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## An Empirical Analysis of the Limit Order Book and the Order Flow in the Paris Bourse

BRUNO BIAIS, PIERRE HILLION, and CHESTER SPATT\*

### ABSTRACT

As a centralized, computerized, limit order market, the Paris Bourse is particularly appropriate for studying the interaction between the order book and order flow. Descriptive methods capture the richness of the data and distinctive aspects of the market structure. Order flow is concentrated near the quote, while the depth of the book is somewhat larger at nearby valuations. We analyze the supply and demand of liquidity. For example, thin books elicit orders and thick books result in trades. To gain price and time priority, investors *quickly* place orders within the quotes when the depth at the quotes or the spread is large. Consistent with information effects, downward (upward) shifts in both bid *and* ask quotes occur after large sales (purchases).

MANY OF THE WORLD'S major stock exchanges, such as the New York and Tokyo Stock Exchanges, rely at least partially upon limit orders for the provision of liquidity. Therefore, it is important to understand the placement of limit orders and their contribution to liquidity and price formation. There is a complex relationship between investor order strategies and the short-term dynamics of asset prices, the transmission of information in security markets, the costliness of trading, and the nature of the liquidity available from the market. We are interested in understanding the intertwined dynamics of the order flow and order book: how the order flow reacts to the state of the order book and informational events in the marketplace, mechanically updates the

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state of the book, and influences the subsequent evolution of the order book and trading activity in the market. The Paris Bourse offers a particularly appropriate testing ground for examining these issues because 1) it relies solely upon order placement, 2) time and price priority is strictly enforced, 3) the data generated fully capture the order flow and execution process since the market is computerized and centralized, and 4) the market is very transparent, so that agents can use detailed information about the order book in their order placement strategies.<sup>1</sup>

The recency of the availability of order flow data as well as its richness and complexity make it necessary to design new ways to study it.<sup>2</sup> Our focus on the determinants of the order flow is different from that of Lee, Mucklow, and Ready (1993), who analyze the determinants of (and relation between) the depth and the bid-ask spread on the New York Stock Exchange (NYSE). In a contemporaneous study, Harris and Hasbrouck (1992) analyze the performance of different types of orders conditional on the size of the spread on the NYSE. As in Harris and Hasbrouck (1992), we differentiate orders and trades in terms of their aggressiveness. But, while they focus on the profitability of orders, we emphasize the interaction between the order book and order flow. For example, we characterize the order book using summary statistics and also analyze the determinants of the order flow using contingency tables that report the conditional frequency of different types of orders and trades. These descriptive methods are designed to capture important economic features of order placement such as liquidity, priority, and information effects. To illustrate our results, we also present plots of bid and ask quotes and trades for a single stock on a given day. Our methods and substantive insights may be useful in studying a variety of alternative market structures.

Because of the descriptive nature of our approach, data-snooping could be a potential concern. Therefore, we used a pilot sample of 6 trading days in June and July 1991 to develop the empirical analysis and design and to decide what statistics to compute for our main dataset of 19 trading days from October and November 1991. The results obtained in the pilot sample are quite similar to those obtained "out of sample." The same associations between variables are observed, and the same qualitative results are obtained in the main sample.<sup>3</sup>

<sup>1</sup> The five best quotations and associated depths on each side of the book as well as the time stamping of the orders and executions are continuously displayed to investors.

<sup>2</sup> The very nature of order flow data makes it less suitable for using tightly parameterized statistical models. In such models one would typically restrict the focus to studying the behavior of such variables as the midquote, the bid-ask spread, and trades (illustrative examples of such analyses include the studies of Glosten and Harris (1988), Hasbrouck (1988, 1991), and Hausman, Lo, and MacKinlay (1992)). This would not reflect such features of the data as the order flow and state of the book away from the quotes, the different types of orders (e.g., the aggressiveness of the orders), and the timing of orders and trades.

<sup>3</sup> Our findings in the pilot sample are not reported in this version of the article, but can be found in previous drafts, such as the March 1992 draft. In five instances we decided to undertake additional empirical work after we began the analysis of the full sample. i) In the analysis of the relation between the state of the book and the order flow we investigated finer conditioning (on the depth on *each* side of the market). The results were very weak and not economically significant, so

We find a variety of evidence documenting how liquidity is supplied and consumed in the marketplace and the interaction of liquidity and priority considerations. The conditional probability that investors place limit orders (rather than hitting the quotes) is larger when the bid-ask spread is large or the order book is thin. Conversely, investors tend to hit the quote when the spread is tight. Thus, the investors provide liquidity when it is valuable to the marketplace and consume liquidity when it is plentiful.<sup>4</sup> In order to obtain time priority under these circumstances, investors place limit orders relatively quickly when the liquidity has diminished.

We also analyze how the procedure for handling market orders enables these orders to obtain liquidity at relatively low cost. Market orders for a larger amount than the depth available at the quotes are not fully executed. Rather they are partially executed at the best price in the book, while the remainder of the order is converted into a limit order at that price. We find that after a market order has been placed, the probability that the next order will provide liquidity to it is relatively high. This illustrates the interaction between the buy and sell sides of the market. We also find that the market response to market orders tends to be rapid, which reflects competition in supplying liquidity. Our findings about the market response to market orders and to the state of the book suggest the existence of potential liquidity supply outside the book, i.e., traders monitoring the book, waiting for favorable trading or order placement opportunities.

We find that the flow of order placements is concentrated at and inside the bid-ask quote. A large fraction of the order placements improves upon the best bid or ask quote. Such improvements on one side of the quotes tend to occur in succession (undercutting), which reflects competition in the supply of liquidity. The time interval between such improvements is relatively small, which reflects the competition for time as well as price priority. In addition, improvement in the best quote is especially frequent when the depth at the quotes is large. This reflects the tradeoff between the execution probability and price: when the depth at the quotes is already large, new orders at that price are less likely to be executed, so it is optimal to undercut the best quote, to obtain a larger probability of execution, at the cost of a less favorable execution price. This type of tradeoff is analyzed in Kumar and Seppi (1993), which examines the competition for price priority. In our empirical setting, the tradeoff also reflects time priority considerations in that investors also do not wish to stand

we decided not to report them. ii) In the analysis of the time interval between orders or trades we decided to condition *jointly* on the different types of explanatory variables that we consider, to check that the results did not reflect spurious correlation. iii) In order to better document the average order book we computed time-weighted averages in addition to arithmetic averages. iv) In response to the referee's suggestion, we computed some summary statistics concerning hidden orders. v) To assess the robustness of our one-lag analysis of the order flow, we extended it to take into account additional lags. We found evidence of similar effects at additional lags.

<sup>4</sup> This behavior induces mean reversion in market liquidity, as measured, for example, by the bid-ask spread (also discussed by Handa and Schwartz (1991)). These liquidity effects also result in negative serial correlation for changes in the midquote.

behind the queue. Finally, despite the concentration of order activity at the quote, the quantities in the order book are not concentrated near the quote, and the bid-ask spread is somewhat wider than twice the difference between adjacent quotes on each side of the book. This is a consequence of trading activity consuming liquidity at the quotes.

Our empirical findings also offer evidence of information effects in the order process. After large sales (purchases), which consume liquidity at the quote and thus induce a decrease in the bid (increase in the ask), there is often a new sell (buy) order placed within the quotes, which generates a decrease in the best ask (increase in the best bid), and reflects the adjustment in the market expectation to the information content of the trade. This is similar to the rational updating behavior of market makers in Glosten and Milgrom (1985) or Easley and O'Hara (1987). This illustrates the positive serial cross-correlation in changes in quotes across the two sides of the market generated by information events (i.e., similar successive changes in quotes on both sides of the market).<sup>5</sup> Further, consistent with the analysis of insider trading in Easley and O'Hara (1987 and 1992), large purchases (sales) tend to occur in succession and rather quickly. Finally, the bid-ask spread, and to a lesser extent the spread between other adjacent quotes in the book, is larger than the minimum tick size. This suggests that the discreteness in the spread is (at least partly) endogenous. In the case of the bid-ask spread, this could reflect adverse information, as shown by Glosten (1994).

The placement of new orders and small trades tend to be concentrated in the morning, when price discovery occurs, whereas cancellations and large trades tend to occur late in the trading day. The latter finding may reflect large trades occurring after price discovery has largely been achieved, fund managers being evaluated with respect to the closing price, or strategic investors splitting their orders during the day and unwinding their remaining exposure late in the trading day. We also find strong persistence in the time interval between orders or trades, after controlling for the time of the day. Short time intervals tend to follow short time intervals, while long time intervals tend to follow long time intervals. This provides an additional characterization of clustering.

The structure of the article is as follows. In Section I the structure of the Paris Bourse and the dataset are presented. In Section II the depth of the order book is analyzed. We examine the order flow in Section III. Section IV analyzes the time interval between orders or trades. In Section V we attempt to assess the robustness of our results and intuitions by comparing them to those obtained in other descriptive studies of limit order markets, such as Harris and Hasbrouck (1992) and Hamao and Hasbrouck (1995). Section VI offers some concluding comments.

