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Article *in* Review of Finance · February 2005

DOI: 10.1007/s10679-005-7590-6 · Source: RePEc

# Aggressive Orders and the Resiliency of a Limit Order Market

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This version: 2002-07-01

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We thank Theo Nijman for comments on an earlier draft as well as seminar participants at Leuven and Tilburg. The first and last author gratefully acknowledge financial assistance from FWO-Flanders under contract G.0333. Correspondence can be sent to hans.degryse@econ.kuleuven.ac.be.

# Aggressive Orders and the Resiliency of a Limit Order Market


**Abstract**

We analyze the resiliency of a pure limit order market for large and small capitalization stocks as well as stocks with different tick sizes. We explore the issue of resiliency by investigating the order flow around aggressive orders that move prices. The impact of aggressive orders is gauged in three complementary ways. First, we look at the order flow before and after aggressive orders. We find strong persistence in the submission of aggressive orders. It takes about 50 subsequent orders before the order flow returns to its unconditional pattern. Second, we describe and estimate the effect of aggressive orders on prices. The estimated price impact is realized immediately, i.e. there are no lagged price effects. However, due to correlated order flow, prices do move both before and after the submission of aggressive orders. As an explanatory variable, both aggressiveness and order size of aggressive orders are important in explaining price effects. Both firm size and tick size are important in explaining the variation of the impact of order aggressiveness. Small firms exhibit a larger price impact. A larger tick size implies somewhat larger price effects.



*JEL Classification*: G15

*Keywords*: limit orders, tick size, price impact, depth, liquidity supply, spread

# 1 Introduction

Throughout the world, there exists a wide diversity of trading systems. In a recent survey of equity markets, Domowitz and Steil (1999) observe that many new trading systems and recently restructured markets apply a limit order design. In such a trading structure, unfilled limit orders are stored in a limit order book, waiting for possible future execution. Given the recent upswing in this type of market, an important question is how efficiently limit order markets operate. The main aspect of the performance of a trading mechanism is its liquidity. In a liquid market, traders do not need to be concerned about the time in between the submission and the execution of their orders, nor about the price impact or execution costs. Domowitz and Steil (1999) report evidence suggesting that pure limit order markets have lower execution cost than other markets. Harris (1990) distinguishes four dimensions that are associated with liquidity: width (the bid-ask spread for a given number of shares), depth, immediacy and resiliency. Though the literature has already studied extensively the issue of liquidity, a characteristic that has received little attention in empirical research so far is resiliency. It is this feature of the market is at the focus of this paper. Harris (1990) defines it as how quickly prices revert to former levels after they change in response to large order flow imbalances initiated by uninformed traders. We will use a slightly broader definition and refer to resiliency as how quickly various measures of liquidity revert to their former levels after the market has been hit by a shock. We do not only look at prices because of the interactions that exist between the several dimensions. Our definition refers to how easy a market can absorb such a shock, e.g. after a transaction with a substantial price impact. In a dealership market, a specialist has an obligation to assure the liquidity of a market in all circumstances, which is cited frequently as one of the important reasons for their presence. In contrast, in a limit order market, the limit order book is the only source of liquidity. Depending on the willingness to provide limit orders, liquidity will vary over time and may even be absent at certain times. Although Stigler (1964) already stressed the importance of resiliency, it is a relatively unexplored area in market microstructure research. Exceptions are Bhattacharya and Spiegel (1998) who study trading suspensions on the NYSE and Coppejans, Domowitz and Madhavan (2001), who investigate the resiliency of the Swedish stock index futures market (OMX).

The goal of this paper is to study the resiliency of a pure limit order market. We focus on an eminent example of such a market, namely the Paris Bourse (nowadays Euronext Paris). In particular, we analyse the impact on order flow of orders that immediately lead to a transaction and move the best bid or ask price. Such “aggressive orders” are the natural candidates to study the resiliency of a limit order market. We explore the issue of resiliency by making groups of stocks on the basis of the market capitalization of a stock and tick size. In particular we are interested whether the resiliency of limit order markets is related to these two properties of a stock. Theory suggests that the order submission behaviour – the choice between market orders and limit orders and their aggressiveness – may depend on the tick size and the stock's market capitalization. Our approach adds to the work of Coppejans et al. (2001). That paper is not specific about the sources of the shocks. In this paper, we will focus on shocks to depth caused by large transactions, that consume a significant part of the liquidity in the book.

Several aspects of the impact of an aggressive order are studied. First, we examine the relation between aggressive orders and the state of the limit order book. We look at the order size, order timing and frequency of the different order types. Also, using conditional probabilities, we look at the order types following an aggressive order. In this way, we can determine whether liquidity after an aggressive order is restored. We extend the analysis of Biais, Hillion and Spatt (1995), henceforth BHS95, by not only studying the next order, but also subsequent orders.

Secondly, we investigate the market impact of aggressive orders. In a descriptive approach, we directly look at what happens in the limit order book, and more specifically at the best quotes, the depth at the best quotes, the relative spread and the duration between best quote updates. Although the immediate price impact of a trade is a well-studied topic[1], the price effects beyond this immediate price impact are less well investigated. We examine whether aggressive orders have 'long run' price effects. The central hypothesis is that all price effects are incorporated in the first transaction price, as predicted by semi-strong form market efficiency (Glosten and Milgrom (1985)). We also look at how the bid-ask spread and depth at the best quotes develop before and after an aggressive order. These are probably the most direct measures of market resiliency. We investigate how fast they revert to their normal level after an aggressive order. Actually, a more general approach would be to study the depth of the market for different order sizes, but data limitations prevent us from doing so.

Next to this descriptive approach, we also employ a more formal analysis, using regression techniques. In this way, we take into account the fact that orders may show an autoregressive pattern. Moreover, we are able to quantify the separate effects that order size and order aggressiveness may exhibit.

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[1] See the pioneering work of Glosten and Harris (1988) and the subsequent literature. Hasbrouck (1995) advocates to use Vector Autoregressions for the long run price impacts of trading.

We also provide an analysis of the effect of the tick size on the recovery of the bid-ask spread by considering stocks with a tick size of 0.1 FF, as well as stocks with a tick size of 1 FF, which is quite large compared to the $1/16 on the NYSE. The spread for the latter stocks is often just one tick, which makes submission of competitive limit orders within the best quotes impossible. This may have an impact on the speed of restoration of liquidity. Moreover, we infer whether resiliency depends on the market capitalization of a stock.

We study resiliency in two ways, by looking at order flow and price effects. Our findings can be summarized as follows. When considering the relationship between aggressive orders and the order flow, we find as a first result that order size is increasing in order aggressiveness and the capitalisation of the stock but decreasing in tick size. Furthermore, aggressive orders are more frequent at the end of the trading day, while in the morning, less aggressive orders are relatively more frequent. Thirdly, in contrast with BHS95, the least aggressive order types turn out to be the most frequent ones, while the most aggressive types are least frequent. Next to looking at unconditional frequencies, it is interesting as well to consider probabilities conditional upon the current order type. We confirm the diagonal effect as reported in BHS95. This means that an order of a given type is likely to be followed by an order of the same type. Moreover, we show that this effect persists over time in the sense that it not only applies to the next order, but also to subsequent orders. Nevertheless, over time conditional probabilities converge to their unconditional levels. Moreover, liquidity is provided to the market when needed.

The market impact of aggressive orders is first analyzed using a descriptive approach. More specifically, we construct a window of 10 updates of the best quotes before and 20 updates after the aggressive order. In this window, we look at the evolution of the best quotes, the depth at the best quotes, the relative spread and the duration between quote updates. Although differences exist between order types and across stocks, in general we can conclude that the Paris Bourse recovers quickly after an aggressive order since the variables return to their pre-order levels within a few quote updates. These results indicate that the Paris Bourse is a resilient market. Our results also confirm the findings of BHS95 and Hedvall and Niemeyer (1997) who find empirical evidence for the presence of traders watching the limit order book and provide liquidity when spreads are large. We also find evidence of strategic timing of aggressive orders, i.e. fast order submission when the spread is relatively small. Our regression results show that both order aggressiveness and order size are important in explaining order-to-order returns. The most aggressive orders exhibit the largest price impact. Moreover, the impact of order size of the most aggressive orders is larger than for other order types.

The remainder of this paper is organized as follows. Section 2 provides an overview of the related literature. Section 3 describes the market structure on the Paris Bourse, the data set and the classification of orders according to aggressiveness. The empirical results are presented in three sections. Section 4 describes the data used in our paper. Section 5 deals with the issue of order aggressiveness and order flow. Section 6 analyzes the impact of aggressive orders on prices as well as on resiliency. Section 7 concludes.

## 2 Related Literature

### 2.1 Resiliency and aggressive orders

The topic of *resiliency* of financial markets did not yet receive much attention in the empirical literature. A recent paper that studies resiliency is Bhattacharya and Spiegel (1998), who investigate NYSE trading suspensions. They define resiliency as the ability to absorb very large shocks. A cross-sectional analysis of all trading suspensions during the period 1974-1988 shows that the various dimensions of liquidity are substitutes: large cap-stocks have lower bid-ask spreads but halt more often. Our paper focuses on resiliency of a limit order market under less extreme circumstances, i.e. after aggressive orders. Coppejans, Domowitz and Madhavan (2001) study the resiliency of the Swedish stock index futures market (OMX). They find that shocks to depth are restored in less than 60 minutes. These results suggest a self-correcting ability for a stock index futures market.

Our paper focuses on shocks to depth caused by large transactions that consume a significant part of the liquidity in the limit order book of specific stocks. Biais, Hillion and Spatt (1995) emphasize the interaction between the order book and order flow for the Paris Bourse. They find that *aggressive orders* consuming liquidity at the quote are followed by new orders within the bid-ask quotes at the other side of the market. We extend the analysis of BHS95 by not only studying the next order, but also subsequent orders.

There is an extensive literature on order submission in limit order markets. The pioneering work in this area is by Cohen, Maier, Schwartz and Whitcomb (1981). Recent work includes Hollifield, Miller, Sandas and Slive (2001), who study the order submission on the Vancouver Stock Exchange. Hollifield, Miller and Sandas (2002) provide a theoretical model for the tradeoff between supplying liquidity by issuing a limit order and consuming liquidity by issuing a market order, and test the model on data from the Swedish stock exchange. Griffiths, Smith, Turnbull and White (2000) measure price effects of aggressive orders on the

Toronto Stock Exchange from the perspective of the market participant that submitted the order. The price effect is measured as the realized price of the order[2] compared to the price immediately prior to the order. They find that only aggressive orders lead to a significantly positive price impact. The price impact of less aggressive orders (e.g. small limit orders or orders that do not generate immediate execution) is small or even negative (conditional on being executed). They find that from the order return perspective, the optimal trading strategy is to buy using limit orders at the bid and to sell using limit orders at the ask. However, this strategy has substantial execution risk.

The type of work just discussed requires data on the time to completion of an order. The SBF data set we use does not allow tracking the execution of an order until completion, however. In our paper we therefore take the perspective of the market as a whole (or all the other participants) and look at a short period of time just before and after the submission of the aggressive order. This enables us to investigate whether the market perceives price effects of aggressive orders as correct or whether the market corrects these effects. Apart from the analysis of the resiliency of the market as a whole, our research differs in two other ways from that from Griffiths et al (2000). First, we examine the Paris Bourse, where there is no designated market maker as on the TSE. So our research is one of the first to address these issues for a pure limit order market.[3] Second, our dataset comprises a longer period (six months instead of one).

## 2.2 Tick size and order flow

A number of contributions deal with *tick size* as a determinant of the order flow composition. We are interested in the dynamics after an aggressive order, therefore we restrict ourselves to theoretical papers considering sequential price formation.[4] Parlour (1998) shows that systematic patterns in prices and order placement strategies may arise even with only liquidity traders since order placement hinge on past and future expected actions of investors. Aggressive orders will often induce a spread of two-ticks. Parlour (1998) obtains that in a two-tick market it is more likely to see a drop in the ask after a drop in the bid occurred and vice versa. Cordella and Foucault (1999) show that when the bidding process is sequential, there are cases where dealers are better of only undercutting by one tick. This occurs only when the tick size is small. With large tick sizes the wedge between the competitive price and

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[2] Griffiths et al. (2000) analyze the impact of orders until full completion.
[3] On the TSE the market maker only has a limited role compared to e.g. the NYSE specialist. On the one hand his main role is to provide liquidity and thus may improve resiliency to the market. But on the other hand he mainly provides liquidity to small orders and since the focus here is on aggressive orders (which are usually large), his role would have been limited. So whether this difference in market structures will lead to a difference in resiliency between the Paris Bourse and the TSE remains an empirical question.
[4] See, for example Seppi (1997) for the effects of tick-size in a static setting.

the expected asset value increases. Then a dealer can secure a greater profit by posting the competitive price earlier than a competing dealer. This implies that the time to adjust to the competitive price decreases when the tick size increases. Foucault, Kadan and Kandell (2001), however, show that when the tick size is small, traders may find it optimal to undercut or outbid the best quotes by more than one tick in order to speed up execution. Ultimately, it is an empirical question how a market's resiliency functions and to what extent its liquidity is re-established after an aggressive order. It is precisely this question that we address in this paper.

A number of empirical papers have investigated the impact of tick size changes on market quality. Bacidore (1997), Ahn et al. (1998) and Griffiths et al. (1998) consider the April 1996 reduction in tick size on the Toronto Stock Exchange, while Goldstein and Kavajecz (2000) deal with the changes in tick size and the liquidity provision on the NYSE. Chordia, Roll and Subrahmanyam (2001) study the effect of the reduction in tick size on the NYSE. They show that after the reduction in tick size, the inside spread significantly decreased, but depth at the best bid and ask also decreased. Depth the spread level before the reduction in tick size remained the same, or even improved. Bourghelle and Declerck (2002) investigate the market quality of the Paris Bourse following the introduction of the Euro. Interestingly, they find that only the depth at the best quotes is significantly affected whereas the spreads remain unaltered. Stocks obtaining a decrease (increase) in tick size experience a decrease (increase) in the depth at the best quotes.

## 2.3 Firm size and market liquidity

Theory also suggests that heterogeneity with respect to *firm size* is important for liquidity and order flow. Empirically, there is a negative relation between firm size and the bid-ask spread (see McInish and Wood (1992), and the review in Madhavan (2000)). Cordella and Foucault (1999) argue that for a given tick size, the speed of adjustment to the competitive quotes must be faster for large firms. Foucault (1999) shows that when asset volatility increases the proportion of limit orders should increase. Since volatility is negatively related to equity capitalization (see Hasbrouck (1991)), the proportion of limit orders for small capitalization stocks must be larger than for stocks with large capitalization.

## 3 Market Structure of the Paris Bourse

The Paris Bourse is a computerized limit order market that uses a centralized electronic system, known as CAC (Cotation Assistée en Continu).[5] Similar systems are used in Brussels (NTS), Stockholm (SAX) and Toronto (CATS). The exchange opens at 10:00 a.m. with a batch auction after which a continuous auction takes place until 5:00 p.m. Note that nowadays the exchange opens at 9:00 am and runs until 5:30 p.m., but the times mentioned here were valid during our sample period (March-August 1998). There are no market makers or floor traders. Liquidity is provided by the public limit order book only. A trader can choose between different types of orders. He can submit a limit order, which specifies the quantity to be bought or sold, the price and the date when the order will be withdrawn (unless the order is 'good till cancelled'). A trader can also choose to submit a market order, which only specifies the quantity and direction of the trade and is executed immediately at the best possible price (provided the limit order book is not empty). If the total quantity of the available orders in the limit order book at the best price does not suffice to fill the whole market order, the remaining part of the market order is transformed into a limit order at the transaction price. Hence, market orders do not automatically walk up the limit order book, and do not always provide immediate execution of the whole order. The way of achieving full execution of an order is to use an aggressive limit order, meaning an order that improves the best quotes at the other side of the market and walks up the limit order book. An aggressive limit order therefore provides a faster execution of a large transaction than a market order. Finally, traders can also submit hidden orders, which are limit orders that are not fully visible to other traders. For more details on hidden orders, we refer to BHS95.

