unweighted averages across the stocks in each group are drawn.

Figure 8: **Spread Model: Impulse Responses after a Positive Liquidity Shock on the Ask Side**

7 Conclusion

In this paper we analyzed different dimensions of liquidity, being prices, depth, duration and resiliency, for an order driven market. Our econometric model allows for taking into account relations between bid and ask sides of the market, as well as between prices, depth and duration. A VAR-model was estimated, taking into account cointegration. Several interesting results emerged. First, we show that prices and depths are related. Ask depth has a negative impact on bid and ask returns, while the sign of depth at the best bid is positive in the return equations. Ask (bid) returns on the other hand are positively (negatively) correlated with depths. Secondly, a relation exists also between bid and ask sides of the market: ask and bid returns are negatively correlated, while depth at the best bid and ask are positively related. This is in line with models such as Parlour (1998) and Rosu (2006), and was also argued by Harris (1990). Thirdly, for duration, we find a econometrically significant relation with returns and depths, but economically, the effect is very small, as predicted by Easley and O'Hara (1992), who show that long durations are not informative. This result is also found by Engle and Patton (2004) in a hybrid market. Fourthly, the composition of order flow, i.e. the type of submitted orders, and order size both have an impact on returns, depths and duration. The effect of order size is small but can not be neglected.

Although the main conclusions discussed above are valid among different groups of stocks, some notable differences emerge on the order of magnitude of the effects, depending on size and tick size of a stock. Holding the tick size of a stock constant, the interaction between returns (prices) and depth is weaker for smaller stocks. The effect of aggressive orders on returns is larger for smaller stocks while the impact of such orders on depths is smaller. The latter is likely a consequence of the lower depth at the best prices for smaller stocks. Holding the size of a stock constant, the impact of aggressive orders on returns at the own side of the market is larger for stocks with a large tick size, while it is smaller for returns at the opposite side. Moreover, for small tick stocks, aggressive buy orders have (in absolute value) a larger influence on the ask return than aggressive sell orders on the bid return. This shows that shocks to the ask and bid side of the market may have asymmetric impacts. Also, focussing on large stocks, the effect of an aggressive buy (sell) order type order on the depth at the best ask (bid) is much larger for large tick stocks.

To address the issue of resiliency, we simulated liquidity shocks, using the VAR-model. Four types of shocks were considered: a negative shock at the ask or bid side (measured as an aggressive buy or sell order that increases the spread) and a positive shock at ask or bid side (measured by a buy or sell order that decreases the spread). A negative liquidity shock has a permanent effect on prices at the side of the market at which the shock occurred, but the impact is realized almost instantaneously, as is predicted by Glosten and Milgrom (1985). However, in line with Rosu (2006), we also document an effect on the best price at the other side of the market, which partly offsets the effect of the own side on the spread. Depth increases after a negative liquidity shock, but mainly at the side of the market of the shock. At the other side of the market, the impact is small. Duration increases after the negative shock, but converges within 10 blim updates to a new value. Also the impact of a positive shock is realized very quickly, but it remains limited to the side of the shock, at the other side of the market, little effect is found. Depth at the best prices decreases (because of the undercutting), but recovers quickly afterwards.

Again some differences between groups of stocks are found. The effect of shocks on both returns and depth is much larger for large tick stocks, taking size as given. This may indicate that tick size is a binding constraint for these stocks. On the other hand, shocks on bid and ask side of the market have similar effects. Taking the minimum price variation of a stock as given, the impact of a shock on returns is larger for smaller stocks, but still realized quickly. The impact on depth however is smaller. In general, these differences between stocks are found both after a negative and positive liquidity shock. For duration, the impact of a shock is larger for small stocks. Across stocks with different tick sizes, results are mixed.

Summarizing, our results clearly demonstrate the importance of incorporating different dimensions of liquidity in the analysis. In case of a negative liquidity shock, we find a permanent effect on prices, with returns (in absolute value) ranging from 0.06 to 0.16% (depending on size and tick size of the stock). Also, we find an initial widening of the spread, but it becomes smaller again in subsequent periods. On the other hand, depth at the best prices increases, initially with up to 20%. Symmetric results are obtained for a positive liquidity shock. It implies on the one hand an improvement of liquidity since the spread narrows, but at the same time, another dimension of liquidity deteriorates since depth at the best prices decreases. These results clearly demonstrate the need to account for interaction and complementarity between different dimensions of liquidity. A second main conclusion is that an analysis of liquidity should also allow for asymmetries in dynamics at bid and ask side of the market, while at the same time accounting for the existence of a relationship between them. This is in contrast with the methodology used in a vast majority of the current literature. In general, the analysis in this paper indicates that Euronext Paris is a liquid market. Impacts of shocks are realized quickly, i.e. within a few best limit updates. As in Hasbrouck (1991), permanent effects on prices exist, while depth recovers to its pre-shock level. In other words, the limit order book is able to provide sufficient liquidity to the market. This holds both for large, frequently traded stocks that are included in the CAC40 stock index, and smaller, less frequently traded stocks outside that index. As a qualification, it needs to be remarked that although the stocks in our sample account for both a large part of trading and market capitalization, we did not consider very infrequently traded stocks.