<sup>5</sup> This positive serial cross-correlation in the quotes induces positive serial correlation in the midquote. In this respect, liquidity and information effects have contrasting implications.

## I. Description of the Market and the Dataset

### A. The Structure of the Paris Bourse

From 1986 to 1990 the Paris Bourse gradually shifted from a daily call auction to a computerized limit order market in which trading occurs continuously from 10 a.m. to 5 p.m.<sup>6</sup> The opening price at 10 a.m. is determined by a call auction. Prior to this call auction, a sequence of tentative call auctions occurs before the opening, in order to facilitate the price discovery process.<sup>7</sup>

The computerized market mechanism is known as CAC (Cotation Assistée en Continu, which translates as continuous-time computer-assisted quotation system).<sup>8</sup> Investors place orders in the computerized market through brokers.<sup>9</sup> There are no market makers or floor traders with special obligations, such as maintaining a fair and orderly market or differential access to trading opportunities in the market. Therefore, the adverse selection problem highlighted in Rock (1990), that limit orders can be executed on the floor or referred to the limit order book, is mitigated on the Bourse.

Investors can submit limit orders at any price on a prespecified pricing grid, defined by the tick size. Typical sizes of round lot orders are 5, 10, 25, 50, or 100 shares. The size of the pricing grid depends upon the price level of the security. For prices below French francs (FF) 5 the tick size is FF 0.01; for prices between FF 5 and FF 100 the tick size is FF 0.05; for prices between FF 100 and FF 500 the tick size is FF 0.1; and for prices above FF 500 the tick size is FF 1. During the sample period a French franc was worth approximately \$.18. In our sample all stocks are typically above FF 100. For stocks with prices below FF 500, the tick size is much lower than in the U.S.

The orders are stored and executed in the sequence that they are received by the market. Transactions occur when a trader on the opposite side of the market hits the quote. The limit orders for a specified quantity and price are stored and executed using time priority at a given price and price priority across prices. Computerization ensures that priority rules are enforced.<sup>10</sup> The status of the security's book is updated (almost instantaneously) on traders'

<sup>6</sup> In April 1992, for the less liquid stocks, continuous trading was replaced by two daily auctions. The stocks in our sample were not affected by this change.

<sup>7</sup> In our analysis, we focus on the continuous market and do not use data from the opening call. In a more recent paper (Biais, Hillion, and Spatt (1995)), we study price discovery and order placement during the preopening period.

<sup>8</sup> Huang and Stoll (1991) and Hamon and Jacquillat (1992) provide a description of the microstructure of the Paris Bourse.

<sup>9</sup> Commissions are negotiable. They are often of the order of magnitude of 0.2 percent for large trades. Since the fall of 1991, investors must pay a fixed FF 5 fee for each order placement (this charge was in effect during our sample period). This fixed fee is relatively small in light of the order sizes typically employed.

<sup>10</sup> In contrast, the quantities in the book on the NYSE do not accurately depict execution priority because floor traders can easily (by witnessing a single trade) obtain equal standing with the book. The incentives to use floor traders on the NYSE are particularly great when the book is very deep.

screens, each time there is an order arrival, cancellation, or execution.<sup>11</sup> Brokers and the most active traders in the market can directly route their orders to the CAC system. Electronic transmission of the orders and updating of the screen usually take less than one second. However, when the flow of orders is very thick, the transmission of the orders and updating of the screen are slower, and the order of magnitude of the delay is approximately one minute. When it occurs, this type of overflow typically takes place just after the opening or just before the closing of the market, when the trading activity is the most intense.

Investors can place limit orders that are not fully visible to other traders. These orders are called "hidden orders." A fraction of the order (at least as large as ten times the minimum number of shares that can be traded in the stock) is visible in the book, while the remaining fraction is present in the book, but invisible to other investors. However, the order is observable to surveillance officials. The invisible fraction of the order retains price priority, but not time priority. Once the visible fraction of the order has been fully executed, another portion of the hidden order (equal to the amount initially disclosed) becomes visible. For example, if an investor desires to sell 10,000 shares (a relatively large order), the investor might permit only 1000 of them to be initially visible, while the remaining 9,000 are not visible although they are retained in the book at the same price. After each 1000 shares have been sold, another 1000 shares becomes visible automatically. Analogously, a variety of types of hidden orders on the NYSE provide price, but not time priority (e.g., "all or none" orders). One difference is that in Paris, an order improving the quotes cannot be fully hidden, while in the NYSE it could.

"Market orders" in the Paris Bourse are not handled in the same way as in the NYSE. They are executed against the best price on the opposite side of the limit order book, but any excess that cannot be executed at that price is converted into a limit order at that price rather than being executed at less favorable prices by walking up (down) the book. If an investor wishes to buy (sell) shares by walking up (down) the book, he can use an appropriate limit order. As a result of this market feature, "market orders" express less impatience than aggressive limit orders. We use the manner in which market orders are handled to differentiate them from limit orders. However, there are two situations where this identification rule need not be accurate. Market orders that are fully executed cannot be distinguished from limit orders for a smaller quantity than that available at the quotes, so we pool these two categories together as "small orders." Second, limit orders that are immediately but partially executed at the best bid or ask quote cannot be distinguished from market orders, so we classify them as market orders. Note that this misidentification is not of consequence because market participants cannot distinguish the two types of orders.

<sup>11</sup> In contrast, except for the prevailing quotation and the depth at that quote, the NYSE book is not disseminated electronically to brokers and investors in real time.

In the next sections we analyze the traders' use of and response to "market orders" in the Paris Bourse. A priori there are several rationales for this mechanism. For example, it enables agents who cannot perfectly monitor the market to place orders at the current quotes rather than walking up the book. Also, Paris Bourse officials suggested to us that this mechanism helps to educate small traders, previously familiar with the daily call market, to limit their market impact in the newly created continuous market. Our results suggest that market orders in the Paris Bourse are also used by more sophisticated and strategic traders, in order to limit the price impact of their trades, attract liquidity from the other side of the book, or test for the presence of hidden orders.

Essentially all trades are executed at the quotes outstanding in the book. The exception is prematched block trades, which can take two forms. First, prearranged trades can be executed between or at the current best bid and ask prices.<sup>12</sup> These are called "applications." Second, a block also can be traded outside the current spread, but then the priority of previously posted limit orders is respected. For example, if the block price exceeds the best ask, then the limit orders between the best ask and the block price are purchased by the block buyer at the block price.

By law the market is centralized, i.e., all trades in French stocks must be executed on the Bourse. In fact, the market is not completely centralized, however. Some of the trading in French stocks, especially block trades, occurs in the London International Stock Exchange Automated Quotation (SEAQ), and thus bypasses both the time and price priority of limit orders on the Paris Bourse.<sup>13</sup> Most of the medium and small trades occur in Paris, however. For the ten most actively traded French stocks, de Jong, Nijman, and Roell (1993) find that 30 percent to 50 percent of the total value of trades occurs in London. They also find that the trades occurring in London are much larger than those executed in the Paris Bourse: while they account for more than one third of the value, they represent only 10 percent of the total number of trades. The market share of London for the stocks in our sample is likely to be smaller than those figures would suggest. First, de Jong, Nijman, and Roell (1993) find that the market share of London is larger for more actively traded stocks. Hence, because the stocks in their sample are, on average, more actively traded than those in our sample, the overall market share of London should be lower, on average, for the stocks in our sample. Second, because of the complexity and multiplicity of reporting procedures in the London market, double reporting of some trades is likely to occur. Further, the impact of trades in London on the orders and quotes in Paris is blurred by the fact that large

<sup>12</sup> When they are executed at the quotes, they bypass the time priority of the limit orders previously posted at that price. There is no size priority in the Bourse.

<sup>13</sup> Pagano and Roell (1990) discuss the trading of French shares in London. Note that the absence of a transaction tax in the International SEAQ contributes to the attractiveness of the London market. In 1991, the transaction tax in the Bourse ranged from 0.15 percent to 0.3 percent, paid both by the seller and the buyer. It has recently been reduced in two ways. First, there is no tax for trades lower than FF 50,000, or for trades by foreigners. Second, the total tax is limited to FF 4,000, for trades larger than FF 700,000.



trades occurring in the international SEAQ are only reported with delay. As a result the Paris market is less likely to react quickly to these trades. Finally, while the London market attracts the larger orders, because these are in a separate market they only affect indirectly the execution priority within the Paris book.

### *B. The Dataset*

The dataset contains the history of the order book for the 40 stocks in the CAC 40 index, for the 19 trading days between October 29 and November 26, 1991.