The price of a limit order can be any price on the pricing grid determined by the tick size. The tick size of a stock depends upon the price level. Stocks with a price below 5 FF have a tick size of 0.01 FF, if the price is between 5 and 100 FF this is 0.05 FF, between 100 and 500 FF it is 0.1 FF and stocks with prices between 500 and 5000 FF have a tick size of 1 FF. For prices above 5000 FF the tick size is 10 FF.[6] This translates into a relative tick size of minimum 0.2% for stocks with the smallest price. Stocks in subsequent price categories have a relative tick size between 1% and 0.05%, 0.1% and 0.02%, and 0.2 and 0.02% respectively. For stocks with prices above 5000 FF, the relative tick size is maximum 0.2%. This is fairly small compared to other exchanges. Until 1997, NYSE used a tick size of 1/8$ for stocks above one dollar and 1/16$ for stocks between 0.5$ and 1$, which results in a maximum

[5] The Paris Bourse merged in 2000 with the Amsterdam Stock Exchange and the Brussels Stock Exchange into Euronext.
[6] The tick sizes mentioned are these that were in use during our sample period. After the introduction of the Euro, the tick sizes changed, see Bourghelle and Declerck (2002) for a more detailed discussion.

relative tick size of 12.5%. From 24 June 1997 onwards, the minimum price variation for stocks above one dollar was reduced to 1/16$, resulting in a halving of the maximum relative tick size to 6.25%, which is still considerably larger than on the Paris Bourse. See also e.g. Angel (1997) for a comparison of tick sizes across countries.

Shares are traded on a monthly settlement basis. The Société des Bourses Françaises (SBF) acts as a clearing house. The member firms of the Bourse submit orders directly into the CAC system via a local terminal. Transactions occur when the price of a trader hits the quote on the opposite site of the market. Limit orders are stored and executed according to first price priority and then time priority.[7] All market participants can contribute to liquidity by putting limit orders on display. There is some scope for negotiated deals if the limit order book is insufficiently deep. A financial intermediary can negotiate a deal directly with a client at a price within the bid and ask price (also know as the fourchette), provided that the deal is immediately reported to the CAC system as a cross order. For trades at prices outside the fourchette, the member firm acting as a principal is obliged to fill all limit orders displaying a better price than the negotiated price within five minutes.

# 4 Data Description

## 4.1 Data Set

The sample that is used in this paper consists of 20 stocks listed on the Paris Bourse. These stocks are divided into mutually exclusive groups on the basis of two criteria. First, we distinguish stocks with a small and large market capitalization, where the latter are defined as stocks that are included in the CAC40 index, while the former are not. In remainder of the text, we will refer to them as small and large stocks, which should hence always be read as related to their capitalization. Secondly, as mentioned above, listed stocks differ in their tick size, which in our sample can be 0.1 FF or 1 FF. Hence, in total four groups are obtained, each containing five stocks. Groups 1 and 2 are composed of small stocks with tick size 0.1 FF and 1 FF respectively. The large stocks are placed in group 3 when they have a tick size of 0.1 FF and in group 4, when they have a tick size equal to 1 FF[8]. The 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

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[7] Hidden orders loose time priority for the part that is not publicly displayed.
[8] More specifically the following stocks are present in the different groups: group 1: Moulinex, Nord-Est, Pernod Ricard, SCOR and Sidel; group 2: Christian Dior, Imétal, Pathe, SEB and Technip; group 3: Lagardère, Michelin B, Renault, Rhone Poulenc and Thomson-CSF; group 4: Danone, Elf Aquitaine, LVMH, Paribas and Total.

size, i.e. a tick size that changes from 0.1 FF to 1 FF or the other way around, might bias our results.

The data are taken from the SBF database of the Paris Bourse. Since 1990, the Paris Bourse has set up a database, available on CD-ROM, with detailed information on all kind of securities. 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 quotes, as well as the depth at this quotes. Our dataset is therefore similar to the one used in Bisière and Kamionka (2000).

## 4.2 Order classification methodology

In order to characterize the order submission behavior, all incoming orders are classified according to the scheme proposed BHS95 and also used in other papers, see e.g. Bisière and Kamionka (2000). A distinction between orders is made on the basis of the direction of the order (buy or sell), and of its aggressiveness. The classification of buy orders is depicted by Figure 1. They are classified into aggressiveness order types 1 to 6, where 1 is the most aggressive buy order type, and 6 is the least aggressive. As can be seen from Figure 1, 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 better 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 is not allowed to walk up the limit order book above the best ask. The part of these orders that is not executed immediately is converted into a limit 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.

PLEASE INSERT FIGURE 1 AROUND HERE

On both sides of the market, the most aggressive order types immediately result in transactions and cause a price movement. Less aggressive order types, such as 3 and 9, still result in transactions, but do not give rise to an update of the best quotes. They only reduce the depth at the best ask and bid respectively. The sum of these three types of orders is a proxy for “market orders” as in Foucault (1999). Order types 4 and 5, and 10 and 11 do not give rise to transactions while the prices of the least aggressive orders 6 and 12 are even worse than the current best quotes in the market. Since the focus of this paper is on aggressive orders, our attention will mainly go to the two order types on each side of the market that are most aggressive, being types 1 and 2 for buy orders and 7 and 8 for sell orders.

Finally, 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. For a detailed discussion of the pre-opening period and the opening procedure of the Paris Bourse, see Biais, Hillion and Spatt (1999).

### 4.3 Descriptive statistics

In Table 1, the characteristics of the different groups of stocks, their composition and some descriptive statistics of the data can be found. First, the minimum, maximum and average best bid and ask quotes are given. Notice that for small tick stocks, these are located between 100 and 500 FF, while for stocks with a large tick size these are above 500 FF. This ensures the same tick size over the sample period. Also, the average depth at the best quotes is shown. For a majority of the stocks the depth at the best bid is smaller than the depth at the best ask. Also, in general, the depth in number of shares is smaller for small stocks than the depth for large stocks. Next, the average bid and ask return and their standard deviation are calculated. For a majority of the stocks, the average daily return is negative. The standard deviation is smaller for stocks with the large tick size. Finally, the average and median bid-ask spread, expressed in FF, are shown, as well as the proportion of the time the spread was 0, 1, 2, … ticks. A remarkable result is that for stocks with a small tick size (0.1 FF), the proportion of spreads larger than 5 ticks is more than 50%, while for large tick stocks there is a large proportion of 1 or 2 tick spreads. This might be an indication that for stocks with a tick size of 1 FF, this minimum price variation is a binding constraint, while this is not the case for the small tick size. The average relative spread (the ratio of average spread and average midquote) is larger for small stocks. Given the size of the stock, the differences between tick sizes are on average small.

PLEASE INSERT TABLE 1 AROUND HERE

# 5 Order aggressiveness and order flow

## 5.1 Order size and timing of order types

As a first step in the analysis of the effect of order aggressiveness on the order flow, we present the average order size of different order types, as well as their occurrence during a trading day. Table 2 makes a comparison between the average order size of the more aggressive order types and the other order types. Note that by construction, the order size of the aggressive orders is at least as large as the depth at the best quotes at the time the order was submitted. We expect therefore that the aggressive order size may be larger than the size of other order types. The results in the table confirm this intuition: on average, the order size increases with order aggressiveness, a finding that is symmetric across buy and sell orders and across the four groups of stocks. So, the most aggressive orders, these are types 1 and 7 orders, are also the largest orders. Somewhat less aggressive orders, this means type 2 or 8 orders, are still larger than other orders but to a lesser extent than for the most aggressive. Furthermore, order size also increases with the size of the stock, since orders for large stocks, which are in groups 3 and 4, are on average larger than orders for smaller stocks. Thirdly, we find that order size is decreasing with the tick size when the size of the stock is taken as given. More specifically, the order size of group 1 (group 3) is on average larger than the one of group 2 (group 4). Finally, all our conclusions are robust, even in the top deciles of the size distribution. This can be seen by looking at the *Ratio 1*, which is the ratio of type 1 orders and other buy order types (being 3 to 6), and *Ratio 2*, the ratio of type 2 orders and other buy orders. These ratios show that even in the top deciles, type 1 orders are relative the most buy orders, and also type 2 occur relatively more often. Similar conclusions are obtained for sell orders (types 7 and 8).

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PLEASE INSERT TABLE 2 AROUND HERE

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The timing of the different order types is presented in Figure 2. The results confirm the U-shaped pattern of intraday market activity on the Paris Bourse, also documented in other studies, see e.g. BHS95. More orders are submitted at the beginning and at the end of the trading day. Although this U-shape is found for all groups of stocks and all order types, it is more pronounced for large tick sizes (groups 2 and 4). When looking at the different order types, it can be seen that at the beginning of the trading day, less aggressive orders are more frequent; while at the end of the day, the inverse is true: aggressive order types are more frequent than “other buy” and “other sell” orders. A possible explanation for this finding is that traders need to unwind their positions at the end of the day and in order to achieve this, they prefer to trade aggressively, rather than wait until the next day. Another reason might be the response to the news about the opening of the exchanges in the US late in the afternoon, European time.

PLEASE INSERT FIGURE 2 AROUND HERE

## 5.2 Frequency of order types

The frequency of occurring of each of the order types is documented in Table 3. This frequency table shows that the least aggressive order types (6 and 12) have the highest frequency of occurring, followed by types 3 and 9. On the other hand, the most aggressive order types (1 and 7) have the lowest probability of occurring. Somewhat less aggressive orders (types 2 and 8) however have already a much higher frequency. The results are similar for buy and sell orders.

PLEASE INSERT TABLE 3 AROUND HERE

BHS95 also report that the most aggressive order types are most infrequent, but some of their other results are different from ours. In BHS95, type 3 and 9 orders are most frequent, while type 2 and 8 are much more infrequent than in our results. Griffiths et al. (2000) report frequencies for the Toronto Stock Exchange (TSE). They also find that types 3 and 9 are most frequent and types 1 and 7 most infrequent. However, in contrast with BHS95, and in accordance with our results, they also find that type 2 and 8 orders are much more frequent than 1 and 7. On TSE, types 1 and 7 are even more infrequent than on the Paris Bourse. One possible explanation is that some TSE stocks have bid-ask spreads equal to the tick size. This drives traders to trade at the best quotes because they cannot improve the quotes. This may explain why a larger fraction of type 3's (small market orders) and a smaller fraction of type 4's are observed.

The results given above apply to all groups of stocks, but nonetheless there are also some notable differences between groups. Although infrequent in all groups, types 1 and 7 are most infrequent in groups with a large tick size (groups 2 and 4). On the other hand type 2 and 8 are more frequent in these groups than in groups with a small tick size.

### 5.3 Conditional probability of order types

The results in Table 3 are unconditional probabilities. In order to analyze the influence of aggressive orders on the subsequent order flow, we turn in this section to conditional probabilities. Table 4 presents the probabilities that the next order is of a certain type, conditional upon the aggressiveness type of the current order. The table consists of four panels, one per group. Within a panel, each element can be interpreted as the probability that a current order of the type given by the row is followed by an order of the type given by the column. The last row in each panel presents the unconditional probabilities of the type given by the column. The last two columns show the probabilities that an order of the type given by the row is followed by respectively a buy order or sell order.

PLEASE INSERT TABLE 4 AROUND HERE

We find that the probability that an order of a certain type is followed by an order of the same type is relatively high. This is indicated by the fact that the elements on the diagonal of the table are in almost all cases the highest in the column. This is a confirmation of the diagonal effect, also found in other studies (e.g. BHS95). The diagonal effect may result from strategic order splitting strategies, imitating behavior, or similar reactions to events by market participants. The last two columns in each panel show that buy orders are more likely to be followed by buy orders, while sell orders are more likely followed by sell orders. This is in line with Parlour (1998) who showed that systematic patterns in order placement strategies might arrive. Finally, in all panels, there is high probability that an order of type 1 is followed by an order of type 4. i.e. an aggressive order is often follows by a price improving limit order on the same side of the market. This result is in correspondence with BHS95. It shows that new liquidity is provided to the market after it has been consumed. A similar result holds for sell orders: the probability that an order of type 7 is followed by an order of type 10 is relatively high. The bid-ask spread widens after an aggressive buy or sell order (type 1 or 7). Since limit order traders can earn this spread, there is an increased incentive to provide new liquidity within the best bid-ask quotes.

In Table 4, we looked at the first order following an aggressive order. An interesting extension is to study also subsequent orders. In Figure 3, the evolution of the diagonal effect over time is drawn. More specifically, for each group (see the different panels in the figure), the probability is given that an order of type $i$, $i$ = 1..12, at time $t$ is followed by an order of the same type $i$ at time $t+k$, $k$ = 1..75. We find that the diagonal effect persists beyond one order. But the conditional probabilities do converge to the unconditional levels. This convergence is smoother for large stocks than for small stocks and occurs slightly faster for the smaller stocks for the more aggressive order types. This suggests that the diagonal effect also persist after one order. Remarkable is also the difference between orders of type 4 and 10 and other types. The probability that an order of these types is followed by an order of the same type is relatively small, compared with the other order types. Often further undercutting becomes impossible and the provided liquidity needs to be consumed first before similar order types become possible. The next order that again provides liquidity within the quotes will only be some orders later. For this reason, convergence for these types is not as pronounced as for the other types. Finally, Figure 3 shows that there is only a small difference between groups with different tick sizes, taking capitalization as given.

PLEASE INSERT FIGURE 3 AROUND HERE

Important in the interpretation of Figure 3 is that the *x*-axis is expressed in order time and not in calendar time. This means that although convergence is faster for smaller stocks when expressed in order time, this is not necessarily the case when expressed in calendar time. In calendar time convergence will be even faster for large stocks, the intuitive reason for this being that orders for smaller stocks occur less frequently than for large stocks, i.e. the average duration between orders is much smaller for large stocks[9]. The distinction between calendar time and order time will also be important later in this paper, when we study the duration between best quote updates.

# 6 Market impact of aggressive orders

## 6.1 Descriptive approach

As a first step in analyzing the market impact of aggressive orders, we employ a descriptive, event study type of approach. To study resiliency, we look directly at what happens in the limit order book in a small period of time around an aggressive order. The advantage of this methodology is that we describe what in reality is going on in the limit order book. The results of this descriptive approach are presented in Figure 4. Panel A of Figure 4 starts from an order of type 1. A window around the submission of such order is created. More specifically, we consider a window of 10 updates of the best quotes before and 20 updates after the submission. Within each window, the best quotes, the depth at the best quotes, the relative spread and the duration between best quote updates are studied. The values of the variables are calculated relative to the value at the time of the submission of the order of type 1, which was set equal to 100. The means across the stocks within the different groups are plotted. Panels B, C and D show the results starting from order types 2, 7 and 8 respectively. Notice that by looking at what happens before and after the submission of aggressive orders, we generalize the BHS95 analysis to order submission behavior. They find shifts in both bid and ask quotes after large transactions.

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PLEASE INSERT FIGURE 4 AROUND HERE

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We start our discussion of the results by looking at the evolution of the *best quotes (prices)*. As a consequence of the definitions used in the classification of orders, the ask moves up after the most aggressive buy order. Indeed, we see that the best ask, given by the dashed line, jumps up after an order of type 1. The largest effect is found for groups 1 and 2, which are the small stocks. The best bid, drawn in full lines, increases as well, but there is no jump. The mirror image is obtained for the most aggressive sell orders: the bid jumps down, while the ask does not, although the latter decreases as well after the order, but in a more gradual way. Again the effects are more pronounced for smaller stocks. The ask price jumps upwards after a less aggressive buy order (type 2), but now also the bid jumps, but less strongly than the ask. The intuition for the difference in results between the two most aggressive order types is that the unexecuted part of order type 2 pops up at the other side of the market inducing an immediate shift in the bid. Again, the jumps are the largest for small stocks. However, the magnitude of the effect is also larger after a type 2 order than after a type 1 order. After less aggressive sell orders (type 8), the jump in the bid is much smaller and also the subsequent decrease is smaller than after type 7 orders.

Note that our measure of price impact is computed in the time window around the aggressive order and thus describes the immediate market impact of the aggressive order. In this way, it differs from the methodology in Griffiths et al. (2000), who use the fill price of an order in their computation of price impact. Given that an order may be filled over time, their measure computes price impact from the trader's viewpoint, while ours measures the immediate price impact from the market's perspective. The order of magnitude of the price impacts found by Griffiths et al. (2000) is similar, however.

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[9] More specifically, the average duration between subsequent orders (of whatever type) is 52 seconds for group 1, 77 seconds for group 2, 13 seconds for group 3 and 14 seconds for group 4.