References

Admati, A., P. Pfleiderer, 1988, A Theory of Intraday Patterns: Volume and Price Variability, *Review of Financial Studies*, 1, pp. 3-40.

Beltran, H., A. Durré, P. Giot, 2004, How Does Liquidity React to Stress Periods in a Limit Order Market, *National Bank of Belgium Working Paper 49*.

Biais, B., P. Hillion, C. Spatt, 1995, An Empirical Analysis of the Limit Order Book and the Order Flow in the Paris Bourse, *Journal of Finance*, 50, pp. 1655-1689.

Coppejans, M., I. Domowitz, A. Madhavan, 2004, Resiliency in an Automated Auction, *Working Paper*.

Degryse, H., F. de Jong, M. van Ravenswaaij, G. Wuyts, 2005, Aggressive Orders and the Resiliency of a Limit Order Market, *Review of Finance*, 2, pp. 201-242.

Dufour, A., R. Engle, 2000, Time and the Price Impact of a Trade, *Journal of Finance*, 55, pp. 2467-2498.

Easley, D., M. O'Hara, 1987, Price, Trade Size, and Information in Securities Markets, *Journal of Financial Economics*, 19, pp. 69-90.

Easley, D., M. O'Hara, 1992, Time and the Process of Security Price Adjustment, *Journal of Finance*, 47, pp. 577-605.

Engle, R., A. Patton, 2004, Impact of Trades in an Error-Correction Model of Quote Prices, *Journal of Financial Markets*, 7, pp. 1-25.

Escribano, A., R. Pascual, 2000, Asymmetries in Bid-Ask Responses to Innovations in the Trading Process, *Working Paper*.

Foucault, T., O. Kadan, E. Kandel, 2005, Limit Order Book as a Market for Liquidity, *Review of Financial Studies*, 18, pp. 1171-1217.

Glosten, L., P. Milgrom, 1985, Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders, *Journal of Financial Economics*, 14, pp. 71-100.

Griffiths, M., B. Smith, D. Turnbull, R. White, 2000, The Costs and Determinants of Order Aggressiveness, *Journal of Financial Economics*, 56, pp. 65-88.

Harris, L., 1990, Liquidity, Trading Rules, and Electronic Trading Systems. *New York University Salomon Center Monograph Series in Finance*, Monograph # 1990-4.

Hasbrouck, J., 1991, Measuring the Information Content of Stock Trades, *Journal of Finance*, 46, pp. 179-207.

Jang, H., P. Venkatesh, 1991, Consistency between Predicted and Actual Bid-Ask Quote Revisions, *Journal of Finance*, 4, pp. 433-446.

Kavajecz, K., E. Odders-White, 2001, An Examination of Changes in Specialists' Posted Price Schedules, *Review of Financial Studies*, 14, pp. 681-704.

Parlour, C., 1998, Price Dynamics in Limit Order Markets, *Review of Financial Studies*, 11, pp. 789-816.

Ranaldo, A., 2004, Order Aggressiveness in Limit Order Book Markets, *Journal of Financial Markets*, 7, pp. 53-74.

Rosu, I., 2006, A Dynamic Model of the Limit Order Book, *Unpublished Working Paper.*

Spierdijk, L., T. Nijman, A. van Soest, 2002, The Price Impacy of Trades in Illiquid Stocks in Periods of High and Low Market Activity, *Unpublished Working Paper.*

Appendix A: Order Classification Methodology

In order to characterize the order submission behavior, all incoming orders are classified according to the scheme proposed by Biais, Hillion and Spatt (1995) and also used in other papers, see e.g. Griffiths et al. (2000) or Ranaldo (2004). A distinction between orders is made on the basis of the direction of the order (buy or sell), and of its aggressiveness. Buy orders are classified into aggressiveness order types 1 to 6, where 1 is the most aggressive buy order type, and 6 is the least aggressive. An order of type 1 is an order to buy a larger quantity than is available at the best ask at a price that is higher than the best ask. This means that these orders walk up the limit order book and result in multiple trades. An order of type 2 is an order for a larger quantity than available at the best ask, but that does not walk up the limit order book above the best ask. The reason for this can be twofold. First, the order can be a limit order with a price equal to the best ask, but with a larger quantity than the depth at the best ask. Secondly, the order can be a market order which has an order size larger than the one available at the best price. In the latter case, the rules of the Paris Bourse forbid such market order to walk up the limit order book. For both, the part of the order that is not executed immediately is converted into a limit buy order. Orders of type 3 are orders to buy a quantity that is lower than the one offered at the best ask, hence they result in full and immediate execution. In contrast, the remaining buy order types are not executed immediately, so they do not result instantaneously in a transaction. Type 4 orders have a price worse than the best ask, but better than the best bid price, while type 5 orders have a price exactly at the best bid. The remaining orders are collected in type 6. Sell orders are classified in a symmetric way, resulting in order types 7, the most aggressive sell order, to 12, which is the least aggressive sell order type.