For each transaction, the dataset reports the price, execution time and the quantity exchanged, while for each order revision, the dataset reports the time, the best five bid and offer prices and the number of shares demanded or offered at each of the five bid and ask quotes.<sup>14</sup> We do not observe order placement or cancellation outside of the five best buying or selling limit orders.<sup>15</sup> We cannot observe directly the hidden orders in our dataset. From successive snapshots of the book, we compute the investor's orders (price, quantity and direction), executions, and cancellations. The ability to classify accurately buyer- or seller-initiated trades enhances the reliability of our inferences (for example, in analyzing the informational content and motives of trades and orders).

In contrast to our dataset from the Paris Bourse, the Institute for the Study of Security Markets (ISSM) data summarizing NYSE transactions includes the prevailing quotations, but not orders away from the quote. In addition, the electronic book on the NYSE contains only about 30 percent of the executed trading volume. The electronic order book and order flow data from the NYSE (such as the new Trades, Orders, Reports, and Quotes (TORQ) database) do not include many orders processed in this market, such as some market maker orders and most large orders.

All the information in our dataset is available to market participants in real time through computerized information dissemination systems. All brokers are directly connected to the CAC system. Most banks and fund managers dealing in French stocks, in Paris as well as in London or New York, obtain the information in real time through information vendors, such as Reuters, Telekurs, or from a subsidiary of the Bourse. Our dataset does not include bids and offers outside these best five quotations nor the identities of the bidding brokers. However, both of these types of information are available to brokers electronically and the brokers can provide this information to their customers. In that sense the information sets of the econometrician and investors, though similar, are not identical.

<sup>14</sup> If one trade is executed at different prices by walking up (or down) the book, the dataset includes several execution messages, one for each order hit in the book. Once the order has been executed, the refreshed state of the book is displayed in the data. We use this feature to aggregate the different execution prices as one trade, to reflect the trade being generated by a single order.

<sup>15</sup> This feature of the data, among others, would make it difficult to track limit orders over time as their location in the book and time priority evolve. For example, we do not have indications of when orders are placed or cancelled outside the five best bid and ask quotes.

**Table I**  
**Summary Statistics on Daily Market Activity**

For the 19 trading days in the period between October 29 and November 26, 1991, for each stock included in the CAC 40 index at that time, we compute the daily mean return, difference between highest and lowest price divided by the lowest price (hi-lo), number of trades, number of orders (that were not immediately executed), number of “applications,” trading volume in shares, value of shares traded (in millions of French francs), value of “applications,” and the number of times a hidden order is hit. The table reports summary statistics about the cross sectional distribution of these 9 daily averages across the 40 stocks.

	Mean	Min	First Quartile	Median	Third Quartile	Max
Return (%)	-0.19	-0.77	-0.4	-0.17	-0.03	0.4
Hi-Lo (%)	1.8	0.7	1.4	1.8	2.2	2.9
Number of trades	148.6	43.7	76.8	113.7	196.4	448
Number of orders	160.6	76	106.8	140.5	198.8	429.8
Number of “applications”	6.8	1.6	3.5	6	10	15.5
Trading volume in thousands of shares	55.62	1.32	15.95	29.06	66.70	310.37
Value of shares traded (in millions of French francs)	29.7	2.89	8.84	20.98	40.51	145.9
Value of “applications” (in millions of French francs)	4.65	0.368	1.38	2.71	5.54	18.39
Number of times a hidden order is hit	18.27	1.95	8.22	18.18	25.05	54.58

Table I presents some summary statistics about our dataset. The average daily number of trades per stock in our sample is 148.6, whereas the average number of orders that were not immediately executed is 160.6. These numbers reflect the rather high level of trading activity in these stocks. Also, the average of the market value of daily trading volume per stock is FF 30 million (less than 6 million dollars). The average daily number of “applications” is relatively small (around 6.8), but “applications” amount to a relatively large fraction of the total value of shares traded (approximately one sixth). This reflects the large size of these prenegotiated trades. While we are unable to observe hidden orders directly, we can infer that there was a hidden order in the book when, after a trade, the updated state of the book is not what was anticipated given i) the previous state of the book and ii) the trade. Using this feature of the dataset, we find that the average daily number of times a hidden order is hit per stock is 18.27. Thus, since the average daily number of trades is 148.6, approximately one trade out of eight is partially executed against a hidden order. We also compute the average number of shares executed against the hidden part of the orders, when a hidden order is hit. It is equal to 387.9. This measure underestimates the importance of hidden orders, since we only observe those hidden orders that are hit by trades. However, part of the hidden orders become disclosed and become visible offers and demands as they get hit. The average number of shares appearing in the book when a hidden order is hit and gets partially disclosed is equal to 717.18.

## II. The Order Book

Theoretical research in market microstructure has extensively studied the price schedule, mapping trades into execution prices. Kyle (1985), Glosten and Milgrom (1985), and Easley and O'Hara (1987) provide models of market maker quotations, while Rock (1990), Glosten (1994), and Bernhardt and Hughson (1993b and c) analyze limit order markets. In these models the price impact of trades reflects their informational content. Previous empirical studies provide indirect evidence on the slope of the price schedule, by analyzing the price movements following trades in a time-series context.<sup>16</sup> Because we observe the order book, we can provide direct evidence on the features of the price schedule.<sup>17</sup> This section presents and discusses descriptive statistics concerning the order book.

### A. *The Slope of the Order Book*

Using the five best bid and ask quotes and the associated depth at these quotes (the number of shares offered and demanded at these ten different quotes in the book), we construct supply and demand curves, similar to those represented in Glosten (1994, Figure 2). For each stock we compute the (time-series) average of the best ask and the best bid, as well as the average of the 8 other quotes in the book, and the average of the quantity offered or demanded at these 10 quotes.<sup>18</sup> Then we compute the cross-sectional mean of these time-series means across the 40 stocks in our sample. To control for differences in tick size, we compute the cross-sectional means for two different subsamples: one composed of the stocks with tick size equal to one franc, the other composed of the stocks with tick size equal to one tenth of a franc.<sup>19</sup> Figure 1 graphically represents our results.

These empirical results can be used to study the slope of the book. First, we analyze the spreads between adjacent quotes in the book. We find that the bid-ask spread is larger than twice the difference between adjacent quotes on each side of the book, while the latter are fairly constant.<sup>20</sup> From inspection of Figure 1, the difference between the bid-ask spread and the other spreads is not striking, though it is statistically significant. To establish this we ran

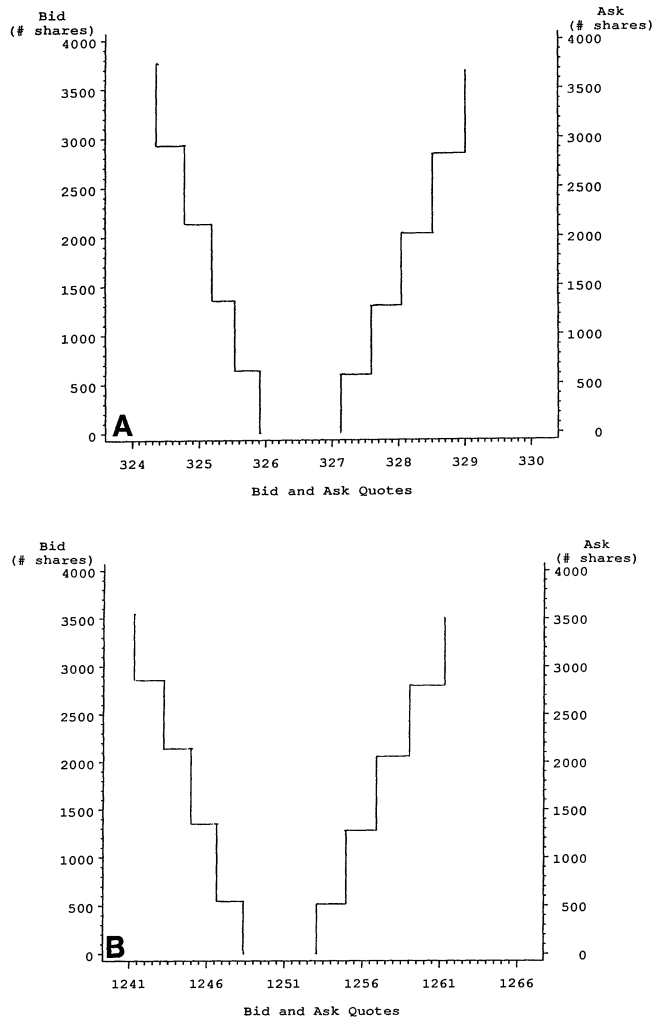
<sup>16</sup> See, for example, Hasbrouck (1988, 1991), Glosten and Harris (1988), and Madhavan and Smidt (1991).

<sup>17</sup> Lee, Mucklow, and Ready (1993) analyze the bid-ask spread and the depth at the quotes. In addition to the best quotes, and the associated depth, we consider the four next best quotes and associated depths on each side of the book.

<sup>18</sup> These averages are arithmetic means where all observations are equally weighted.

<sup>19</sup> When stocks have prices fluctuating around FF 500, their tick size switches from one franc to ten centimes. For each of those stocks we create two subsets, one with observations with tick equal to one franc, the other with the observations with tick equal to ten centimes. These subsets are then included in the two subsamples of stocks.