Now we turn to the evolution of the *depth* at the best quotes around an aggressive order. The depth at the best ask is given by the dashed lines in Figure 4, second column, the depth at the best bid by the solid lines. The depth sharply decreases until the moment that an aggressive order is submitted. After such an order, the depth strongly increases again, an effect that is most pronounced for large orders. In contrast with the results for the best quotes, there are considerable differences in the depth between buy and sell orders since after an aggressive buy order (type 1 and 2): the increase in the depth is about five times larger than after an aggressive sell order (type 7 and 8). In addition to the direction of an order, the tick size matters: given the size of a stock, the effect on the depth is stronger for stocks with a larger tick size. Finally, remark that the evolution of the depth at the best ask does not differ much from the evolution at the best bid. These results suggest that shocks to depth from aggressive orders are restored quickly.

In a final point in this section, we investigate if traders who use aggressive orders try to minimize their price impacts by timing their trades. Timing in aggressive order submission can be examined by looking at the *spreads* and the *durations* around the submission of the aggressive order. In Figure 4, the relative spread is drawn, which is defined as the difference between the bid and ask, divided by the midquote. On average, the relative spread before an aggressive order decreases. At this point, aggressive orders are submitted quickly, as can be seen from the fact that the average duration between best quote updates is much shorter around an aggressive order. Griffiths et al. (2000) find a positive relation between the bid-ask spread and the aggressiveness of the order but do neither report how much smaller the spread is before its submission nor do they look at durations.

Some more observations can be made from the different panels of Figure 4. First, it can be seen that the order of magnitude of the movement in the relative spread is increasing in order aggressiveness: the effect is stronger for an order of type 1 (type 7) than for an order of type 2 (type 8). When taking the size of a stock as given, the relative spread moves more heavily for stocks with a small tick size, this property is even more pronounced for buy orders than for sell orders. For the duration between best quote updates, similar inferences can be made. The duration is more volatile after an aggressive order than before. Moreover, the largest effect is found for the most aggressive order types (type 1 and 7), it is about two times larger than for less aggressive orders (type 2 and 8 respectively). The movement in duration is decreasing in stock size, since it moves more heavily for small stocks (groups 1 and 2). Finally, because the duration of stocks with a small tick size moves stronger than the duration of stocks with a large tick size, we find that duration is also decreasing with tick size.

Briefly summarizing the findings in this section, we can state that there are, sometimes even large, effects around an aggressive order, but that the market recovers quickly after an aggressive order. After an aggressive order, the levels of the best quotes, the depth at the best quotes, the relative spread and the duration between quote updates return to their levels before such order within a few quote updates[10]. These results suggest that the Paris Bourse is a resilient market. Of course, the approach in this section 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 certain type, another order of the same type might occur. This complicates the analysis of the effect of a specific order type since it is difficult to attribute the change in the order book to a certain order. Furthermore, there is likely to be noise in the data. Therefore, in the next section, we further explore this issue in a more formal way.

## 6.2 Analytical approach

In the descriptive methodology of the previous subsection, we did not take into account that there might be other aggressive orders in the window, defined around the aggressive order. In this subsection, we employ a more formal approach, i.e. we define and estimate various regression models. This method allows us to correct for the persistence in order types, as well as for noise in the data.

### *6.2.1 Impact on order to order ask return*

In a first regression, we estimate the price impact of various types of orders. To avoid problems of nonstationarity, we use the percentage return on the best ask after the order, which we denote by $R_{t,}$. The order type is included as an explanatory variable. More precisely, for each order type $a$ we incorporate a dummy variable $D_{a,t-l}$ which is one if the order at time $t$-$l$ is of type $a$, with $a \in A = \{1, 2, \dots, 11\}$. So $A$ is the set of order types, excluding the last order type to avoid perfect multicollinearity in estimation. A second variable that may influence the price impact is the order size, which is confirmed by Griffiths et al. (2000). Hence, we add this as an independent variable defining order size in number of stocks. Finally, we also allow the impact of order size to be conditional on the type of order that was submitted by including interaction terms. To account for dynamic effects, we not only consider current values of the variables, but also lags. Bringing all these elements together, we get the following equation that will be estimated:

[10] Recall that Figure 4 is expressed in order time. One could however use the average durations between orders mentioned in footnote 9 to obtain an idea of the calendar time.

$$R_t = \alpha + \sum_{a=1}^{A}\sum_{l=0}^{L}\beta_{a,l}D_{a,t-l} + \sum_{l=0}^{L}\gamma_l Ordersize_{t-l} + \sum_{a=1}^{A}\sum_{l=0}^{L}\delta_{a,l}D_{a,t-l}Ordersize_{t-l} + \sum_{l=0}^{L}\phi_l R_{t-1-l} + \varepsilon_t \tag{1}$$

The coefficients to be estimated are α, $\beta_{a,l}$, $\gamma_l$, $\delta_{a,l}$ and $\phi_l$. Remark that also lagged returns are included to capture the dynamics of returns in a better way. In the estimations we included one lag of each variable, so $L$ is set equal to one. Finally, $\varepsilon_t$ is the error term which is assumed to be i.i.d.$(0,\sigma^2)$. The coefficients $\beta_{a,0}$ capture the price impact of a specific order type as such compared to the base (order type 12). The coefficient $\gamma_l$ represents the impact of an increase in one unit of order size for type 12. Finally, the sum of $\gamma_l$ and $\delta_{a,l}$ gives the impact of order size of a certain order type. Assuming that price impacts of aggressive orders are equally distributed throughout the day there is no need to include order submission time in the model. The model is estimated for each of the four groups using OLS. We used the 95 % percentile for order size to avoid biasing our results by a few outliers[11]. Hausman et al. (1992) use a similar approach for order volume, but use the 99.5% percentile. The regression results are reported in Table 5, significant coefficients at the 5% level are indicated in bold.

PLEASE INSERT TABLE 5 AROUND HERE

We clearly find that the return on the best ask is influenced by the order type, since most coefficients of the current order-dummies are significant. The effect is largest for the most aggressive buy orders, followed by type 2 orders. Comparing across groups, aggressive orders have the largest impacts for small stocks (groups 1 and 2). When taking the size of the order as given, and in general the effect of the most aggressive orders is larger for stocks with a larger tick size.

Moreover, not only the current order has an influence on the return, also the type of the previous order is significant, although its impact is smaller. This is not surprising given the persistence in order flow found earlier. Remark however that while the signs of the most aggressive buy orders (type 1 and 2) are the same as their lags, this is no longer true for aggressive sell orders (type 7 and 8), the dummies have a negative sign, but their lags have a positive sign.

Order size for the base case, order type 12, has a negative sign meaning that larger orders have a more negative return. This effect is again stronger for smaller stocks.

[11] This means that if the order size of an order exceeds the 95 % percentile of the empirical distribution of order size for a stock, we set the order size equal to the 95 % percentile.

Finally, we also find that the interaction terms are significant. Almost all have a positive sign, indicating that a given order type has a stronger effect on the return on the best ask if the order size of that order is larger. This result is in line with theoretical predictions (see e.g. Easley and O'Hara (1987) and previous findings (see e.g. de Jong, Roëll and Nijman (1995)).

To assess the economic impact of orders of various types and sizes, we calculated their implied impact on the ask return based on the estimates reported in Table 5. The results are reported in Table 6. This table displays the implied impact of order size for the aggressive orders types 1 and 2. The left column shows the impact of the aggressive order as such, i.e. for a very low order size. The magnitudes can be inferred from the coefficients $\beta_{1,0}$ and $\beta_{2,0}$ reported in Table 5. We learn that order aggressiveness as such determines order returns. For example, an order type 1 in group 1 induces an increase of about 8 basispoints (0,08%). We learn that the impact of order type 1 is larger than order type 2. Moreover, market capitalization and tick size matter. In particular, small stocks and stocks with larger tick size exhibit a larger impact. For example, the impact of order type 1 for small stocks with tick size 1 FF equals about 15 basis points compared to 8 basis points for similar stocks with tick size 0.1 FF. The second and third columns in Table 6 supply evidence about the impact of order size on the return on the ask. Three results should be kept in mind. First, order size matters for all of the different groups. This can be gauged by the increase in impact on order return for larger orders. For example, an aggressive order of type 1 with size 4000 shares results in an impact of about 20 basis points. Thus both aggressiveness and order size are important in explaining the return on the ask. If order size increases, the impact of aggressive orders is amplified. A large aggressive buy order has an impact of up to more than three times as large as a type 1 order of medium size. Second, the impact of order size is smaller for less aggressive order types. Presumably, large aggressive order types are more initiated by informed traders (see Easley and O'Hara (1987)). Finally, the impact of order size hinges on size of the stock and its tick size. Again, the impact of order size is larger for small stocks and stocks with larger tick size. More specifically, we find that the impact of the most aggressive buy order type on the ask return is twice as large for small stocks (groups 1 and 2) than for large stocks (groups 3 and 4). Taking the market capitalization as given, we find that the effect for large tick stocks is also about the double of the effect for small tick stocks (compare groups 1 and 3, and 2 and 4). Looking at somewhat less aggressive buy orders (type 2), the same picture comes forward, but the impacts are only about half as large.

PLEASE INSERT TABLE 6 AROUND HERE

The results above remain robust when other percentiles of order size are used. When we add more lags in equation (1), the estimated coefficients of the variables in Table 5 remain virtually the same. Moreover, we find (results available from the authors upon request) that the effect of previous orders on the return becomes smaller when these orders are located further into the past. This suggests that the market reverts quickly to its previous level.

Equation (1) was also estimated with the return after the order on the best bid as the dependent variable. The results obtained are symmetric to the ones in Table 5, so we do not report them here.

#### *6.2.2 Impact on spread*

Next to the price impact of an aggressive order, we also analyze its effect on liquidity in the market. To evaluate the liquidity of a market, the bid-ask spread is an often-used measure. So, we slightly adapt equation (1) and estimate the following equation:

$$\begin{aligned} AbsSpread_t = \alpha + \sum_{a=1}^{A}\sum_{l=0}^{L}\beta_{a,l}D_{a,t-l} + \sum_{l=0}^{L}\gamma_l\left|Ordersize_{t-l}\right| \\ + \sum_{a=1}^{A}\sum_{l=0}^{L}\delta_{a,l}D_{a,t-l}\left|Ordersize_{t-l}\right| + \sum_{l=0}^{L}\phi_l AbsSpread_{t-1-l} + \varepsilon_t \end{aligned} \tag{2}$$

where *AbsSpread* is the bid-ask spread (in FF) after the order and | | denotes absolute value. The remaining symbols have the same meaning as in equation (1). The results are presented in Table 7, significant coefficients at the 5% level are again indicated in bold. Again the coefficients $\beta_{a,0}$ capture the impact on the absolute spread of a specific order type as such compared to the base (order type 12). The coefficients $\gamma_l$ present the impact of an increase in one unit of order size for type 12. Finally, the sum of $\gamma_l$ and $\delta_{a,l}$ gives the impact of order size of a certain order type.

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PLEASE INSERT TABLE 7 AROUND HERE

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We find that the most aggressive orders (type 1 and 7) significantly increase the spread. For example, an order of type 1 in group 1 induces an increase in the absolute spread of about 0.24 FF, that is more than 2 ticks. The largest effects in FF are found for stocks with the large tick size. However, expressed in terms of ticks, the impact is smaller for stocks with large tick size. Somewhat less aggressive orders (types 2 and 8) increase the spread in some cases, while decreasing it in other cases. Orders of type 4 and 10 significantly reduce the spread, a finding that immediately follows from their definition. The type of the previous order also plays a significant role for the more aggressive order types and types 4 and 10, the direction of the effect is the same as for their current values.

The order size of the current order also increases the spread. This means that it is more costly to submit larger orders.

Finally, the coefficients of the interaction terms are found to be positive and significant, except for the most passive order types. This shows that given the type of the order, the change in the spread is larger if the size of the order is larger.

An economic interpretation of the effect of aggressive orders on the spread is shown in Table 8. The first column presents the results of the aggressive order types as such. The results for aggressive buy and sell orders are remarkably similar. Only order types 1 and 7 seem to have an impact on the spread. Table 8 shows that the impact of the most aggressive orders (type 1 and 7) is much larger than somewhat less aggressive order types 2 and 8. The magnitude in FF is larger for small stocks and stocks with larger tick size. In relative ticks however, the impact is smaller for stocks with larger tick size. Order size again determines the magnitude of the spread. The economic impact can be inferred from the second and third columns of the table. These represent the impact on the spread of an order of about median size and 95 percentile, respectively. An increase from an order size of one to the 95 percentile increases the spread with about 12 basis points for order type 1 in group 1 compared with 24 basis points of order aggressiveness as such. The impact of order size is somewhat larger for small stocks and stocks with large tick size.

PLEASE INSERT TABLE 8 AROUND HERE

The conclusions above do not alter when different percentiles for order size are taken, nor when more lags are added to the equation. From the latter (results available from the authors upon request), it can be seen that the impact of aggressive orders on the spread decreases when they occurred farther in the past.

A possible explanation for the stronger impact of aggressive orders for small stocks could be the fact that analysts follow these stocks less intensively. Moreover, trading in small caps by institutional investors is less intensive, which might cause a larger impact of aggressive orders. The theoretical literature on dynamic limit order markets, see e.g. Parlour (1998) or Foucault (1999), does not model aggressive orders (in fact, due to their assumptions, the most aggressive order types that are the focus of our paper cannot occur in their models).

Disentangling the possible reasons for the differences in impact therefore remains a question open for future research, theoretical as well as empirical.

# 7 Conclusion

Electronic limit order markets are gaining importance as trading mechanism of financial markets. We analyzed the resiliency of a pure limit order market (the Paris Bourse) by examining order flow behavior around aggressive orders (large orders that move prices). We explore the issue of resiliency by making groups of stocks on the basis of stock market capitalization and tick size.

The main findings of the paper are as follows. First, the diagonal effect, i.e. serial correlation in the order flow, as reported by Biais, Hillion and Spatt (1995) is found to be persistent even after one order. It takes about 50 subsequent orders before the order flow returns to its unconditional pattern. The persistency in the diagonal effect also holds for the most aggressive orders. Second, although differences exist between order types and across stocks, in general the Paris Bourse recovers quickly after an aggressive order. In particular, the spreads and the depth return to their pre-order levels within a few quote updates. Third, tick size plays an important role in the dynamics of the order submission behaviour before and after an aggressive order. The spread of stocks with low tick size decreases in the first two orders before and increases in the first two orders after an aggressive order. Afterwards, the spread returns to its pre-aggressive order level due to the submission of orders within the best quotes. These dynamics in order flow are less present for stocks with a large tick size suggesting that tick size determines the composition of the order flow. Finally, the estimated price impact is realized immediately, i.e. there are no lagged price effects. Aggressiveness as such is important in explaining price impact. The impact of aggressiveness is larger for small capitalization stocks and high tick size stocks. Order size of aggressive orders is also important in explaining order to order returns and changes in the absolute spread. Larger orders go together with larger price impact. Moreover, small capitalization stocks and stocks with large tick size amplify the impact of order size. In sum, small firms exhibit larger price impact and a larger tick size implies somewhat larger price effects.

Our findings induce a number of important policy implications. Market resiliency is essential for the risk management of large institutional investors when handling their order flow. It also determines the cost of capital of quoted companies. Our empirical results reveal that limit order markets are relatively resilient. This is consistent with a recent upswing in the importance of limit order markets over the world. Tick size is important in the design of the limit order system. We find that a large tick size induces quite large price impacts when aggressive orders are executed. Moreover, the dynamics of the limit order book depend on tick size. Ultimately, this shapes the liquidity of a financial market.