<sup>20</sup> For stocks with tick equal to FF 0.1, the average quotes are 324.36, 324.78, 325.19, 325.53, and 325.91, on the bid side and 327.13, 327.59, 328.04, 328.51, and 329.01 on the ask side. For stocks with tick size equal to FF 1, the average quotes are 1241.27, 1243.18, 1244.94, 1246.63, and 1248.34 on the bid side, and 1253.07, 1254.95, 1256.91, 1259.04, and 1261.31 on the ask side.



**Figure 1. The Limit Order Book for Stocks.** (A) plots the cross-sectional average (across stocks with tick = FF 0.1) of the time-series averages of the five best ask and bid quotes and their associated depth. (B) plots the cross-sectional average (across stocks with tick = FF 1) of the time-series averages of the five best ask and bid quotes and their associated depth.

multivariate tests similar to those in Shanken (1985).<sup>21</sup> As reported in Table II, the hypothesis that the bid-ask spread and twice the difference between adjacent quotes on each side of the book are not statistically different is

<sup>21</sup> To test the null hypothesis that all spreads (including the bid-ask spread) are equal we proceed as follows. First, for each stock and for each of the 19 days we compute the daily average relative bid-ask spread, and the 4 daily relative spreads on each side of the book. This results in a 19 by 9 table, each row corresponding to a day, each column corresponding to a relative spread, and each cell reporting the average for that day and spread across the 40 stocks. Second, (for

**Table II**  
**Multivariate Test of Equality of Spreads and Depths Across Levels in the Book**

For the 19 trading days in the period between October 29 and November 26, 1991, for each stock included in the CAC 40 index at that time, we compute multivariate statistics (as in Shanken (1985)) to test if the bid-ask spread and the spreads away from the quotes are equal, and whether the depth at the best quotes and the depth at the other quotes in the book are equal. The Table reports the number of stocks out of 40 for which equality was rejected at the 5 percent level.

Hypothesis	Number of Rejections (of 40)	Test Statistic
Equality of all spreads including bid-ask spread	40	F(8,11)
Equality of all spreads excluding bid-ask spread	17	F(7,12)
Equality of all depths including depths at the quotes	33	F(9,10)
Equality of all depths excluding depths at the quotes	4	F(7,12)

rejected for all stocks at the 5 percent level. In contrast, after excluding the bid-ask spread, the difference between spreads on each side of the book was significant (at the 5 percent level) for only 17 stocks.

Holding quantities constant, if the bid-ask spread is larger than twice the other spreads, then the slope of the book is steeper at the quotes than away from the quotes. The evidence on quantities reinforces the relative steepness of the book at the quotes. The average number of shares offered at the best bid is 633.99 for stocks with tick size equal to 0.1 FF and 547.1 for stocks with tick size equal to 1 FF. The average number of shares offered at the best ask is 592.8 for stocks with tick size equal to 0.1 FF and 517.78 for stocks with tick size equal to 1 FF. The depth is lower at the bid-ask spread than away from the best quote.<sup>22</sup> This difference is not striking from Figure 1. Still, using multivariate tests (as in Shanken (1985)) we find it is statistically significant for 33 stocks of 40 (as reported in Table II). In contrast we find that the depth away from the bid-ask spread does not vary significantly across quotes (see Table II). This pattern in the depth illustrates that the provision of liquidity at the bid-ask quotes is only a small portion of the overall depth in the order book.

normalization purposes) we subtract the first column from the other eight, thus obtaining an eight column table. Third, we compute the following  $T^2$  statistics:

$$T^2 = 19R'S^{-1}R$$

where  $R$  is the (8, 1) vector of the 8 means of the 8 columns, and  $S^{-1}$  is the sample variance-covariance matrix.  $T^2$  (19, 8) follows a Fisher  $F(8, 11)$  distribution. For each stock we compute this Fisher statistic.

<sup>22</sup> For stocks with tick size equal to FF 0.1, the average depth ranges between 718.28 shares and 833.35 shares at other quotes on the bid side and between 701.09 shares and 845.39 on the ask side. For stocks with tick size equal to FF 1, the average depth ranges between 688.41 shares and 803.80 shares at other quotes on the bid side and between 706.15 shares and 780.57 on the ask side.

Because the spread is larger and the depth is lower, the price schedule is steeper at the best quotes than away from the quotes.<sup>23</sup> From an auction-theoretic perspective the shape of the order book may reflect the correlation in the value of the security to various bidders on the same side of the market, the extent of competition among bidders on the same side of the market and the shading of bids compared to the underlying reservation values. Alternatively, if the slope of the book arises from informational asymmetries (as in Rock (1990), Glosten (1994), or Bernhardt and Hughson (1993b and c)), then our findings suggest that the marginal information content of trades is decreasing with trade size. Our empirical results are at odds with the theoretical results of Glosten (1994) and Bernhardt and Hughson (1993c), however. The price schedule we observe is weakly concave, and does not depart strongly from linearity. In Figure 2 in Glosten (1994), there is no clear pattern in the slope of the price schedule, while in Bernhardt and Hughson (1993c) the price schedule is convex. This difference between our empirical findings and the theoretical results may reflect i) the contrast between the static nature of these models and the dynamic environment from which the data is generated, or ii) the parametric assumptions made in Glosten (1994) or in Bernhardt and Hughson (1993c). Further work could investigate whether relaxing these parametric assumptions would improve the fit between the theoretical price schedule and the observed data.

We also investigated intraday patterns in the order book, and found that the bid-ask spread and the relative spreads on each side of the book exhibit a U-shaped pattern, while the depth at the best quotes is largest in the last two trading hours. For brevity these results are not reported in the article.

### *B. Price Discreteness*

We compute the time-series median number of ticks between the bid and ask quotes for each stock in the sample. Then we compute the cross-sectional median of these time-series medians, across the 40 stocks. For stocks with tick size equal to FF 1, the median number of ticks is 3. For stocks with tick size equal to FF 0.1, the median is 9 ticks. Consequently, the bid-ask spread is larger than the minimum tick size and the discreteness in the bid-ask spread is, at least partly, endogenous. This is consistent with the adverse information theories of the bid-ask spread developed by Rock (1990), Glosten (1994), and Bernhardt and Hughson (1993b and c). They point out that the best quotes in the book are hit by all trades and can be run over by large trades, exceeding the quantity posted at these quotes. Hence, the information content of trades

<sup>23</sup> Hasbrouck (1991) also finds nonlinearities in the estimated price response. For actively traded stocks, Madhavan and Smidt (1991) obtain an S shape, not unlike our findings. These papers study the price impact of actual trades, by regressing changes in the midquote on quantities traded. Thus, they indirectly characterize the price schedule. In contrast, we directly observe the price schedule and thus characterize the potential cost of immediacy for a given trade. However, our analysis is limited because we do not observe the hidden orders and therefore underestimate the depth of the book.

hitting the best quotes is not infinitesimal, even if the depth at these quotes is small. Consequently, the difference between the best bid and the best ask quote is discrete. Glosten (1994) refers to this feature as the “small trade spread.”

Further, we compute the median number of ticks between adjacent quotes away from the bid-ask spread. We find that the typical number of ticks is often larger than one, i.e., there is not an order at each point in the pricing grid. For stocks whose tick size is FF 0.1, the median number of ticks between two consecutive ask quotes or two consecutive bid quotes ranges from 2 to 4. In contrast, for stocks whose tick size is one franc, the median is equal to one tick. For these stocks, the tick size constraint is likely to be binding, i.e., if the pricing grid were tighter, the spread between adjacent quotes on the same side of the book would be smaller.<sup>24</sup>

These findings suggest that, for stocks with a small tick size (0.1 FF), the discreteness in the book away from the best quotes is, at least partly, endogenous. Such “holes” in the order book could reflect the strategic bidding behavior of traders exploiting the discreteness of the pricing grid. Bernhardt and Hughson (1993a) analyze this issue in the case of market makers. The intuition obtained in their analysis can be extended to a limit order market, as is illustrated in the following example. Assume the tick size is FF 0.1 and the current best ask quote is 155, while the current second best quote on the ask side is 155.3. Assume further that 155 is a “fair price” for the best ask, i.e., at this price the supplier of liquidity breaks even, while a “fair price” for the second best quote would be 155.1. Should the potential suppliers of liquidity, monitoring the market, post an ask quote at 155.1? If an agent posts a quote at 155.2, he can earn a surplus. However, because of the discreteness of the pricing grid, it is not profitable to compete away this profit. The next agent has no incentive to place a quote at 155.1, because at this price his expected profit would be zero. Hence, he has no incentive to place such an order. Instead, he should queue up at 155.2, where he might earn positive profits. This example emphasizes i) the first mover advantage obtained by liquidity suppliers in a limit order market with a discrete pricing grid, and ii) the incentive to supply liquidity created by this discreteness and time priority. These themes are also discussed in Harris (1994).

### III. The Order Flow

Trades and orders are differentiated according to i) direction (whether the trade is seller- or buyer-initiated, or whether this is a limit order to buy or to sell), and ii) aggressiveness.<sup>25</sup> On the buy side, we define seven categories of events, corresponding to decreasing degrees of aggressiveness. The three most

<sup>24</sup> In a more in-depth analysis concerning the NYSE, Harris (1994) predicts that a reduction in the tick size would generate a reduction in the spread.

<sup>25</sup> Although they use a different classification scheme, Harris and Hasbrouck (1992) also rank limit orders by aggressiveness.

aggressive types of orders result in immediate execution. The most aggressive is “large buy,” an order to buy a larger quantity than that available at the best ask, where the investor specifies a limit price above the best ask. The second category is “market buy,” an order to buy a quantity larger than that offered at the best ask, which is not allowed to walk up the book above the best ask. The third category is “small buy,” an order to buy a quantity lower than that offered at the best ask, which results in full and immediate execution. The remaining orders on the buy side do not result immediately in execution. They are limit orders to buy within the best bid and ask quotes, limit orders to buy that match the best bid, limit orders to buy below the best bid, and cancellation of previously posted limit orders to buy. The trades and orders on the sell side are defined analogously. The final category is “applications,” which are prearranged trades put through the market at or within the best quotes. This defines 15 different types of orders or trades.

#### *A. The Unconditional Probabilities of Orders and Trades*

The frequency of occurrence of each of these 15 different events is documented in Table III. The most frequent events are “small trades.” This might reflect the presence of small investors, or the ability of investors to split their orders to limit market impact. The next most frequent events are new orders placed within or at the spread. Hence, most of the activity is within or at the quotes.<sup>26</sup>

We also analyzed the order flow away from the quotes in more detail, i.e., instead of pooling all limit sell (buy) orders placed above (below) the best ask (bid) quote, we analyzed separately the orders placed at each of the five best quotes on each side of the book.<sup>27</sup> For brevity the detailed results are not reported here. We found that order placement decreases monotonically as one moves away from the quotes. A similar, but less pronounced pattern prevails for order cancellations.<sup>28</sup>

Our results concerning the order flow may seem at odds with our results on the order book. While the order flow is concentrated at or within the best quotes, the order book is less deep at these quotes. On the other hand, while the order book is deeper away from the best quotes, orders are less frequently placed outside the best quotes. These seemingly contradictory results can be reconciled by analyzing further the dynamic interaction between the order book and order flow.

First, the larger depth away from the best quotes reflects the accumulation of old, unexecuted, uncanceled orders. Second, by definition, trades first hit the best quotes in the book, widening the bid-ask spread, and reducing the

<sup>26</sup> For the NYSE, Harris and Hasbrouck (1992) also find that limit orders away from the quotes are infrequent.

<sup>27</sup> This analysis was only run in the pilot sample of six trading days in June and July, 1991.

<sup>28</sup> The difference between order cancellations and order placement reflects i) orders at or close to the best quotes being executed before the investors have the opportunity to cancel them, and ii) the cancellation of old orders from which the market has moved away.



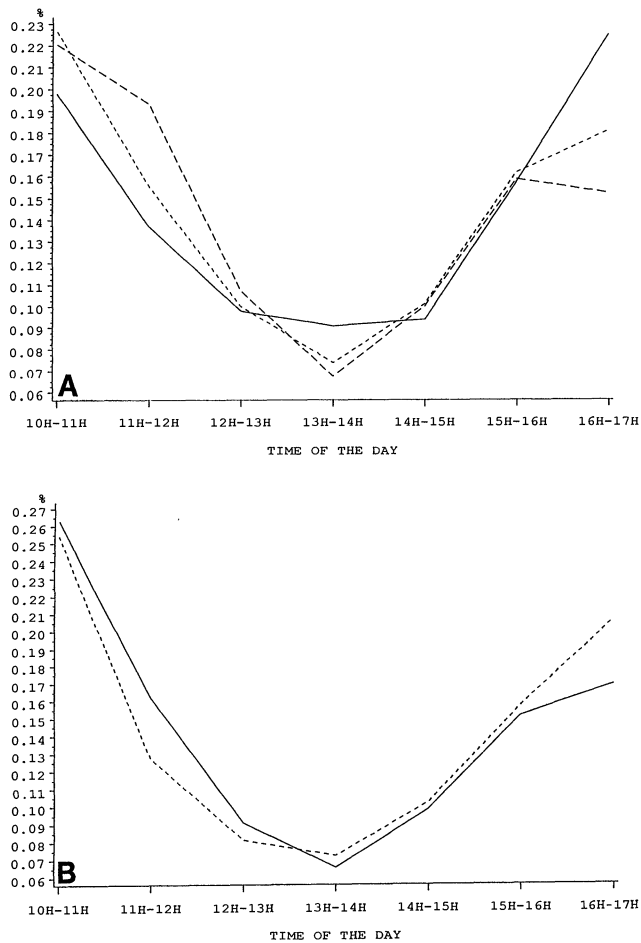
**Table III**  
**Frequency of Orders and Trades**

For the 19 trading days in the period between October 29 and November 26, 1991, for the stocks included in the CAC 40 index at that time, Table III reports the frequency of the 15 categories of orders and trades, which add up to 100%. The frequency of each of these 15 categories is computed in the following way: For each stock, the total number of times each category of events occurs is computed. These totals are added across the 40 stocks. To obtain percentages, they are divided by the total number of observations.

Event Type		Unconditional Frequency in % Terms
Panel A: Buy Side		
Trades	Large buy	2.4
	Market buy	2.1
	Small buy	12.5
Orders	New bid within the quotes	9.0
	New bid at the quotes	5.3
	New bid below the quotes	7.4
	Cancel bid quotes (irrespective of level)	4.7
Panel B: Sell Side		
Trades	Large sell	3.8
	Market sell	2.4
	Small sell	24.0
Orders	New ask within the quotes	8.3
	New ask at the quotes	4.3
	New ask above the quotes	7.0
	Cancel ask quote (irrespective of level)	4.8
	Application	2.2

depth at these quotes. Other things equal, this leads to a steeper price schedule at the best quotes than further away in the book. However, we show in the next subsection that widening of the spread and decreases in the depth at the best quotes are transient: they attract new orders at or within the quotes, which restore depth, and narrow the spread. This is consistent with our finding that order placement is concentrated at or within the quotes.

These remarks suggest that our results from the previous section (about the order book) might be subject to a measurement issue. By computing equally-weighted order books we may have overweighted transient observations. To assess the extent of this problem we compute the *time-weighted* average order book. We find that the time-weighted average depth at the quotes is indeed larger than the arithmetic average (895 shares versus 585). Also the time-weighted average percentage spread (0.36 percent) is somewhat tighter than the arithmetic average (0.4 percent).



**Figure 2. Intraday patterns in trades and orders.** (A) plots, for each of the seven trading hours of the trading day, the empirical frequency of different types of trades. The full line represents large trades. Small dashes represent market orders. Long dashes represent small trades. (B) plots, for each of the seven trading hours of the trading day, the empirical frequency of different types of orders. The full line represents new orders, while the dashed line represents cancellations.

### *B. The Probabilities of Orders and Trades Conditional on the Time of the Day*

Figure 2 shows the intraday pattern in orders and trades. In general, orders and trades exhibit a U-shaped pattern. Market orders, small trades and new limit orders not immediately executed are most frequent in the morning.<sup>29</sup> Large trades are most frequent later in the trading day. The pattern of trades fits the intraday pattern in the depth at the quotes. Small trades occur in the

<sup>29</sup> For the NYSE, Harris and Hasbrouck (1992) also find that the intraday pattern of market and limit orders is U-shaped, with particular concentration in the morning.

morning, when the depth is low, while larger trades occur in the late afternoon, when the depth is large. We offer four different interpretations of this behavior. First, small trades in the morning contribute to price discovery, while large trades tend to occur in the late afternoon, after price discovery has already occurred. Second, fund managers, who are likely to initiate a significant fraction of the large trades, are evaluated with respect to the closing price. Third, the relatively high frequency of small trades in the morning could reflect banks transmitting the small orders from their customers, received (but not processed) prior to the market opening. Fourth, the intraday pattern in trades could reflect strategic investors splitting their orders during the day, and unwinding their remaining exposure as the end of the trading day approaches. This type of behavior is similar to the results obtained in experimental studies of bargaining. For example, Roth, Murnighan, and Schoumaker (1988) find what they call a “deadline effect,” i.e., they observe that a great majority of agreements were concluded near the end of the bargaining horizon. This could stem from asymmetric information: the bargaining parties use the time before the deadline to test one another and find out the reservation value of their opponents. In the case of the Bourse, the information asymmetry could be about the fundamental value of the asset, or about the private values of the agents, reflecting their degree of risk aversion, their inventory position, or the extent to which they are liquidity constrained.