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**Table 1: Descriptive statistics**

| | | Group 1 | | | | | Group 2 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Moulinex | Nord Est | Pernod Ricard | SCOR | Sidel | Christian Dior | Imetal | Pathe | SEB | Technip |
| | Tick Size | 0.1 FF | 0.1 FF | 0.1 FF | 0.1 FF | 0.1 FF | 1 FF | 1 FF | 1 FF | 1 FF | 1 FF |
| | Capitalization | Small | Small | Small | Small | Small | Small | Small | Small | Small | Small |
| Bid | min | 122.50 | 117.00 | 374.30 | 306.10 | 388.60 | 607.00 | 699.00 | 1057.00 | 660.00 | 571.00 |
| | max | 193.60 | 144.00 | 464.00 | 435.10 | 498.20 | 858.00 | 887.00 | 1336.00 | 1050.00 | 872.00 |
| | avg | 158.31 | 131.23 | 416.26 | 374.37 | 450.20 | 772.42 | 804.40 | 1212.40 | 865.20 | 731.59 |
| Ask | min | 123.60 | 117.00 | 375.00 | 308.00 | 389.00 | 608.00 | 699.00 | 1062.00 | 662.00 | 572.00 |
| | max | 194.30 | 145.10 | 465.90 | 437.00 | 498.90 | 858.00 | 888.00 | 1337.00 | 1054.00 | 875.00 |
| | avg | 159.31 | 132.32 | 417.64 | 376.34 | 451.86 | 776.09 | 808.34 | 1219.58 | 870.19 | 735.79 |
| Depth | bid | 644.66 | 506.85 | 415.37 | 579.64 | 332.97 | 373.67 | 240.69 | 160.36 | 234.75 | 294.22 |
| | ask | 809.20 | 466.00 | 467.37 | 625.13 | 392.32 | 367.60 | 298.19 | 137.96 | 241.00 | 352.19 |
| Bid Daily Return | avg | -0.00076 | -0.00296 | -0.00050 | 0.00029 | -0.00092 | -0.00034 | -0.00213 | 0.00265 | -0.00092 | -0.00193 |
| | s.d. | 0.18307 | 0.24785 | 0.09203 | 0.13712 | 0.10563 | 0.14384 | 0.15120 | 0.18120 | 0.16872 | 0.17461 |
| Ask Daily Return | avg | -0.00116 | -0.00151 | -0.00084 | -0.00042 | -0.00044 | -0.00076 | -0.00245 | 0.00046 | -0.00112 | -0.00181 |
| | s.d. | 0.18433 | 0.26711 | 0.10111 | 0.13892 | 0.10915 | 0.15120 | 0.14905 | 0.20202 | 0.15956 | 0.16861 |
| Spread | avg | 1.00 | 1.09 | 1.38 | 1.97 | 1.66 | 3.67 | 3.94 | 7.18 | 5.00 | 4.20 |
| | median | 0.90 | 0.90 | 1.00 | 1.60 | 1.30 | 3.00 | 3.00 | 5.00 | 4.00 | 3.00 |
| | avg rel spread | 0.63 | 0.83 | 0.33 | 0.52 | 0.37 | 0.47 | 0.49 | 0.59 | 0.58 | 0.57 |
| | % 0 ticks | 0.42 | 0.64 | 0.26 | 0.46 | 0.21 | 0.44 | 0.46 | 0.33 | 0.41 | 0.38 |
| | % 1 ticks | 3.43 | 3.26 | 0.56 | 0.32 | 0.56 | 15.71 | 17.49 | 8.60 | 12.57 | 15.65 |
| | % 2 ticks | 3.49 | 2.58 | 5.07 | 2.44 | 3.81 | 20.18 | 19.26 | 8.42 | 15.29 | 18.14 |
| | % 3 ticks | 1.80 | 2.71 | 0.49 | 0.29 | 0.38 | 19.89 | 18.66 | 9.87 | 14.81 | 16.57 |
| | % 4 ticks | 5.57 | 3.96 | 6.58 | 4.10 | 5.86 | 15.59 | 13.22 | 10.52 | 13.77 | 13.56 |
| | % 5 ticks | 16.73 | 15.90 | 7.14 | 5.19 | 6.12 | 10.20 | 9.31 | 12.81 | 11.23 | 10.85 |
| | % 6 ticks | 3.24 | 3.02 | 1.11 | 0.53 | 0.59 | 6.92 | 6.42 | 6.60 | 6.85 | 6.96 |
| | % 7 ticks | 4.60 | 3.49 | 6.63 | 3.81 | 4.52 | 4.31 | 4.67 | 6.04 | 5.78 | 5.00 |
| | % 8 ticks | 2.65 | 4.06 | 1.20 | 0.80 | 1.07 | 2.73 | 3.28 | 6.29 | 4.63 | 3.91 |
| | % 9 ticks | 6.69 | 6.63 | 10.96 | 8.35 | 9.94 | 1.59 | 2.13 | 5.58 | 3.77 | 2.68 |
| | % 10 ticks | 16.94 | 15.53 | 10.06 | 8.58 | 11.43 | 0.85 | 1.66 | 5.73 | 2.64 | 1.93 |
| | % 11-15 ticks | 17.54 | 17.23 | 16.70 | 15.05 | 13.83 | 1.26 | 2.58 | 10.93 | 5.86 | 3.65 |
| | % 16-20 ticks | 9.96 | 10.76 | 15.92 | 16.59 | 17.10 | 0.25 | 0.69 | 5.11 | 1.75 | 0.54 |
| | % 20-25 ticks | 3.61 | 4.82 | 5.88 | 8.35 | 6.51 | 0.06 | 0.12 | 1.95 | 0.53 | 0.14 |
| | % > 25 ticks | 3.34 | 5.42 | 11.42 | 25.14 | 18.08 | 0.02 | 0.07 | 1.24 | 0.10 | 0.03 |

**Table 1: Descriptive statistics (continued)**

| | | Group 3 | | | | | Group 4 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Lagardere | MichelinB | Renault | Rhone Poulenc | Thomson CSF | Danone | Elf Aquitaine | LVMH | Paribas | Total |
| | Tick Size | 0.1 FF | 0.1 FF | 0.1 FF | 0.1 FF | 0.1 FF | 1 FF | 1 FF | 1 FF | 1 FF | 1 FF |
| | Capitalization | Large | Large | Large | Large | Large | Large | Large | Large | Large | Large |
| Bid | min | 216.20 | 280.10 | 194.70 | 265.00 | 201.40 | 1171.00 | 637.00 | 1009.00 | 548.00 | 605.00 |
| | max | 293.50 | 408.00 | 398.20 | 350.50 | 264.00 | 1879.00 | 890.00 | 1375.00 | 696.00 | 808.00 |
| | avg | 248.00 | 358.86 | 299.20 | 308.31 | 233.01 | 1538.69 | 776.18 | 1226.20 | 621.05 | 709.87 |
| Ask | min | 217.00 | 280.60 | 195.00 | 265.50 | 201.80 | 1175.00 | 639.00 | 1010.00 | 550.00 | 606.00 |
| | max | 294.80 | 408.90 | 399.90 | 351.90 | 265.20 | 1885.00 | 891.00 | 1379.00 | 698.00 | 810.00 |
| | avg | 248.78 | 359.63 | 300.09 | 308.83 | 233.82 | 1541.65 | 777.69 | 1228.88 | 622.42 | 711.48 |
| Depth | bid | 763.91 | 788.58 | 890.42 | 1228.55 | 772.04 | 419.00 | 1951.67 | 414.50 | 1855.30 | 1628.65 |
| | ask | 811.08 | 881.82 | 994.75 | 1347.05 | 830.03 | 474.87 | 2065.86 | 412.48 | 2090.77 | 1720.88 |
| Bid Daily Return | avg | 0.00003 | -0.00028 | 0.00037 | -0.00013 | -0.00007 | 0.00036 | 0.00000 | 0.00012 | -0.00021 | -0.00003 |
| | s.d. | 0.09122 | 0.06256 | 0.07985 | 0.05004 | 0.09693 | 0.06144 | 0.05922 | 0.06960 | 0.06678 | 0.07380 |
| Ask Daily Return | avg | -0.00014 | -0.00033 | 0.00039 | -0.00017 | -0.00037 | 0.00024 | -0.00005 | 0.00004 | -0.00028 | -0.00011 |
| | s.d. | 0.09347 | 0.06317 | 0.08602 | 0.05222 | 0.09708 | 0.06513 | 0.06099 | 0.07160 | 0.06520 | 0.07311 |
| Spread | avg | 0.78 | 0.77 | 0.89 | 0.52 | 0.81 | 2.95 | 1.51 | 2.68 | 1.37 | 1.61 |
| | median | 0.60 | 0.60 | 0.70 | 0.40 | 0.60 | 2.00 | 1.00 | 2.00 | 1.00 | 1.00 |
| | avg rel spread | 0.31 | 0.21 | 0.30 | 0.17 | 0.35 | 0.19 | 0.19 | 0.22 | 0.22 | 0.23 |
| | % 0 ticks | 0.11 | 0.07 | 0.10 | 0.05 | 0.17 | 0.06 | 0.06 | 0.05 | 0.05 | 0.07 |
| | % 1 ticks | 5.64 | 2.37 | 3.39 | 4.10 | 7.80 | 28.73 | 63.98 | 32.18 | 71.33 | 58.56 |
| | % 2 ticks | 8.04 | 13.38 | 10.20 | 21.63 | 6.97 | 24.38 | 25.83 | 25.79 | 22.34 | 28.33 |
| | % 3 ticks | 3.42 | 2.12 | 2.18 | 3.52 | 4.04 | 18.05 | 6.99 | 17.74 | 4.68 | 8.96 |
| | % 4 ticks | 10.25 | 15.15 | 11.91 | 22.54 | 8.22 | 11.62 | 2.05 | 10.53 | 1.15 | 2.57 |
| | % 5 ticks | 16.68 | 11.81 | 12.36 | 13.79 | 17.89 | 7.07 | 0.69 | 6.13 | 0.31 | 0.88 |
| | % 6 ticks | 4.82 | 2.42 | 2.72 | 2.50 | 5.32 | 3.76 | 0.24 | 2.97 | 0.08 | 0.35 |
| | % 7 ticks | 7.26 | 11.11 | 9.52 | 10.08 | 5.39 | 2.31 | 0.09 | 1.78 | 0.02 | 0.13 |
| | % 8 ticks | 3.11 | 2.03 | 2.20 | 1.63 | 3.63 | 1.43 | 0.04 | 1.10 | 0.01 | 0.08 |
| | % 9 ticks | 8.15 | 11.61 | 10.34 | 8.07 | 6.35 | 0.91 | 0.02 | 0.66 | 0.00 | 0.03 |
| | % 10 ticks | 9.90 | 6.90 | 7.42 | 3.80 | 10.06 | 0.56 | 0.01 | 0.33 | 0.00 | 0.02 |
| | % 11-15 ticks | 12.63 | 11.72 | 13.58 | 5.81 | 12.45 | 0.88 | 0.01 | 0.60 | 0.00 | 0.01 |
| | % 16-20 ticks | 5.90 | 5.59 | 7.64 | 1.83 | 6.16 | 0.13 | 0.00 | 0.09 | 0.00 | 0.00 |
| | % 21-25 ticks | 2.04 | 1.80 | 2.79 | 0.37 | 2.48 | 0.04 | 0.00 | 0.02 | 0.00 | 0.00 |
| | % > 25 ticks | 2.05 | 1.90 | 3.66 | 0.28 | 3.05 | 0.07 | 0.00 | 0.02 | 0.00 | 0.00 |

## Table 2: Average order size

Note: This table presents the average order sizes for different order types. *Ratio 1* in panel A (panel B) is the ratio of the average size of type 1 (type 7) orders and the pool of order types 3 until 6 (9 until 12), expressed in number of stocks. *Ratio 2* is the same ratio for type 2 and type 8 orders.

Panel A: Buy Orders

| | Group 1 Small stocks, tick size 0.1 FF | Group 2 Small stocks, tick size 1 FF | Group 3 Large stocks, tick size 0.1 FF | Group 4 Large stocks, tick size 1 FF |
|---|---|---|---|---|
| Sample mean | | | | |
| Type 1 | 1311 | 1044 | 2331 | 1611 |
| Type 2 | 1056 | 740 | 1827 | 1311 |
| Other buy | 768 | 553 | 1240 | 868 |
| Ratio 1 | 1.76 | 1.93 | 1.90 | 1.85 |
| Ratio 2 | 1.37 | 1.49 | 1.48 | 1.55 |
| 90% percentile | | | | |
| Type 1 | 3391 | 2151 | 5000 | 3514 |
| Type 2 | 2557 | 1956 | 4708 | 3258 |
| Other buy | 1771 | 1000 | 2600 | 1835 |
| Ratio 1 | 1.94 | 2.04 | 1.97 | 1.92 |
| Ratio 2 | 1.44 | 1.81 | 1.82 | 1.74 |
| 95% percentile | | | | |
| Type 1 | 4300 | 3899 | 8975 | 6152 |
| Type 2 | 3849 | 2615 | 5671 | 4238 |
| Other buy | 3362 | 1825 | 4878 | 3435 |
| Ratio 1 | 1.37 | 1.96 | 1.84 | 1.74 |
| Ratio 2 | 1.18 | 1.47 | 1.16 | 1.33 |
| 99% percentile | | | | |
| Type 1 | 10600 | 14121 | 22914 | 15364 |
| Type 2 | 9756 | 5754 | 17616 | 12287 |
| Other buy | 7920 | 5953 | 13303 | 9464 |
| Ratio 1 | 1.34 | 1.78 | 1.74 | 1.53 |
| Ratio 2 | 1.20 | 1.07 | 1.33 | 1.28 |

**Table 2: Average order size (continued)**

Panel B: Sell orders

| | Group 1 Small stocks, tick size 0.1 FF | Group 2 Small stocks, tick size 1 FF | Group 3 Large stocks, tick size 0.1 FF | Group 4 Large stocks, tick size 1 FF |
|---|---|---|---|---|
| Sample mean | | | | |
| Type 7 | 1642 | 630 | 2847 | 1872 |
| Type 8 | 1252 | 601 | 1711 | 1221 |
| Other sell | 1157 | 456 | 1517 | 1037 |
| Ratio 1 | 1.48 | 1.43 | 1.85 | 1.71 |
| Ratio 2 | 1.06 | 1.35 | 1.12 | 1.25 |
| 90% percentile | | | | |
| Type 7 | 3869 | 1488 | 6000 | 4028 |
| Type 8 | 2915 | 1210 | 4282 | 2940 |
| Other sell | 2989 | 1115 | 3598 | 2452 |
| Ratio 1 | 1.39 | 1.39 | 1.66 | 1.62 |
| Ratio 2 | 0.95 | 1.16 | 1.21 | 1.26 |
| 95% percentile | | | | |
| Type 7 | 5981 | 2200 | 10542 | 6912 |
| Type 8 | 4739 | 2055 | 6708 | 4646 |
| Other sell | 4943 | 1937 | 5868 | 4030 |
| Ratio 1 | 1.29 | 1.22 | 1.79 | 1.64 |
| Ratio 2 | 0.95 | 1.12 | 1.13 | 1.18 |
| 99% percentile | | | | |
| Type 7 | 13076 | 5000 | 31331 | 20026 |
| Type 8 | 12446 | 5320 | 19493 | 13161 |
| Other sell | 13000 | 5318 | 18560 | 12552 |
| Ratio 1 | 1.01 | 0.95 | 1.65 | 1.44 |
| Ratio 2 | 0.94 | 1.00 | 1.05 | 1.05 |

## Table 3: Frequency of order types

Note: This table presents the frequency of occurring, expressed in %, of the different order types for the various groups of stocks. The last row gives the total number of orders for the specific group.

| | Group 1 Small stocks, tick size 0.1 FF | Group 2 Small stocks, tick size 1 FF | Group 3 Large stocks, tick size 0.1 FF | Group 4 Large stocks, tick size 1 FF |
|---|---|---|---|---|
| Type 1 | 3.89 | 2.82 | 3.46 | 1.91 |
| Type 2 | 5.70 | 5.76 | 5.63 | 6.11 |
| Type 3 | 10.27 | 10.40 | 10.41 | 11.29 |
| Type 4 | 8.54 | 7.16 | 8.69 | 4.22 |
| Type 5 | 5.91 | 7.17 | 6.36 | 8.39 |
| Type 6 | 17.33 | 16.11 | 16.08 | 14.79 |
| Type 7 | 3.75 | 3.03 | 3.42 | 1.86 |
| Type 8 | 5.40 | 6.53 | 5.97 | 7.39 |
| Type 9 | 7.80 | 8.84 | 10.49 | 14.68 |
| Type 10 | 7.04 | 6.73 | 7.72 | 4.10 |
| Type 11 | 6.38 | 7.37 | 5.97 | 8.16 |
| Type 12 | 17.98 | 18.09 | 15.79 | 17.10 |
| Total Orders | 294775 | 199073 | 1048215 | 1141954 |

**Table 4: Order to order transition probabilities**

Note: This table presents conditional or transition probabilities. Element $p_{ij}$ of the table shows the probability that an order of type *i*, given by the row, is followed by type *j*, given by the column. The last row in the table gives the unconditional frequency of occurring of order type *j*. The last two columns correspond to the probability that an order of type *i* is followed by a buy or sell order.

Panel A: Group 1: Small stocks, tick size 0.1 FF

| | Type 1 | Type 2 | Type 3 | Type 4 | Type 5 | Type 6 | Type 7 | Type 8 | Type 9 | Type 10 | Type 11 | Type 12 | Buy | Sell |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Type 1 | 12.54 | 7.53 | 9.15 | 12.47 | 6.72 | 14.31 | 2.26 | 3.24 | 5.21 | 6.17 | 6.31 | 14.10 | 62.71 | 37.29 |
| Type 2 | 5.00 | 11.69 | 11.29 | 9.01 | 6.64 | 16.85 | 2.32 | 4.51 | 6.22 | 5.60 | 6.60 | 14.28 | 60.47 | 39.53 |
| Type 3 | 4.01 | 7.09 | 17.98 | 8.53 | 5.63 | 16.04 | 3.13 | 4.10 | 6.79 | 5.63 | 6.20 | 14.88 | 59.27 | 40.73 |
| Type 4 | 4.60 | 5.32 | 9.39 | 10.46 | 9.05 | 19.51 | 3.84 | 4.97 | 6.98 | 8.14 | 4.91 | 12.84 | 58.33 | 41.67 |
| Type 5 | 4.28 | 5.62 | 9.65 | 11.05 | 9.44 | 17.99 | 1.97 | 5.86 | 9.34 | 6.04 | 5.42 | 13.33 | 58.03 | 41.97 |
| Type 6 | 3.35 | 5.10 | 10.27 | 7.95 | 5.60 | 27.07 | 3.28 | 4.67 | 6.81 | 5.72 | 5.06 | 15.11 | 59.35 | 40.65 |
| Type 7 | 2.61 | 3.95 | 6.70 | 8.67 | 5.48 | 13.99 | 10.15 | 7.47 | 8.49 | 9.70 | 7.65 | 15.13 | 41.41 | 58.59 |
| Type 8 | 2.99 | 5.27 | 8.02 | 6.81 | 5.40 | 13.41 | 5.60 | 10.88 | 8.66 | 7.63 | 7.70 | 17.61 | 41.91 | 58.09 |
| Type 9 | 3.04 | 4.56 | 8.90 | 7.54 | 5.50 | 14.73 | 4.07 | 7.44 | 14.01 | 7.74 | 6.29 | 16.17 | 44.28 | 55.72 |
| Type 10 | 4.02 | 5.39 | 8.16 | 8.04 | 4.88 | 12.30 | 4.96 | 5.44 | 7.61 | 10.08 | 9.33 | 19.78 | 42.80 | 57.20 |
| Type 11 | 1.75 | 4.36 | 10.63 | 8.53 | 5.11 | 14.01 | 4.44 | 5.61 | 7.25 | 8.99 | 9.50 | 19.82 | 44.39 | 55.61 |
| Type 12 | 3.19 | 4.95 | 9.08 | 7.56 | 4.57 | 14.47 | 3.14 | 4.62 | 7.62 | 6.67 | 5.88 | 28.25 | 43.83 | 56.17 |
| Uncond | 3.89 | 5.70 | 10.27 | 8.54 | 5.91 | 17.33 | 3.75 | 5.40 | 7.80 | 7.04 | 6.38 | 17.98 | 51.65 | 48.35 |

**Table 4: Order to order transition probabilities (continued)**

Panel B: Group 2: Small stocks, tick size 1 FF

| | Type 1 | Type 2 | Type 3 | Type 4 | Type 5 | Type 6 | Type 7 | Type 8 | Type 9 | Type 10 | Type 11 | Type 12 | Buy | Sell |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Type 1 | 9.46 | 8.31 | 9.12 | 11.06 | 8.16 | 13.25 | 2.04 | 3.72 | 6.04 | 6.74 | 7.43 | 14.66 | 59.36 | 40.64 |
| Type 2 | 3.89 | 12.71 | 11.20 | 7.50 | 8.12 | 16.42 | 2.00 | 5.08 | 6.29 | 4.93 | 7.90 | 13.97 | 59.84 | 40.16 |
| Type 3 | 2.69 | 7.29 | 19.91 | 7.69 | 7.06 | 14.84 | 2.20 | 4.86 | 7.07 | 5.08 | 7.50 | 13.82 | 59.49 | 40.51 |
| Type 4 | 3.15 | 5.57 | 9.57 | 8.90 | 10.87 | 18.42 | 3.20 | 6.54 | 8.35 | 8.10 | 5.24 | 12.08 | 56.49 | 43.51 |
| Type 5 | 3.27 | 5.58 | 9.67 | 8.72 | 11.40 | 18.02 | 1.55 | 6.25 | 10.40 | 5.99 | 5.94 | 13.24 | 56.64 | 43.36 |
| Type 6 | 2.46 | 4.91 | 10.04 | 7.05 | 6.92 | 26.87 | 2.51 | 5.40 | 7.29 | 6.25 | 5.77 | 14.53 | 58.25 | 41.75 |
| Type 7 | 2.25 | 2.91 | 5.65 | 7.13 | 6.23 | 13.04 | 9.78 | 9.43 | 9.10 | 10.00 | 8.49 | 16.00 | 37.21 | 62.79 |
| Type 8 | 2.15 | 4.97 | 7.79 | 5.37 | 5.84 | 12.38 | 4.50 | 12.66 | 9.98 | 7.23 | 8.79 | 18.36 | 38.49 | 61.51 |
| Type 9 | 2.34 | 4.74 | 8.13 | 5.77 | 6.95 | 12.91 | 3.45 | 8.73 | 15.95 | 7.19 | 7.57 | 16.26 | 40.85 | 59.15 |
| Type 10 | 3.16 | 6.02 | 9.40 | 6.77 | 5.40 | 11.04 | 3.74 | 6.26 | 8.18 | 8.04 | 11.30 | 20.68 | 41.80 | 58.20 |
| Type 11 | 1.47 | 4.78 | 10.60 | 7.17 | 6.04 | 12.09 | 3.43 | 6.64 | 8.40 | 8.31 | 10.63 | 20.44 | 42.15 | 57.85 |
| Type 12 | 2.51 | 4.79 | 8.51 | 6.59 | 5.70 | 12.69 | 2.70 | 5.70 | 8.42 | 6.57 | 6.61 | 29.22 | 40.78 | 59.22 |
| Uncond | 2.82 | 5.76 | 10.40 | 7.16 | 7.17 | 16.11 | 3.03 | 6.53 | 8.84 | 6.73 | 7.37 | 18.09 | 49.41 | 50.59 |

**Table 4: Order to order transition probabilities (continued)**

Panel C: Group 3: Large stocks, tick size 0.1 FF

| | Type 1 | Type 2 | Type 3 | Type 4 | Type 5 | Type 6 | Type 7 | Type 8 | Type 9 | Type 10 | Type 11 | Type 12 | Buy | Sell |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Type 1 | 8.35 | 7.76 | 10.66 | 13.07 | 6.62 | 14.80 | 2.61 | 3.99 | 7.47 | 6.67 | 4.93 | 13.08 | 61.26 | 38.74 |
| Type 2 | 4.66 | 10.38 | 11.67 | 7.87 | 7.01 | 16.70 | 2.84 | 5.01 | 8.64 | 5.21 | 6.93 | 13.09 | 58.29 | 41.71 |
| Type 3 | 3.92 | 7.62 | 17.87 | 8.90 | 6.00 | 14.88 | 2.62 | 4.91 | 8.95 | 5.66 | 5.63 | 13.05 | 59.19 | 40.81 |
| Type 4 | 4.08 | 5.69 | 10.45 | 10.24 | 9.44 | 17.68 | 3.22 | 4.34 | 8.17 | 8.87 | 4.96 | 12.86 | 57.58 | 42.42 |
| Type 5 | 3.62 | 5.65 | 10.03 | 12.03 | 8.60 | 16.16 | 1.71 | 6.57 | 10.80 | 6.92 | 5.01 | 12.90 | 56.09 | 43.91 |
| Type 6 | 3.21 | 5.30 | 9.97 | 8.50 | 6.23 | 23.42 | 2.99 | 5.08 | 8.69 | 7.16 | 5.20 | 14.24 | 56.64 | 43.36 |
| Type 7 | 2.70 | 3.56 | 7.66 | 7.31 | 5.09 | 13.21 | 7.61 | 7.77 | 11.22 | 12.79 | 6.39 | 14.71 | 39.53 | 60.47 |
| Type 8 | 3.29 | 4.94 | 8.91 | 6.56 | 5.32 | 13.20 | 4.61 | 11.73 | 11.60 | 7.09 | 6.36 | 16.38 | 42.22 | 57.78 |
| Type 9 | 2.59 | 4.60 | 8.82 | 7.23 | 5.69 | 13.23 | 4.18 | 7.48 | 17.67 | 8.13 | 5.55 | 14.83 | 42.16 | 57.84 |
| Type 10 | 3.27 | 3.85 | 7.84 | 7.98 | 5.54 | 13.62 | 4.34 | 6.35 | 10.94 | 9.86 | 8.55 | 17.86 | 42.10 | 57.90 |
| Type 11 | 1.75 | 4.72 | 10.62 | 8.25 | 5.71 | 13.47 | 3.94 | 6.09 | 10.44 | 10.27 | 8.11 | 16.63 | 44.52 | 55.48 |
| Type 12 | 3.12 | 5.09 | 8.88 | 8.44 | 5.65 | 14.31 | 3.13 | 5.30 | 10.10 | 7.38 | 5.74 | 22.86 | 45.49 | 54.51 |
| Uncond | 3.46 | 5.63 | 10.41 | 8.69 | 6.36 | 16.08 | 3.42 | 5.97 | 10.49 | 7.72 | 5.97 | 15.79 | 50.63 | 49.37 |

**Table 4: Order to order transition probabilities (continued)**

Panel D: Group 4: Large stocks, tick size 1 FF

| | Type 1 | Type 2 | Type 3 | Type 4 | Type 5 | Type 6 | Type 7 | Type 8 | Type 9 | Type 10 | Type 11 | Type 12 | Buy | Sell |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Type 1 | 5.46 | 7.50 | 10.47 | 10.62 | 8.33 | 13.32 | 1.84 | 4.71 | 10.00 | 6.02 | 7.07 | 14.67 | 55.68 | 44.32 |
| Type 2 | 2.46 | 9.27 | 11.64 | 3.64 | 9.77 | 15.64 | 2.14 | 6.69 | 12.12 | 2.66 | 9.63 | 14.34 | 52.42 | 47.58 |
| Type 3 | 2.31 | 8.37 | 17.47 | 4.21 | 8.60 | 13.15 | 1.34 | 6.14 | 12.60 | 2.93 | 8.22 | 14.65 | 54.12 | 45.88 |
| Type 4 | 2.26 | 5.44 | 10.63 | 4.20 | 10.81 | 18.21 | 2.59 | 6.24 | 11.41 | 7.04 | 7.16 | 14.01 | 51.55 | 48.45 |
| Type 5 | 1.93 | 6.37 | 12.02 | 5.57 | 10.11 | 15.30 | 0.92 | 7.50 | 15.36 | 3.74 | 7.10 | 14.08 | 51.30 | 48.70 |
| Type 6 | 1.70 | 5.62 | 10.66 | 4.12 | 8.36 | 21.69 | 1.76 | 6.56 | 12.84 | 4.09 | 7.28 | 15.32 | 52.15 | 47.85 |
| Type 7 | 1.94 | 4.33 | 7.33 | 6.19 | 7.51 | 13.08 | 5.31 | 8.65 | 12.33 | 10.27 | 8.07 | 15.00 | 40.38 | 59.62 |
| Type 8 | 2.01 | 5.82 | 10.20 | 3.10 | 7.60 | 12.71 | 2.25 | 11.59 | 14.99 | 3.49 | 8.98 | 17.24 | 41.45 | 58.55 |
| Type 9 | 1.43 | 5.08 | 9.90 | 3.22 | 7.70 | 12.55 | 2.12 | 9.14 | 20.97 | 3.94 | 7.99 | 15.95 | 39.89 | 60.11 |
| Type 10 | 2.58 | 5.42 | 9.13 | 4.94 | 7.75 | 13.07 | 2.10 | 6.58 | 13.76 | 4.32 | 10.10 | 20.25 | 42.89 | 57.11 |
| Type 11 | 0.97 | 4.83 | 11.45 | 4.17 | 7.93 | 12.71 | 1.93 | 7.59 | 15.36 | 5.24 | 9.98 | 17.83 | 42.07 | 57.93 |
| Type 12 | 1.78 | 5.77 | 9.81 | 4.18 | 7.76 | 13.08 | 1.64 | 6.48 | 13.98 | 3.86 | 7.79 | 23.86 | 42.39 | 57.61 |
| Uncond | 1.91 | 6.11 | 11.29 | 4.22 | 8.39 | 14.79 | 1.86 | 7.39 | 14.68 | 4.10 | 8.16 | 17.10 | 46.70 | 53.30 |

## Table 5: Estimated price effects of aggressive orders: Return on best ask

Note: This table presents the results of OLS estimation of the following regression:

$$R_t = \alpha + \sum_{a=1}^{A}\sum_{l=0}^{L}\beta_{a,l}D_{a,t-l} + \sum_{l=0}^{L}\gamma_l Ordersize_{t-l} + \sum_{a=1}^{A}\sum_{l=0}^{L}\delta_{a,l}D_{a,t-l}Ordersize_{t-l} + \sum_{l=0}^{L}\phi_l R_{t-1-l} + \varepsilon_t$$

with: $R_t$ the percentage return on the best ask after the order; $D_{a,t-l}$ a dummy variable that is one if the order at time $t-l$ is of type $a$, with $a \in A = \{1, 2, \dots, 11\}$ and $A$ the set of order types, excluding the last order type; $Ordersize_{t-l}$ the signed size of the order, expressed in number of stocks. The coefficients to be estimated are $\alpha$, $\beta_{a,l}$, $\gamma_l$, $\delta_{a,l}$ and $\phi_l$ and $\varepsilon_t$ is the error term which is assumed to be i.i.d.$(0,\sigma^2)$. The number of lags $L$ is set equal to one. Significant coefficients at the 5% level are indicated in bold.

| Dependent variable: Ask Return | Group 1 Small stocks, tick size 0.1 FF | | Group 2 Small stocks, tick size 1 FF | | Group 3 Large stocks, tick size 0.1 FF | | Group 4 Large stocks, tick size 1 FF | |
|---|---|---|---|---|---|---|---|---|
| | coeff | s.e. | coeff | s.e. | coeff | s.e. | coeff | s.e. |
| constant | **0.002300** | -0.000700 | **0.003900** | -0.000900 | **0.003200** | -0.000200 | **0.002600** | -0.000200 |
| $D_{1.t}$ | **0.082900** | -0.001400 | **0.148700** | -0.002200 | **0.042200** | -0.000500 | **0.074200** | -0.000500 |
| $D_{2,t}$ | **0.057400** | -0.001100 | **0.076000** | -0.001500 | **0.022700** | -0.000300 | **0.034600** | -0.000300 |
| $D_{3,t}$ | **0.006900** | -0.000900 | **0.013800** | -0.001100 | **0.001200** | -0.000300 | **0.002900** | -0.000200 |
| $D_{4,t}$ | -0.000300 | -0.001000 | -0.000600 | -0.001400 | **-0.001600** | -0.000300 | **-0.000800** | -0.000300 |
| $D_{5,t}$ | -0.001700 | -0.001200 | -0.001800 | -0.001400 | **-0.001800** | -0.000300 | **-0.001400** | -0.000200 |
| $D_{6,t}$ | **-0.001800** | -0.000800 | **-0.002600** | -0.001000 | **-0.001900** | -0.000200 | **-0.001500** | -0.000200 |
| $D_{7,t}$ | **-0.007800** | -0.001500 | **-0.011800** | -0.002100 | **-0.002000** | -0.000500 | 0.000000 | -0.000500 |
| $D_{8,t}$ | **-0.073500** | -0.001200 | **-0.066500** | -0.001400 | **-0.028200** | -0.000300 | **-0.026600** | -0.000200 |
| $D_{9,t}$ | -0.000600 | -0.001000 | -0.000200 | -0.001200 | **-0.000700** | -0.000300 | **-0.000600** | -0.000200 |
| $D_{10,t}$ | **-0.132200** | -0.001100 | **-0.191300** | -0.001400 | **-0.067600** | -0.000300 | **-0.107100** | -0.000300 |
| $D_{11,t}$ | **-0.003100** | -0.001200 | **-0.004700** | -0.001400 | **-0.002800** | -0.000400 | **-0.002100** | -0.000200 |
| $D_{1,t-1}$ | **0.005500** | -0.001400 | **0.016900** | -0.002300 | **0.001600** | -0.000500 | **0.006400** | -0.000500 |
| $D_{2,t-1}$ | **0.005000** | -0.001100 | **0.008500** | -0.001500 | 0.000600 | -0.000300 | **0.001400** | -0.000300 |
| $D_{3,t-1}$ | -0.000400 | -0.000900 | 0.000300 | -0.001100 | **-0.000700** | -0.000300 | 0.000200 | -0.000200 |
| $D_{4,t-1}$ | **-0.002100** | -0.001000 | **-0.003200** | -0.001400 | **-0.002000** | -0.000300 | **-0.002400** | -0.000300 |
| $D_{5,t-1}$ | 0.000600 | -0.001200 | **-0.004100** | -0.001400 | -0.000600 | -0.000300 | **-0.001200** | -0.000200 |
| $D_{6,t-1}$ | -0.000900 | -0.000800 | **-0.004100** | -0.001000 | **-0.001100** | -0.000200 | **-0.000600** | -0.000200 |
| $D_{7,t-1}$ | **0.005300** | -0.001500 | **0.004500** | -0.002100 | -0.000400 | -0.000500 | **0.001600** | -0.000500 |
| $D_{8,t-1}$ | **0.010200** | -0.001200 | **0.011100** | -0.001400 | **0.002500** | -0.000300 | 0.000400 | -0.000200 |
| $D_{9,t-1}$ | -0.000600 | -0.001000 | 0.001100 | -0.001200 | **-0.000800** | -0.000300 | **-0.001000** | -0.000200 |
| $D_{10,t-1}$ | **-0.003900** | -0.001100 | **-0.007600** | -0.001500 | **-0.005600** | -0.000300 | **-0.007700** | -0.000300 |
| $D_{11,t-1}$ | **-0.002900** | -0.001200 | **-0.005000** | -0.001400 | **-0.001900** | -0.000400 | **-0.002800** | -0.000200 |
| $Ordersize_t$ | **-0.000006** | 0.000000 | **-0.000015** | -0.000001 | **-0.000002** | 0.000000 | **-0.000002** | 0.000000 |
| $Ordersize_{t-1}$ | 0.000000 | 0.000000 | 0.000000 | -0.000001 | **0.000000** | 0.000000 | 0.000000 | 0.000000 |