*C. The Probabilities of Orders and Trades, Conditional on the Last Order or Trade*

The frequency of each of the 15 categories of orders and trades conditional upon the type of the previous order or trade is given in Table IV. Table IV is a contingency table (or a transition probability matrix), where each row is a probability vector, summing up to one. The table is somewhat overwhelming, because it displays so many numbers. In the following discussion, in order to focus the analysis we systematically compare the probabilities within each column. Thus we can analyze how the probability of a given event (“the explained variable”) varies as a function of the previous event (“the explanatory variable”). Also to facilitate examination of the table, the three largest numbers in each column are in bold type.

One striking feature of Table IV is that the numbers on the diagonal tend to be larger than the others in the same column: the probability that a given type of order or trade occurs is larger after this event has just occurred than it would be unconditionally (we will refer to this as the “diagonal effect”).<sup>30</sup> For example, large (small) trades on one side of the market are most frequent after large (small) trades on the same side of the market.<sup>31</sup> Similarly, new orders at or away from the quotes on one side of the book are particularly frequent after

<sup>30</sup> We checked, but do not report in detail in tabular form, that this positive serial correlation in the type of orders is pervasive well beyond one lag.

<sup>31</sup> Evidence of positive serial correlation in buy-sell indicators in the Paris Bourse is also provided by Eikeboom and Kempthorne (1992). We examine the broader dynamics of the order flow, including an analysis of order placements and cancellations as well as actual executions.

Table IV  
**Frequency of Orders and Trades, Given the Last Order or Trade**

For the 19 trading days in the period between October 29 and November 26, 1991, for the stocks included in the CAC 40 index at that time, Table IV reports the empirical percent frequency on each of the 15 events, conditional upon the type of the previous event. Each row corresponds to a given event at time  $t-1$ . Each column corresponds to a given event at time  $t$ . Each row can be thought of as a probability vector and adds up to 100 percent. The empirical frequencies are obtained after pooling all stocks. To facilitate interpretation, the three largest numbers in each column are in bold face type.

Application t-1	Appli- cation	Large			Market			Small			Cancel			New			New		
		Buy	Buy	Buy	Buy	Buy	Buy	Buy	Buy	Buy	Bid	Bid	Bid	Below	At	Within	Ask	Ask	Above
Application	0.00	<b>3.56</b>	1.98	13.25	9.45	5.42	6.44	5.93	4.15	2.49	21.53	9.10	4.87	6.19	5.64				
Large buy	<b>2.94</b>	<b>7.29</b>	<b>3.41</b>	15.34	<b>13.05</b>	5.01	5.90	5.21	1.80	1.11	14.39	7.26	4.65	6.83	<b>5.81</b>				
Market buy	1.94	3.20	2.47	<b>17.11</b>	2.14	<b>6.88</b>	<b>11.33</b>	<b>7.92</b>	3.35	<b>6.16</b>	23.49	2.78	2.45	4.84	3.94				
Small buy	2.43	<b>3.71</b>	<b>2.89</b>	<b>20.49</b>	9.67	5.27	6.33	4.02	2.35	1.75	19.77	5.88	4.54	6.20	4.72				
New bid within	2.33	3.19	2.14	13.12	<b>13.62</b>	6.87	<b>9.21</b>	5.22	3.01	1.98	18.58	8.28	2.92	5.42	4.11				
New bid at	1.92	2.23	2.40	14.01	<b>16.52</b>	<b>6.88</b>	7.36	4.93	1.61	0.90	22.64	6.05	3.84	5.30	3.40				
New bid below	1.90	1.90	1.60	11.50	7.50	<b>7.99</b>	<b>18.24</b>	4.45	3.23	2.41	19.99	6.92	3.37	5.58	3.42				
Cancel bid	<b>2.67</b>	2.27	1.71	10.56	12.45	5.21	8.05	<b>9.70</b>	3.80	2.26	19.54	8.70	3.57	5.79	3.72				
Large sell	<b>2.49</b>	0.92	0.93	6.46	8.82	4.54	6.53	<b>5.97</b>	<b>9.84</b>	<b>3.33</b>	<b>23.91</b>	12.57	3.33	4.99	5.37				
Market sell	1.27	2.89	<b>6.33</b>	<b>16.16</b>	2.28	2.92	4.28	3.60	<b>4.82</b>	<b>3.04</b>	<b>29.35</b>	2.21	4.98	<b>9.50</b>	<b>6.37</b>				
Small sell	2.16	1.59	1.60	10.27	6.92	4.78	5.80	4.37	<b>4.82</b>	2.96	<b>33.87</b>	7.88	4.00	5.29	3.71				
New ask within	2.15	2.01	1.87	9.86	9.43	4.03	6.04	4.06	4.44	2.60	22.67	<b>12.61</b>	<b>5.53</b>	<b>7.76</b>	4.94				
New ask at	1.94	1.41	0.97	12.79	6.41	4.81	5.65	3.83	3.00	2.48	23.10	<b>14.74</b>	<b>6.65</b>	7.30	4.92				
New ask above	2.08	2.24	2.15	10.81	7.24	4.12	5.86	3.36	2.81	2.10	21.35	5.85	<b>7.07</b>	<b>19.36</b>	3.60				
Cancel ask	2.48	2.03	1.85	9.95	8.73	4.39	6.10	4.51	4.06	2.13	19.19	<b>13.84</b>	3.95	7.57	<b>9.24</b>				
Unconditional	2.2	2.4	2.1	12.5	9.0	5.3	7.4	4.7	3.8	2.4	24.0	8.3	4.3	7.0	4.8				

new limit orders have just been placed on the same side of the book. A third example is cancellations, which are particularly frequent after cancellations on the same side of the book. Note also that the buy and sell sides exhibit similar effects, as can be visually inferred from the symmetry in the patterns of large numbers that are bold in the table.

The diagonal effect reflects several alternative hypotheses.

- The succession of identical types of orders could reflect strategic order splitting. An example of the latter is the case of a trader willing to buy for noninformational reasons, and splitting his order to reduce market impact. Another example is the case of an insider with positive information about the value of the stock. He repeatedly buys the stock, until his private information is revealed in the prices. Easley and O'Hara (1987) model a situation where sequences of large purchases arise when insiders with positive signals are present in the market. He and Wang (1995) also show that insiders with good news tend to buy repeatedly.
- Alternatively, different traders could be imitating each other. Imitation can arise when certain market participants observe the trades and orders of other market participants, whom they know are likely to be informed. Sarkar (1990) analyzes such "piggy-backing." In his model the broker imitates the trades of his informed client. Anticipating this, the informed agent reduces the sensitivity of his trades to his signal. This gives rise to trading patterns which are observationally similar to order splitting. Consider the case where the insider would have bought a large quantity, in absence of "piggy-backing." In the case of "piggy-backing," the insider only trades a small amount, to reduce information disclosure, and the broker imitates this trade. Hence, a sequence of small trades is observed.
- Finally, traders could react similarly, but successively, to the same events. This hypothesis is consistent with the observation by Bourse officials, that a small number of large traders, either banks or brokers, monitor the market and the performance of the economy and react similarly to their evolutions. The succession of cancellations can be interpreted along these lines. For example, in the event of an information release making the current quotes irrelevant, several traders are likely to cancel their orders quasi-simultaneously.

To separate (to some extent) these different interpretations, we study in the next section of the paper, the time interval between two consecutive similar events. Consider the example of the noninformed agent splitting his order to reduce market impact. He first buys a given limited amount, for example consuming the liquidity outstanding at the ask quote. Then the trader pauses, hoping that additional liquidity will be provided on the ask side of the book. If that does not happen, however, the trader may eventually hit the quotes with another buy order. In that case a sequence of two purchases separated by a long time interval is observed. Hence, long time intervals would be consistent with the order splitting hypothesis. On the other hand, short time intervals would be consistent with quasi-simultaneous and similar reactions.

In the case of new limit orders within the quotes, the diagonal effect has a distinct interpretation. New limit orders within the quotes on one side of the market are most frequent after the placement of new limit orders at or within the quotes on the same side of the market. This reflects the undercutting (or outbidding) behavior of traders competing to supply liquidity.<sup>32</sup> Such undercutting actually occurs in sequences, where limit orders within the quotes are placed repeatedly.<sup>33</sup>

The frequent succession of new orders, at or away from the quotes, observed in the table can reflect instances when several agents intended to undercut the current quote. For example, suppose that at time  $t$ , the bid and ask quotes are 149.1 and 150.9, respectively. Suppose the bid-ask spread is relatively large because the ask is particularly high. The agents react quickly to this favorable order placement opportunity. Shortly after time  $t$ , several agents place new orders to sell, slightly below 150.9. Because they act quasi-simultaneously, none of these agents can observe the quotes submitted by their competitors. As a result the agents may be uncertain as to their rank and priority in the order book. To see more clearly how this can generate patterns similar to those documented in Table IV, consider the following example. Assume 3 agents place orders to sell, each one of them intends to undercut the current ask: agent 1 places an order to sell at 150.7 at time  $t + \epsilon$ , agent 2 places another order to sell at 150.8 at time  $t + 2\epsilon$ , and agent 3 places an order to sell at 150.8 at time  $t + 3\epsilon$ . In our classification this generates the following sequence: the first order is within the quotes, the second is above the quotes, the third order is also above the quotes. This illustrates that our classification scheme captures the outcome of investors' strategies, which may differ from their intentions. In this context, with price discreteness and unobservable quotes, the agents may find it optimal to select their quotes using mixed strategies. This is reminiscent of the mixed strategy equilibria analyzed in Bernhardt and Hughson (1993a) in the case of market makers and discrete prices.