## Table 5: Estimated price effects of aggressive orders: Return on best ask (continued)

| Dependent variable: Ask Return | Group 1 Small stocks, tick size 0.1 FF | | Group 2 Small stocks, tick size 1 FF | | Group 3 Large stocks, tick size 0.1 FF | | Group 4 Large stocks, tick size 1 FF | |
|---|---|---|---|---|---|---|---|---|
| | coeff | s.e. | coeff | s.e. | coeff | s.e. | coeff | s.e. |
| $D_{1.t}$*$Ordersize_t$ | **0.000035** | -0.000001 | **0.000086** | -0.000003 | **0.000019** | 0.000000 | **0.000029** | 0.000000 |
| $D_{2,t}$*$Ordersize_t$ | **0.000029** | -0.000001 | **0.000065** | -0.000002 | **0.000015** | 0.000000 | **0.000021** | 0.000000 |
| $D_{3,t}$*$Ordersize_t$ | **0.000022** | -0.000002 | **0.000072** | -0.000004 | **0.000006** | 0.000000 | **0.000006** | 0.000000 |
| $D_{4,t}$*$Ordersize_t$ | **0.000006** | -0.000001 | **0.000015** | -0.000002 | **0.000002** | 0.000000 | **0.000002** | 0.000000 |
| $D_{5,t}$*$Ordersize_t$ | **0.000006** | -0.000001 | **0.000014** | -0.000002 | **0.000002** | 0.000000 | **0.000002** | 0.000000 |
| $D_{6,t}$*$Ordersize_t$ | **0.000005** | -0.000001 | **0.000014** | -0.000002 | **0.000002** | 0.000000 | **0.000002** | 0.000000 |
| $D_{7,t}$*$Ordersize_t$ | **0.000025** | -0.000001 | **0.000076** | -0.000003 | **0.000012** | 0.000000 | **0.000019** | 0.000000 |
| $D_{8,t}$*$Ordersize_t$ | **0.000009** | -0.000001 | **0.000036** | -0.000002 | **0.000009** | 0.000000 | **0.000019** | 0.000000 |
| $D_{9,t}$*$Ordersize_t$ | **0.000004** | -0.000002 | **0.000019** | -0.000005 | **0.000001** | 0.000000 | **0.000001** | 0.000000 |
| $D_{10,t}$*$Ordersize_t$ | 0.000000 | -0.000001 | **-0.000006** | -0.000002 | **-0.000001** | 0.000000 | **0.000003** | 0.000000 |
| $D_{11,t}$*$Ordersize_t$ | **0.000006** | -0.000001 | **0.000015** | -0.000002 | **0.000002** | 0.000000 | **0.000003** | 0.000000 |
| $D_{1.t-1}$*$Ordersize_{t-1}$ | **0.000004** | -0.000001 | **0.000014** | -0.000003 | **0.000002** | 0.000000 | **0.000003** | 0.000000 |
| $D_{2,t-1}$*$Ordersize_{t-1}$ | **0.000006** | -0.000001 | **0.000013** | -0.000002 | **0.000003** | 0.000000 | **0.000004** | 0.000000 |
| $D_{3,t-1}$*$Ordersize_{t-1}$ | 0.000003 | -0.000002 | **0.000015** | -0.000004 | **0.000001** | 0.000000 | **0.000001** | 0.000000 |
| $D_{4,t-1}$*$Ordersize_{t-1}$ | **0.000004** | -0.000001 | **0.000015** | -0.000002 | **0.000002** | 0.000000 | **0.000006** | 0.000000 |
| $D_{5,t-1}$*$Ordersize_{t-1}$ | **0.000002** | -0.000001 | **0.000007** | -0.000002 | **0.000001** | 0.000000 | **0.000003** | 0.000000 |
| $D_{6,t-1}$*$Ordersize_{t-1}$ | 0.000001 | -0.000001 | 0.000002 | -0.000002 | **0.000000** | 0.000000 | 0.000000 | 0.000000 |
| $D_{7,t-1}$*$Ordersize_{t-1}$ | -0.000001 | -0.000001 | **-0.000006** | -0.000003 | **0.000001** | 0.000000 | **0.000002** | 0.000000 |
| $D_{8,t-1}$*$Ordersize_{t-1}$ | 0.000001 | -0.000001 | -0.000002 | -0.000002 | **0.000002** | 0.000000 | **0.000003** | 0.000000 |
| $D_{9,t-1}$*$Ordersize_{t-1}$ | **-0.000005** | -0.000002 | -0.000003 | -0.000005 | 0.000000 | 0.000000 | **0.000001** | 0.000000 |
| $D_{10,t-1}$*$Ordersize_{t-1}$ | **0.000006** | -0.000001 | **0.000016** | -0.000002 | **0.000002** | 0.000000 | **0.000004** | 0.000000 |
| $D_{11,t-1}$*$Ordersize_{t-1}$ | **0.000002** | -0.000001 | **0.000005** | -0.000002 | **0.000001** | 0.000000 | **0.000001** | 0.000000 |
| $AskReturn_{t-1}$ | **-0.1519** | -0.0019 | **-0.1574** | -0.0023 | **-0.1063** | -0.001 | **-0.1053** | -0.0009 |
| $AskReturn_{t-2}$ | **-0.0817** | -0.0017 | **-0.0753** | -0.0019 | **-0.063** | -0.0009 | **-0.0424** | -0.0008 |
| Adj $R^2$ | 0.2072 | | 0.2898 | | 0.1945 | | 0.3433 | |
| Obs | 294775 | | 199073 | | 1048215 | | 1141954 | |

## Table 6: Economic Impact of Aggressive Orders: Impact on the Order to Order Ask Return

Note: This table presents the implied impact on the return on the ask after the order of orders of type 1 and 2 of various order sizes. The calculations are based on the regressions in table 5.

Group 1: Small stocks, tick size 0.1 FF

| | Order size | | |
|---|---|---|---|
| | 1 | 250 | 4000 |
| Type 1 | 0.0829 | 0.0902 | 0.1989 |
| Type 2 | 0.0574 | 0.0632 | 0.1494 |

Group 2: Small stocks, tick size 1 FF

| | Order size | | |
|---|---|---|---|
| | 1 | 250 | 4000 |
| Type 1 | 0.1488 | 0.1665 | 0.4327 |
| Type 2 | 0.0761 | 0.0885 | 0.2760 |

Group 3: Large stocks, tick size 0.1 FF

| | Order size | | |
|---|---|---|---|
| | 1 | 250 | 4000 |
| Type 1 | 0.0422 | 0.0465 | 0.1102 |
| Type 2 | 0.0227 | 0.0260 | 0.0747 |

Group 4: Large stocks, tick size 1 FF

| | Order size | | |
|---|---|---|---|
| | 1 | 250 | 4000 |
| Type 1 | 0.0742 | 0.0810 | 0.1822 |
| Type 2 | 0.0346 | 0.0394 | 0.1106 |

## Table 7: Estimated effect of aggressive orders: Absolute spread

Note: This table presents the results of OLS estimation of the following regression:

$$AbsSpread_t = \alpha + \sum_{a=1}^{A}\sum_{l=0}^{L}\beta_{a,l}D_{a,t-l} + \sum_{l=0}^{L}\gamma_l\left|Ordersize_{t-l}\right| + \sum_{a=1}^{A}\sum_{l=0}^{L}\delta_{a,l}D_{a,t-l}\left|Ordersize_{t-l}\right| + \sum_{l=0}^{L}\phi_l AbsSpread_{t-1-l} + \varepsilon_t$$

with: $AbsSpread_t$ the bid-ask spread (in FF) after the order; $D_{a,t-l}$ a dummy variable that is one if the order at time $t-l$ is of type $a$, with $a \in A = \{1, 2, \ldots, 11\}$ and $A$ the set of order types, excluding the last order type; $Ordersize_{t-l}$ the signed size of the order, expressed in number of stocks. The coefficients to be estimated are $\alpha$, $\beta_{a,l}$, $\gamma_l$, $\delta_{a,l}$ and $\phi_l$ and $\varepsilon_t$ is the error term which is assumed to be i.i.d.$(0,\sigma^2)$. The number of lags $L$ is set equal to one and | | denotes absolute value. Significant coefficients at the 5% level are indicated in bold.

| Dependent variable: Absolute Spread | Group 1 Small stocks, tick size 0.1 FF | | Group 2 Small stocks, tick size 1 FF | | Group 3 Large stocks, tick size 0.1 FF | | Group 4 Large stocks, tick size 1 FF | |
|---|---|---|---|---|---|---|---|---|
| | coeff | s.e. | coeff | s.e. | coeff | s.e. | coeff | s.e. |
| constant | **0.0532** | -0.0027 | **0.1728** | -0.0109 | **0.0321** | -0.0008 | **0.0789** | -0.0020 |
| $D_{1,t}$ | **0.2418** | -0.0051 | **1.1441** | -0.0249 | **0.1252** | -0.0016 | **0.8508** | -0.0054 |
| $D_{2,t}$ | **0.0306** | -0.0041 | **0.1058** | -0.0171 | **-0.0049** | -0.0012 | **0.0249** | -0.0031 |
| $D_{3,t}$ | **0.0193** | -0.0031 | **0.1112** | -0.0129 | **0.0043** | -0.0009 | **0.0380** | -0.0023 |
| $D_{4,t}$ | **-0.3620** | -0.0036 | **-1.5947** | -0.0155 | **-0.1800** | -0.0011 | **-1.0481** | -0.0036 |
| $D_{5,t}$ | -0.0079 | -0.0042 | **-0.0402** | -0.0160 | **-0.0048** | -0.0012 | **-0.0242** | -0.0028 |
| $D_{6,t}$ | -0.0036 | -0.0028 | -0.0131 | -0.0116 | **-0.0019** | -0.0008 | 0.0031 | -0.0022 |
| $D_{7,t}$ | **0.3000** | -0.0053 | **1.2600** | -0.0236 | **0.1508** | -0.0017 | **0.8184** | -0.0054 |
| $D_{8,t}$ | -0.0043 | -0.0042 | **0.0520** | -0.0161 | **-0.0178** | -0.0011 | **-0.0070** | -0.0027 |
| $D_{9,t}$ | **0.0369** | -0.0035 | **0.1296** | -0.0134 | **0.0032** | -0.0009 | **0.0161** | -0.0021 |
| $D_{10,t}$ | **-0.4003** | -0.0039 | **-1.6232** | -0.0159 | **-0.1900** | -0.0012 | **-1.0942** | -0.0037 |
| $D_{11,t}$ | -0.0071 | -0.0042 | **-0.0402** | -0.0161 | **-0.0066** | -0.0013 | **-0.0239** | -0.0028 |
| $D_{1,t-1}$ | **0.0290** | -0.0051 | **0.2078** | -0.0251 | **0.0065** | -0.0016 | **0.0988** | -0.0055 |
| $D_{2,t-1}$ | **0.0312** | -0.0041 | **0.1784** | -0.0171 | **0.0044** | -0.0012 | **0.0286** | -0.0031 |
| $D_{3,t-1}$ | -0.0032 | -0.0031 | -0.0026 | -0.0129 | **-0.0051** | -0.0009 | -0.0039 | -0.0023 |
| $D_{4,t-1}$ | **-0.0246** | -0.0036 | **-0.0896** | -0.0159 | **-0.0217** | -0.0011 | **-0.0851** | -0.0037 |
| $D_{5,t-1}$ | -0.0047 | -0.0042 | **-0.0494** | -0.0159 | **-0.0039** | -0.0012 | **-0.0172** | -0.0028 |
| $D_{6,t-1}$ | -0.0030 | -0.0028 | -0.0105 | -0.0116 | -0.0010 | -0.0008 | **0.0066** | -0.0022 |
| $D_{7,t-1}$ | **0.0516** | -0.0053 | **0.2057** | -0.0238 | **0.0072** | -0.0017 | **0.1017** | -0.0054 |
| $D_{8,t-1}$ | **0.0557** | -0.0042 | **0.1627** | -0.0160 | **0.0080** | -0.0011 | **0.0186** | -0.0027 |
| $D_{9,t-1}$ | 0.0034 | -0.0035 | 0.0139 | -0.0134 | **-0.0042** | -0.0009 | **-0.0094** | -0.0021 |
| $D_{10,t-1}$ | **-0.0200** | -0.0040 | **-0.0920** | -0.0163 | **-0.0189** | -0.0012 | **-0.0871** | -0.0038 |
| $D_{11,t-1}$ | -0.0068 | -0.0042 | **-0.0329** | -0.0160 | **-0.0044** | -0.0013 | **-0.0233** | -0.0028 |
| $Ordersize_t$ | **0.000017** | -0.000001 | **0.000117** | -0.000012 | **0.000007** | 0.000000 | **0.000017** | -0.000001 |
| $Ordersize_{t-1}$ | 0.000000 | -0.000001 | 0.000006 | -0.000012 | **0.000001** | 0.000000 | **-0.000003** | -0.000001 |

## Table 7: Estimated effect of aggressive orders: Absolute spread (continued)

| Dependent variable: Absolute Spread | Group 1 Small stocks, tick size 0.1 FF | | Group 2 Small stocks, tick size 1 FF | | Group 3 Large stocks, tick size 0.1 FF | | Group 4 Large stocks, tick size 1 FF | |
|---|---|---|---|---|---|---|---|---|
| | coeff | s.e. | coeff | s.e. | coeff | s.e. | coeff | s.e. |
| $D_{1.t}$*$Ordersize_{t}$ | **0.000014** | -0.000003 | **0.000162** | -0.000029 | **0.000018** | -0.000001 | **0.000047** | -0.000003 |
| $D_{2,t}$*$Ordersize_{t}$ | **0.000038** | -0.000003 | **0.000203** | -0.000023 | **0.000014** | -0.000001 | **0.000029** | -0.000002 |
| $D_{3,t}$*$Ordersize_{t}$ | **0.000018** | -0.000006 | **0.000310** | -0.000050 | **0.000005** | -0.000001 | 0.000002 | -0.000003 |
| $D_{4,t}$*$Ordersize_{t}$ | **0.000023** | -0.000002 | **0.000145** | -0.000023 | **0.000005** | -0.000001 | **0.000050** | -0.000003 |
| $D_{5,t}$*$Ordersize_{t}$ | **-0.000014** | -0.000003 | **-0.000112** | -0.000021 | **-0.000006** | -0.000001 | **-0.000018** | -0.000002 |
| $D_{6,t}$*$Ordersize_{t}$ | -0.000004 | -0.000002 | **0.000039** | -0.000019 | 0.000000 | 0.000000 | 0.000003 | -0.000002 |
| $D_{7,t}$*$Ordersize_{t}$ | **0.000015** | -0.000003 | -0.000055 | -0.000031 | **0.000012** | -0.000001 | 0.000005 | -0.000003 |
| $D_{8,t}$*$Ordersize_{t}$ | **0.000035** | -0.000002 | **0.000189** | -0.000023 | **0.000012** | -0.000001 | **0.000040** | -0.000002 |
| $D_{9,t}$*$Ordersize_{t}$ | **0.000030** | -0.000006 | **0.000195** | -0.000052 | **0.000014** | -0.000001 | **0.000025** | -0.000003 |
| $D_{10,t}$*$Ordersize_{t}$ | **0.000017** | -0.000002 | **0.000139** | -0.000023 | **0.000004** | -0.000001 | **0.000076** | -0.000003 |
| $D_{11,t}$*$Ordersize_{t}$ | **-0.000016** | -0.000002 | **-0.000115** | -0.000020 | **-0.000006** | -0.000001 | **-0.000021** | -0.000002 |
| $D_{1.t-1}$*$Ordersize_{t-1}$ | 0.000004 | -0.000003 | **0.000062** | -0.000029 | **0.000004** | -0.000001 | -0.000002 | -0.000003 |
| $D_{2,t-1}$*$Ordersize_{t-1}$ | **0.000015** | -0.000003 | **0.000067** | -0.000023 | **0.000004** | -0.000001 | 0.000004 | -0.000002 |
| $D_{3,t-1}$*$Ordersize_{t-1}$ | **0.000014** | -0.000006 | **0.000139** | -0.000050 | **0.000003** | -0.000001 | 0.000000 | -0.000003 |
| $D_{4,t-1}$*$Ordersize_{t-1}$ | 0.000001 | -0.000002 | 0.000023 | -0.000023 | **0.000001** | -0.000001 | **0.000014** | -0.000003 |
| $D_{5,t-1}$*$Ordersize_{t-1}$ | -0.000001 | -0.000003 | -0.000035 | -0.000021 | **-0.000003** | -0.000001 | **-0.000010** | -0.000002 |
| $D_{6,t-1}$*$Ordersize_{t-1}$ | **0.000006** | -0.000002 | 0.000030 | -0.000019 | 0.000000 | 0.000000 | 0.000003 | -0.000002 |
| $D_{7,t-1}$*$Ordersize_{t-1}$ | **0.000011** | -0.000003 | **0.000134** | -0.000031 | **0.000004** | -0.000001 | **0.000009** | -0.000003 |
| $D_{8,t-1}$*$Ordersize_{t-1}$ | **0.000009** | -0.000002 | **0.000095** | -0.000023 | **0.000002** | -0.000001 | **0.000009** | -0.000002 |
| $D_{9,t-1}$*$Ordersize_{t-1}$ | 0.000010 | -0.000006 | 0.000098 | -0.000051 | **0.000004** | -0.000001 | **0.000006** | -0.000003 |
| $D_{10,t-1}$*$Ordersize_{t-1}$ | **-0.000010** | -0.000002 | **-0.000054** | -0.000023 | **-0.000004** | -0.000001 | **-0.000012** | -0.000003 |
| $D_{11,t-1}$*$Ordersize_{t-1}$ | -0.000002 | -0.000002 | -0.000031 | -0.000020 | **-0.000002** | -0.000001 | -0.000002 | -0.000002 |
| $AbsSpread_{-1}$ | **0.8497** | -0.0019 | **0.8342** | -0.0022 | **0.8776** | -0.001 | **0.8855** | -0.0009 |
| $AbsSpread_{-2}$ | **0.1187** | -0.0019 | **0.1364** | -0.0023 | **0.0935** | -0.001 | **0.0929** | -0.001 |

| | | | | |
|---|---|---|---|---|
| Adj $R^2$ | 0.8933 | 0.8867 | 0.8984 | 0.886 |
| Obs | 294775 | 199073 | 1048215 | 1141954 |

## Table 8: Economic Impact of Aggressive Orders: Impact on Absolute Spread

Note: This table presents the implied impact on the return on the absolute bid-ask spread after the order of orders of type 1 and 2 of various order sizes. The calculations are based on the regressions in table 5.

Group 1: Small stocks, tick size 0.1 FF

| | Order size | | |
|---|---|---|---|
| | 1 | 250 | 4000 |
| Type 1 | 0.2418 | 0.2496 | 0.3658 |
| Type 2 | 0.0307 | 0.0444 | 0.2506 |
| Type 7 | 0.3000 | 0.3080 | 0.4280 |
| Type 8 | -0.0042 | 0.0087 | 0.2037 |

Group 2: Small stocks, tick size 1 FF

| | Order size | | |
|---|---|---|---|
| | 1 | 250 | 4000 |
| Type 1 | 1.1444 | 1.2139 | 2.2601 |
| Type 2 | 0.1061 | 0.1858 | 1.3858 |
| Type 7 | 1.2601 | 1.2755 | 1.5080 |
| Type 8 | 0.0523 | 0.1285 | 1.2760 |

Group 3: Large stocks, tick size 0.1 FF

| | Order size | | |
|---|---|---|---|
| | 1 | 250 | 4000 |
| Type 1 | 0.1252 | 0.1315 | 0.2252 |
| Type 2 | -0.0049 | 0.0004 | 0.0791 |
| Type 7 | 0.1508 | 0.1556 | 0.2268 |
| Type 8 | -0.0178 | -0.0131 | 0.0582 |

Group 4: Large stocks, tick size 1 FF

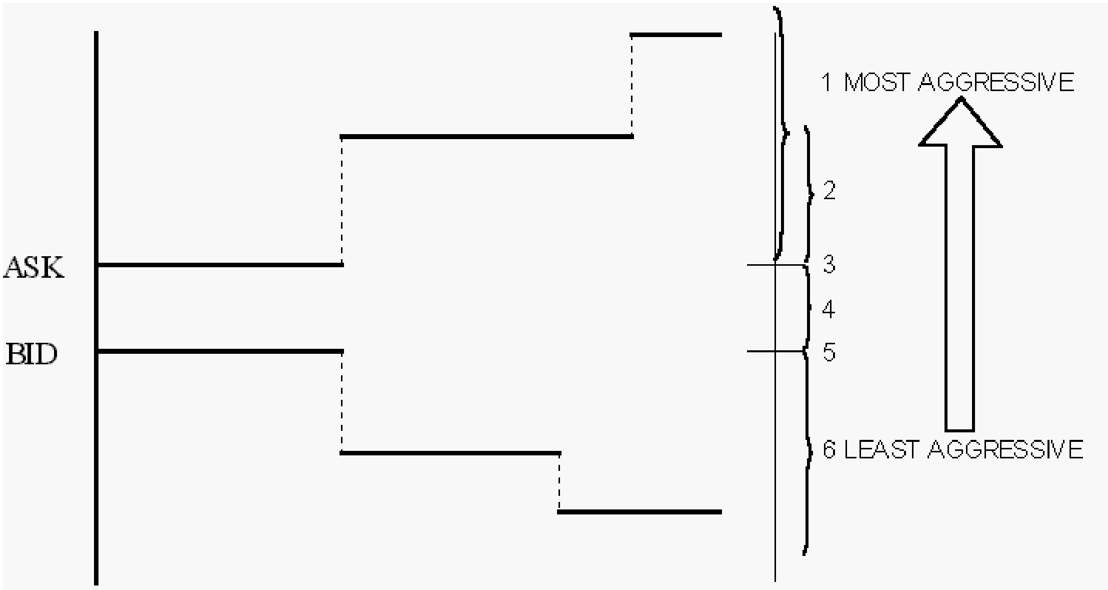
| | Order size | | |
|---|---|---|---|
| | 1 | 250 | 4000 |
| Type 1 | 0.8509 | 0.8668 | 1.1068 |
| Type 2 | 0.0249 | 0.0364 | 0.2089 |
| Type 7 | 0.8184 | 0.8239 | 0.9064 |
| Type 8 | -0.0069 | 0.0073 | 0.2210 |

**Figure 1: Classification of buy orders (BHS95)**

Surprise

Note: This figure depicts the order classification scheme for buy orders (sell orders are classified in a symmetric way). 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 better than the best ask. An order of type 2 is an order for a larger quantity than available at the best ask, but that is not allowed to walk up the limit order book above the best ask The part of these orders that is not executed immediately, is converted into a limit order. Orders of type 3 are orders to buy a quantity that is lower than the one offered at the best ask. 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.

2



# Figure 2: Order timing

Note: This figure presents the timing of the different order types across the trading day.

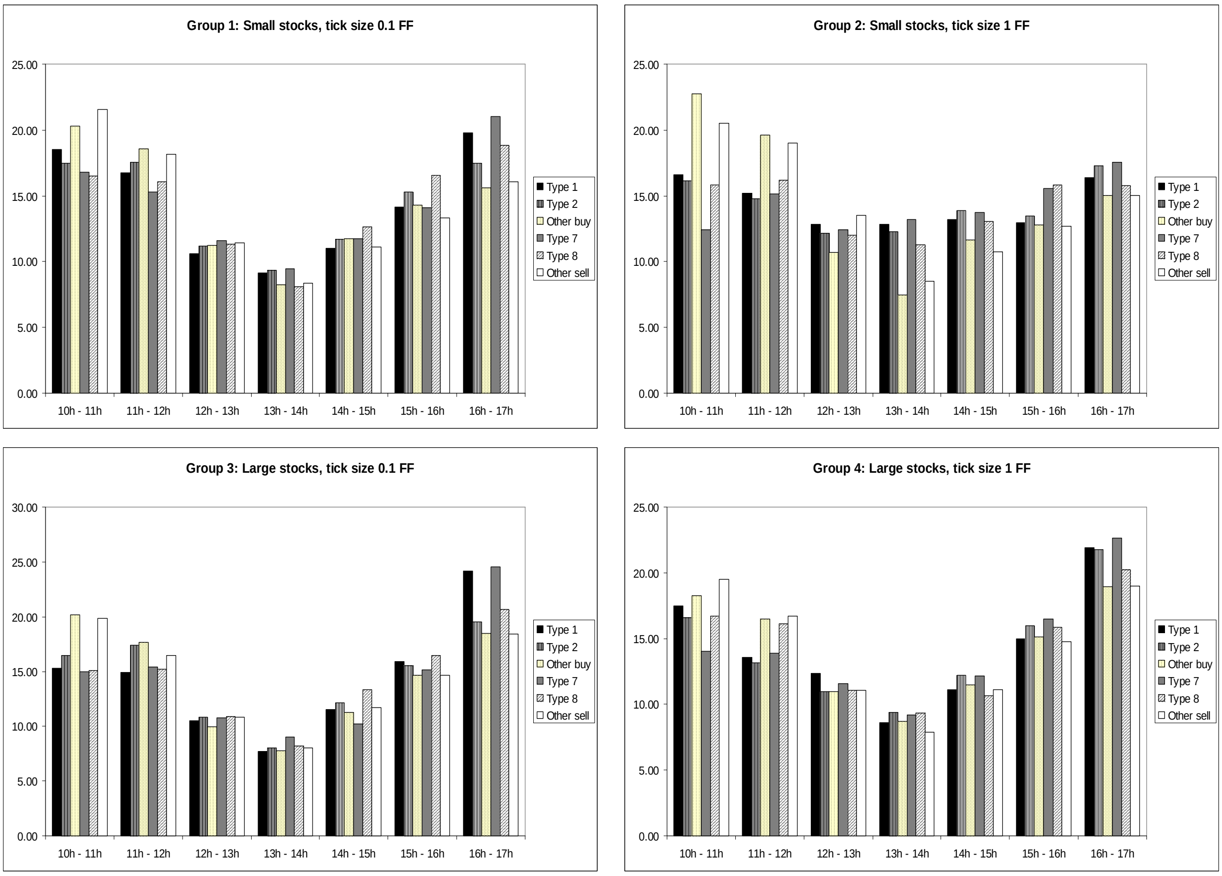


**Figure 3: The diagonal effect over time**

Note: This figure presents the probability that given that an order of type *i*, *i* = 1..12, at time *t* is followed by an order of the same type *i* at time *t*+*k*, *k* = 1..75. The dashed lines present the unconditional frequency of the order types *i*.