New orders within the quotes on the ask (bid) side of the market also are particularly frequent after large sales (purchases). This could reflect information effects. As a result of the negative signal conveyed by the large sale, the order book is shifted downward. Such shifts are *not* observed after small trades or market orders. The downward shift in the book has two components, the decrease in the bid, merely reflecting that the large sale consumed the liquidity offered at that quote, and the subsequent decrease in the ask, reflecting the reaction of the market participants to the large sale. The decrease in the bid could be a transient decrease in the liquidity on this side of the book, or a permanent information adjustment. In our one-lag analysis, we cannot differentiate the two hypotheses. In contrast to the behavior of the bid, the decrease in the ask is likely to reflect the information effect. This behavior generates

<sup>32</sup> This Bertrand price competition is a basic feature in models of competition for the supply of liquidity, as in Ho and Stoll (1983), Kyle (1985), or Biais (1993).

<sup>33</sup> We checked the persistence of new orders within the quotes, by computing frequencies conditional on more than one lag of order flow. For brevity, these runs are not reported in the paper.

positive serial correlation for changes in the midquote. The asymmetry in the response of the ask and bid at the next point in event time illustrates the distinctive pricing consequences of the liquidity and informational hypotheses.<sup>34</sup>

Another feature of Table IV that is consistent with information effects is that cancellations on the bid (ask) side are relatively frequent after large sales (purchases). This could reflect that large sales convey negative information about the value of the stock, making the agents less willing to buy, while large purchases are a positive signal, making it less attractive to sell. Note that this pattern of cancellations is not observed after small trades.

Exceptions to the diagonal effect are illustrated by the reaction to market orders.

- Cancellations on the bid (ask) side of the book are particularly frequent after market buy (sell) orders. As suggested to us by Bourse officials, this is consistent with an investor using a market order to investigate whether there is a hidden order in the book and then cancelling his order in the absence of a hidden order that is hit. In this circumstance the investor is willing to trade at the price of the prospective hidden order, but unwilling to remain exposed to adverse execution at this price level.
- Further, market orders to buy (to sell) are most frequent after market orders to sell (to buy). This is because they provide liquidity to the previously placed market order and restore the initial bid-ask spread and midquote. The agent who places the second market order provides liquidity, while obtaining execution and priority at a favorable price as a reward. Similarly, small trades on one side of the market are relatively more frequent after market orders on the other side of the market. To the extent that market orders frequently attract liquidity, the market does not perceive them as informationally motivated. Indeed, these are not the most aggressive types of orders available to investors (unlike the convention for market orders on the NYSE).
- As noted above, “applications” permit crossing large trades within the bid and ask quotes. An alternative to applications would be to use the block trading procedure. However, after a block, the book must be cleared at the block price. Consequently, the two parties of the application are better off i) clearing the book first, by submitting a large order, hitting the quotes in the book, and ii) then placing an “application.” Consistent with these remarks we find that “applications” are particularly frequent after large trades or cancellations.

<sup>34</sup> However, the decrease in the ask quote following the large sale could also reflect order splitting due to the limited supply of liquidity in the book. For example, an agent with a long position could initially hit the bid quote, and then place an aggressive ask quote in order to unwind the rest of his position. The improvement in the ask quote after the large sale also could stem from the purchaser placing an aggressive ask quote to profitably sell his newly acquired position. However, the magnitude of transaction taxes relative to the size of the spread makes this implausible.

**Table V**  
**Frequency of Order Revisions and Trades,**  
**Given the State of the Book**

For the 19 trading days in the period between October 29 and November 26, 1991, for the stocks included in the CAC 40 index at that time, Table V reports the empirical percentage frequency of the orders or trades, conditional on the previous state of the book. Each row is a probability vector (adding up to 100 percent) conditional on the previous state of the book. The latter is summarized by the magnitude of the bid-ask spread and the depth at the quotes. For each stock, the spread (depth) is defined to be large, if it is larger than its time-series median. To provide a benchmark, the last row gives the unconditional frequency of each order or trade.

	Appli- cations	Buy	New Bid Within	New Bid At	New Bid Below	New Cancel Bid	New Sell	New Ask Within	New Ask At	New Ask Above	New Cancel Ask
Panel A: Large Spread											
Small Depth	2.1	13.1	11.65	6.5	8.6	4.6	18.1	10.9	5	7.25	4.1
Large Depth	2.2	12.8	14.5	5.1	7.15	4.75	24.8	13.5	4	6.6	4.4
Panel B: Small Spread											
Small Depth	2.15	20.7	4.6	5	7.5	4.5	35.3	4.3	4.35	7.3	4.5
Large Depth	2.2	21.25	5.45	4.5	6.3	5.1	34.85	4.8	4	6.8	4.8
Unconditional	2.2	18	9	5.3	7.4	4.7	30.2	8.3	4.3	7	4.8

- Note that both these events lead to an increase in the spread, leaving “more room” for the prearranged trade. This finding may reflect that the agents strategically widen the spread, by hitting or cancelling the quotes, before putting through the application.
- The discussion above involves comparison between the unconditional frequency of orders and trades and their frequency conditional on the type of the last order or trade. For each stock and each type of event we run a  $\chi^2$  test for the statistical significance of the difference between the conditional and the unconditional probability. Except in the case of applications, the differences are significant at the 5 percent level for at least 25 stocks of 40.

#### *D. The Order Flow, Given the State of the Book*

Table V reports the probability of occurrence of the different types of orders and trades, conditional on the previous state of the order book.<sup>35</sup> For simplicity we do not consider the 15 categories of events defined above. Rather we consider only 11 categories of events, by aggregating small purchases and large purchases with market buy orders, as well as small sales and large sales

<sup>35</sup> We provide a simple descriptive analysis and economic interpretation of the Paris Bourse data. An alternative route is taken by Domowitz and Wang (1994) who provide a detailed specification of the dynamic relationship between the order book and order flow, but do not study market data.



with market sell orders.<sup>36</sup> The state of the book is characterized by the size of the bid-ask spread and the number of shares offered or demanded at the quotes (the depth at the quotes). The observations are classified into four categories according to whether the spread is larger or smaller than the time-series median for the given stock and whether the depth at the quotes is larger or smaller than the time-series median for the given stock. The two main features of the table are the following:

First, trades are relatively more frequent when the spread is tight, whereas new orders inside the quotes are relatively more frequent when it is large. Such order placement offers liquidity when it is scarce and consumes it when it is plentiful. This behavior is consistent with the theoretical analyses of Foucault (1993) and Sandas (1994).

In addition to these liquidity effects, that new orders within the spread are particularly frequent when the spread is large could simply reflect random order placement. The placement of new orders within the spread cannot result only from this randomness, however. This is suggested, for example, by our finding in the previous subsection that sequences of new orders within the quotes reflect undercutting or overbidding by traders competing to supply liquidity to the marketplace.<sup>37</sup>

Another feature of the order flow that is not likely to stem from randomness is that new orders within the bid-ask spread are more frequent when the depth at the quotes is large, whereas new orders at the quotes are more frequent when the depth at the quotes is low. This could reflect the price to probability of trade tradeoff between undercutting the best quote to obtain time priority and queuing up at the current quote. When the depth at the best ask quote is large, new limit sell orders at this price are unlikely to be executed. Consequently, traders might be better off undercutting the best ask, by placing limit sell orders within the spread. The impact of the depth on the placement of orders within the quotes is particularly marked when the spread is large, in which case new orders within the spread are an attractive alternative. The depth at the quotes has little impact on the probabilities of purchases and sales, which are not affected by priority issues.

The sensitivity of price undercutting to the current state of the book reflects both competition among suppliers of liquidity on the same side of the book, and the desire to elicit order flow from the other side of the market. The sensitivity of undercutting to the depth at the quotes is more specifically related to the competition from other traders on the same side of the market.

Liquidity effects discussed in this subsection and the previous one have implications for the time-series behavior of such variables as the quotes, the spread and the midquote:

<sup>36</sup> This simplification was suggested by the referee, because large trades, market orders, and small trades did not lead to economically significant patterns.

<sup>37</sup> Additional evidence that the placement of new orders within the spread is not purely random is provided in the next section, which analyzes the timing of orders.

- That new orders tend to be placed within the quotes when the spread is large generates mean-reversion in the bid-ask spread. This suggests that increases in the spread are not permanent but transient changes, due to liquidity shocks.<sup>38</sup>
- That market buy (sell) orders tend to occur after market sell (buy) orders generates negative serial correlation in the changes in both the ask and the bid quotes.