Panel A: Group 1: Small stocks, tick size 0.1 FF

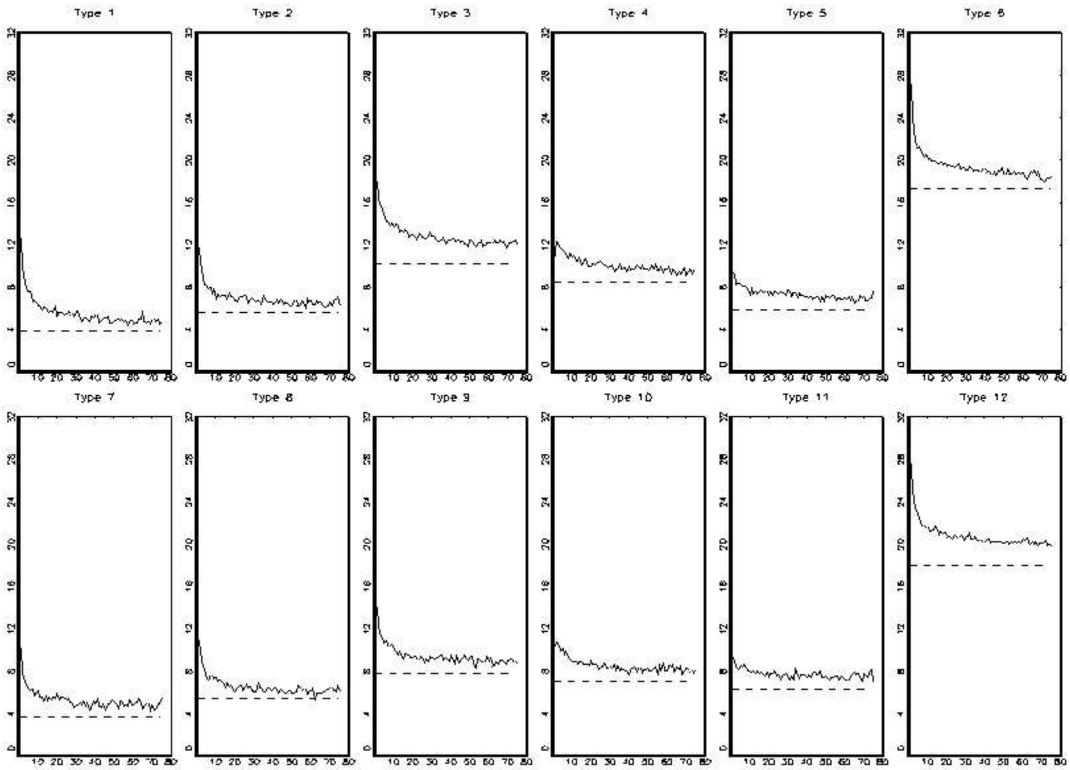


**Figure 3: The diagonal effect over time (continued)**

Panel B: Group 2: Small stocks, tick size 1 FF

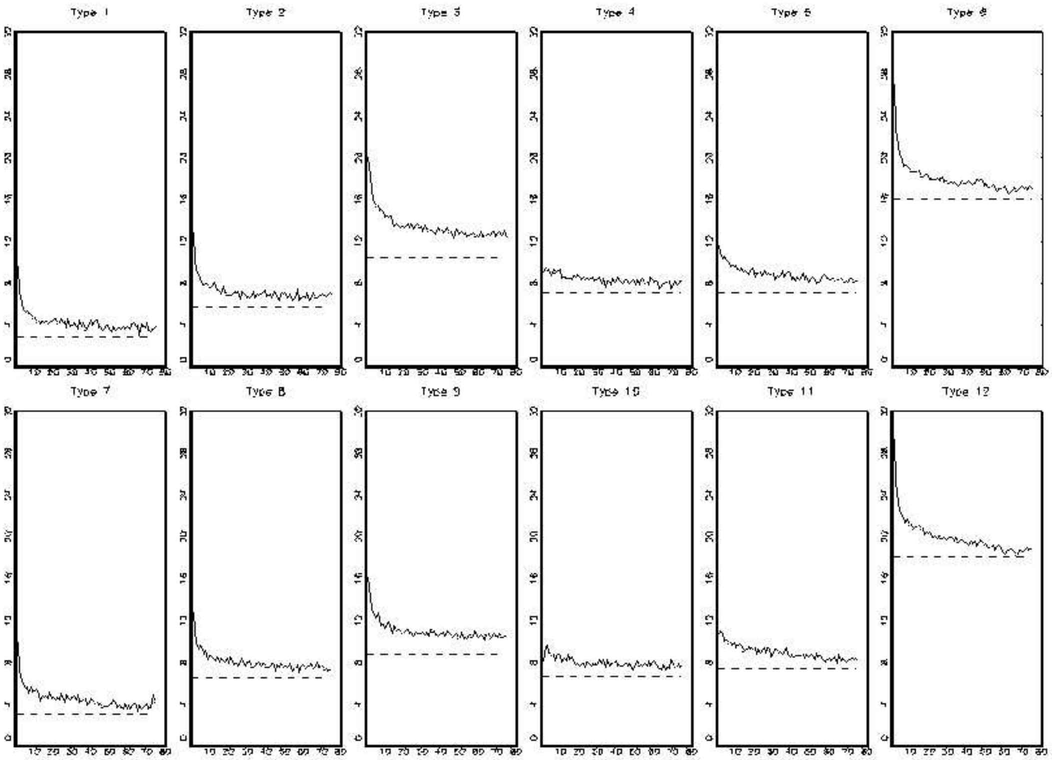


**Figure 3: The diagonal effect over time (continued)**

Panel C: Group 3: Large stocks, tick size 0.1 FF

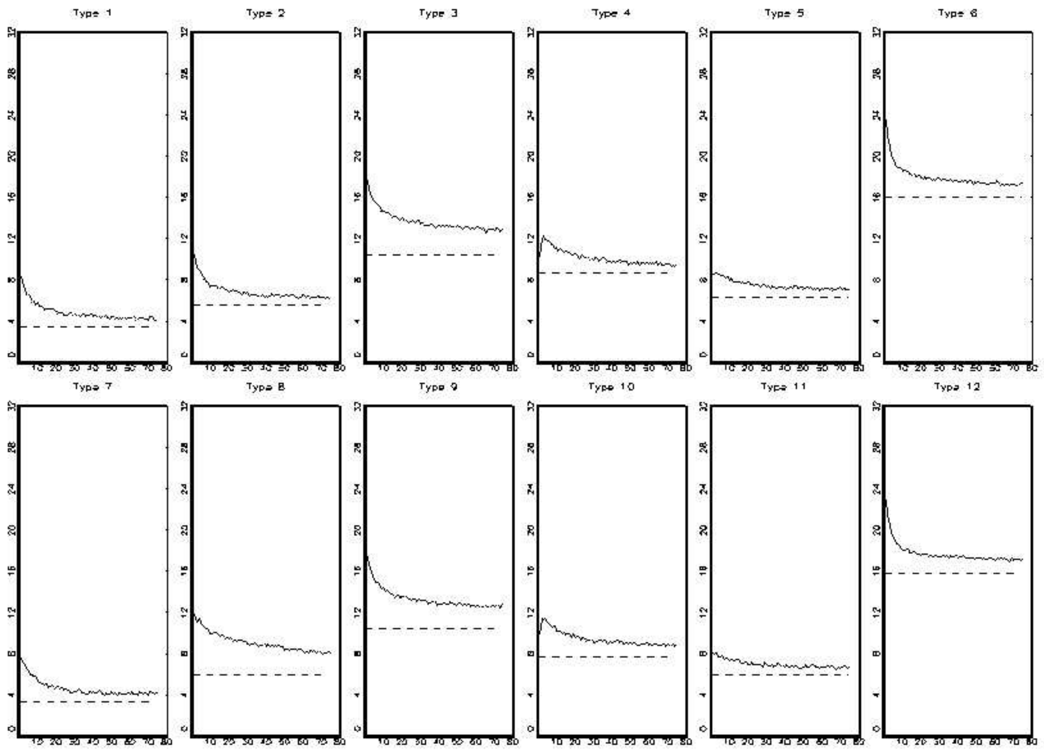
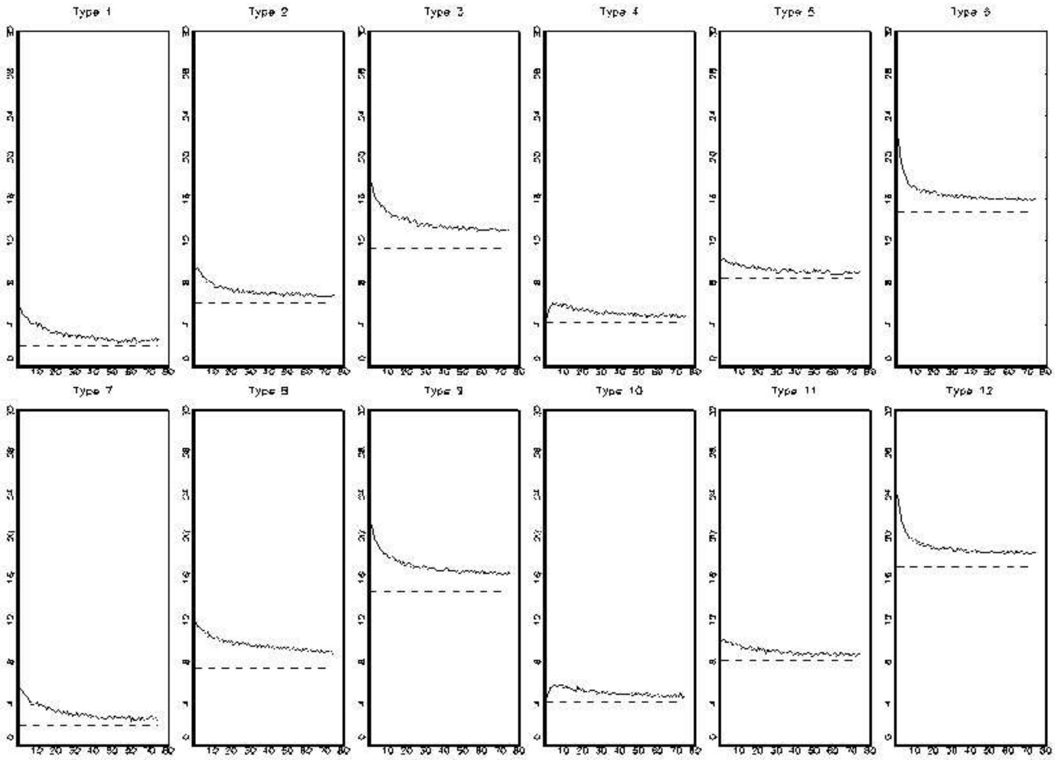


**Figure 3: The diagonal effect over time (continued)**

Panel D: Group 4: Large stocks, tick size 1 FF



## Figure 4: The limit order book around aggressive orders

Note: This figure presents the order book around an order of type *i*, *i* = 1, 2, 7, 8. We consider a window of 10 updates of the best quotes before and 20 updates after the submission. Within each window, the best quotes, the depth at the best quotes, the relative spread and the duration between best quote updates are given. The values of the variables are calculated relative to the value at the time of tsubmission of the order of type *i*, which was set equal to 100. Finally, the means across the stocks within the different groups are plotted. In the graphs for prices and depth, the full lines represent the bid, the dashed lines the ask.

Panel A: Order Type 1

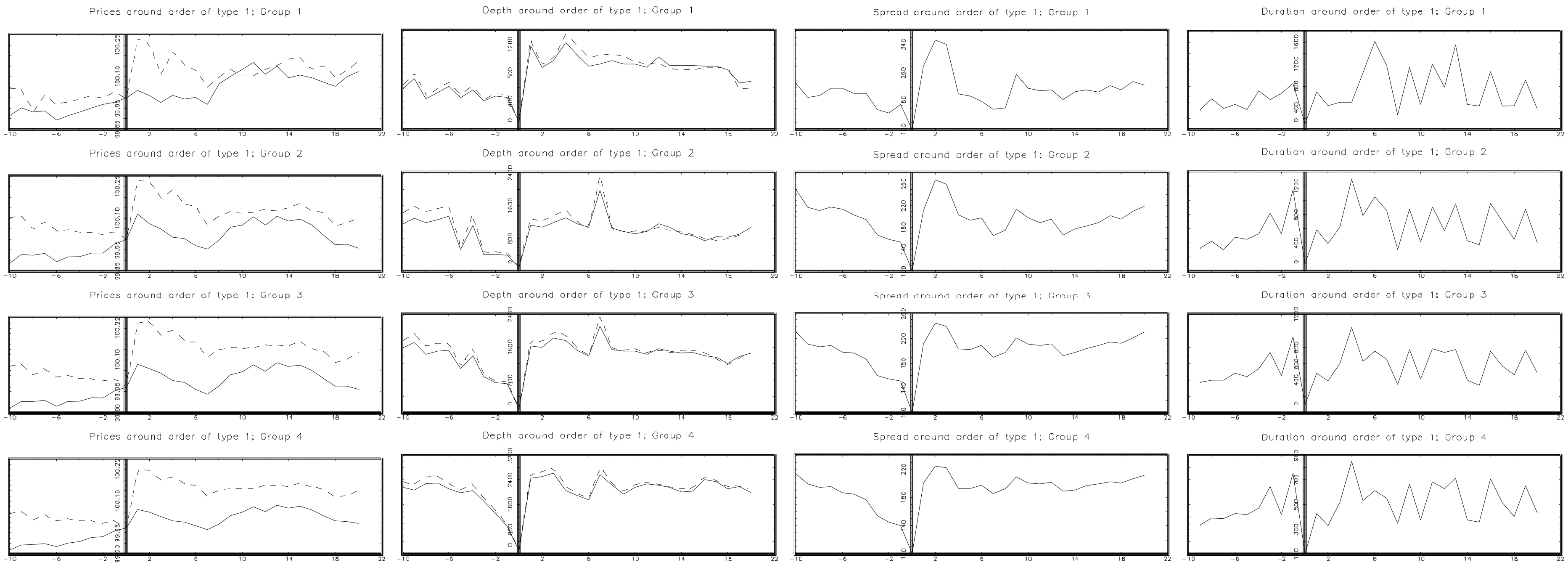


**Figure 4: The limit order book around aggressive orders (continued)**

<u>Panel B</u>: Order Type 2

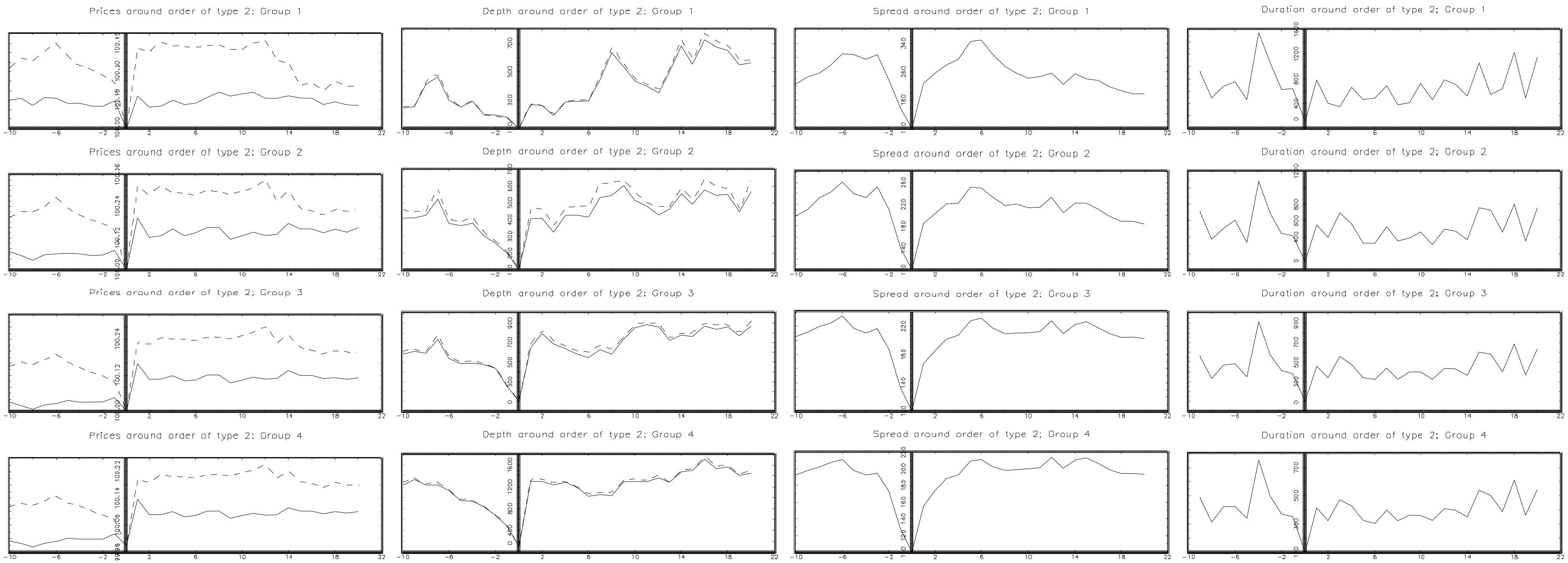


**Figure 4: The limit order book around aggressive orders (continued)**

Panel C: Order Type 7

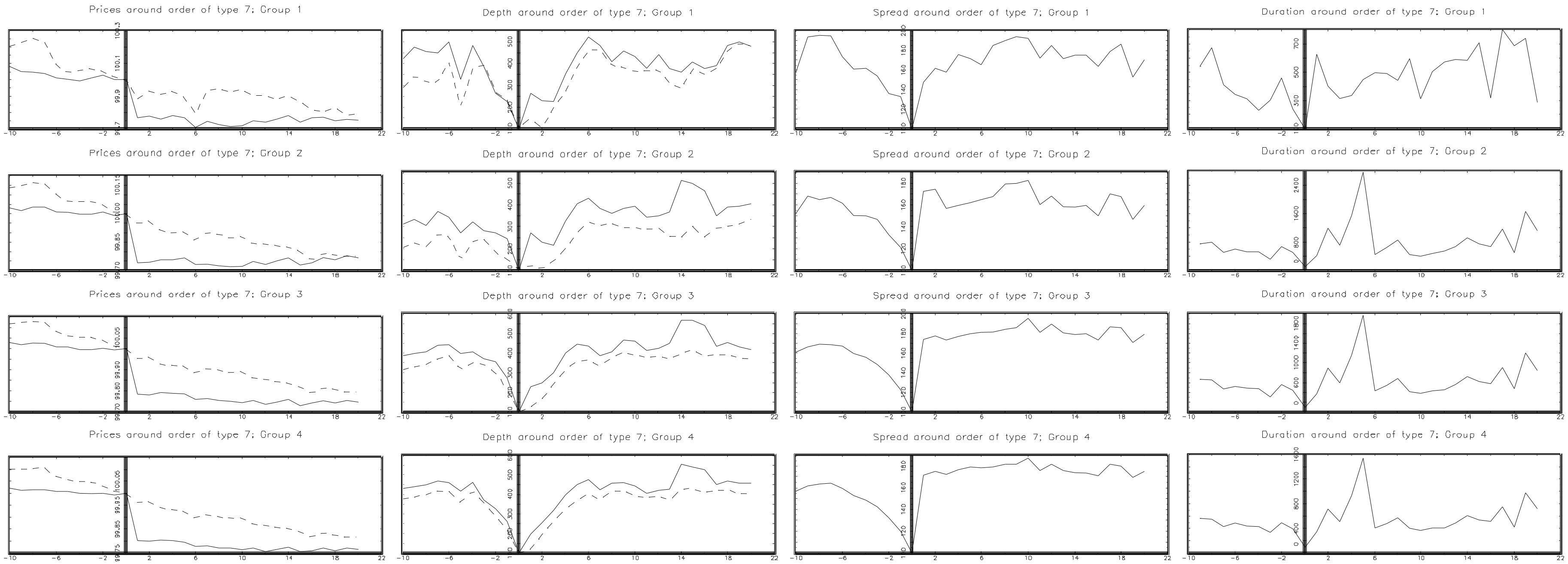


**Figure 4: The limit order book around aggressive orders (continued)**

Panel D: Order Type 8