Assuming a constant spread, that trades lack information content and that the midquote is a martingale, Roll (1984) shows that bid-ask bounce in transaction prices induces negative serial correlation in transaction returns. In contrast with these assumptions, our empirical analysis suggests that there is negative serial correlation in the quote changes and in the spread, reflecting the dynamics in the supply of liquidity on both sides of the market. Also, as discussed above, information effects are consistent with *positive* cross-serial correlation between changes in the ask and bid quotes. Because of the contrast between the implications of the liquidity, transaction costs and information effects, there is additional information in analyzing the dynamics of the ask and bid quotes jointly rather than averaging them through the midquote.<sup>39</sup> Our analysis also suggests that time-series studies of the dynamics of quotes, and in particular of their serial correlation, could be conditional on the types of orders observed in the market.

As in the previous subsection, we run a  $\chi^2$  test of the significance of the findings in Table V. For 39 of 40 stocks, the null that the conditioning variables (the state of the book) did not affect the probability of occurrence of the orders or trades is rejected at the 5 percent level.

### *E. Three Examples of Bid and Ask Quotes and Transaction Price Sequences*

We illustrate the remarks of the previous subsections by considering plots of trades and quotes for a particular stock (Elf-Aquitaine) on a particular day (the ninth trading day in our sample).<sup>40</sup> Figure 3 *a* plots the best bid and ask quotes as well as the transactions prices between 10:50 A.M. and 11 A.M. Initially, the bid is at 435.5, and the ask is at 436. The relative bid-ask spread is quite tight. Until 10:53 a.m. there is a sequence of sales, some of them “large sales” consuming all the liquidity at the bid, and resulting in a decrease in the bid. One of the initial sales is a market sale, and results in a simultaneous decrease in the ask and bid quotes. As a result of this sequence of orders, the spread widens, the bid drops to 432.6 and the ask to 435 (the change in the ask comes from the market sell order). The change in quotes is more pronounced on the

<sup>38</sup> Further evidence that large spreads are transient is provided in the next section, where the timing of orders is analyzed.

<sup>39</sup> Other phenomena analyzed in this section have implications for the behavior of the midquote. For example, the persistence in the types of events occurring in the market place (the “diagonal effect”) tends to generate positive serial correlation in the midquote.

<sup>40</sup> The plot of transaction prices for Alcoa on a single trading day in Glosten and Harris (1988) is another example that this type of representation can illustrate various market-microstructure effects.

bid side, where the trades occurred. Shortly before 10:53, the market starts reacting to this decrease in the liquidity on the bid side of the book. Orders to buy are placed. Most of them are new bid quotes, rapidly outbidding each other. As a result, the bid price reverts to its previous location. There is also a market buy order that drives the ask price back to its original location. Eventually, around 11 A.M., the bid and ask prices have reverted close to their original levels. This illustrates both mean reversion in the spread and competition in the supply of liquidity.

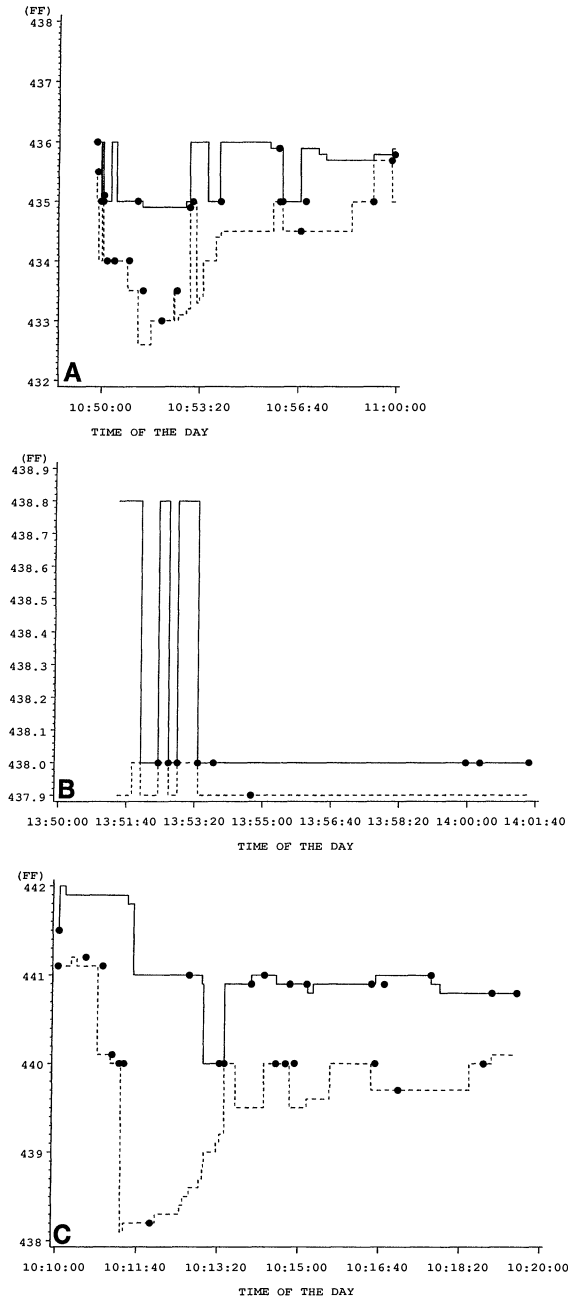
The initial decrease in the bid quote, and increase in the spread between 10:50 and 10:53 are associated with intense trading activity. In contrast, the reversal and stabilization of the quotes between 10:54 and 11:00 is associated with much less trading. This pattern is consistent with the analysis in Easley and O'Hara (1992). The observations between 10:50 and 10:53 are consistent with high trading activity signalling that an insider is likely to be trading, which results in an increase in the spread. In the following observations, between 10:54 and 11:00, because of the decrease in the intensity of trades, the likelihood of insider trading is updated downwards, which leads to a decrease in the spread. The pattern in our figure is not unlike that in Figure 4.b, in Easley, Kiefer, and O'Hara (1993), who provide an econometric analysis of the model in Easley and O'Hara (1992).

Figure 3.b is an illustration of the alternation of market buy and market sell orders discussed in the previous subsection. The initial market buy order drives the bid and ask quotes to artificially high levels. The following market sell order seizes this opportunity to sell at a good price, while restoring the initial liquidity of the book. This sequence of trades is then repeated. Note that although the direction of trades alternates, the transaction price is constant, i.e., there is not bid-ask bounce in transaction prices. This example suggests that the distinction between buyer- and seller-initiated trades could be artificial. Even though one could argue that the whole trading sequence is in fact buyer initiated, the trades are executed alternatively at the ask and at the bid quotes.

Figure 3C is similar to Figure 3A. But in this case the decrease in the bid and ask quotes, following the initial sale, is not fully offset by subsequent behavior of the quotes and spread. In particular, the ask quote stays at (or later in the day below) FF 441. In this case it is likely that the large sale was information motivated. This case illustrates the different ways in which the two sides of the market reflect the information in trades: after the large sale, the bid quote decreases *by construction*, since the liquidity at that price has been consumed by the trade. In addition, the ask side also decreases. This is not a mechanical consequence of the trade, but stems from the placement of new limit ask quotes below the previous best ask, reflecting the downward signal in the sale.

#### IV. The Time Interval Between Orders and Trades

In this section, we investigate the determinants of the time interval between orders and trades. Theory points to at least three specific determinants. First, asymmetric information issues are analyzed by Easley and O'Hara (1992). In



**Figure 3. Transaction prices and bid and ask quotes for Elf-Aquitaine, November 9, 1991.** (A) liquidity effects, undercutting, and mean reversion in the bid-ask spread (between 10:50 and 11:00 A.M.). (B) alternation of market buy and sell orders, and reversion in the spread (between 13:51 and 14:02 A.M.). (C) Information effects and undercutting (between 10:10 and 10:20 A.M.). Dots represent transaction prices, the full line represents the ask quote, and the dashed line represents the bid quote.

their model, insiders are less responsive to the spread than liquidity traders. Hence, high trading frequency signals that insider trading is likely. Second, time priority considerations should affect the frequency of trades. As noted by Harris (1994), and Bernhardt and Hughson (1993a), when the pricing grid is discrete and time priority is enforced, there is a first mover advantage in the supply of liquidity. Consequently, the competing traders monitoring the market have an incentive to place orders as quickly as possible, when liquidity supply is expected to be profitable. Third, the frequency of trades can reflect the clustering of trades, analyzed by Pagano (1989) and Admati and Pfleiderer (1988).

Consistent with the clustering theory, we find that there is a lot of persistence in the time interval between orders or trades. Table VI reports the mean time interval between trades, conditional on the previous time interval being either larger or lower than its time-series median for the stock. The expected time interval after a small time interval is quite small (68.3 seconds), whereas the expected time interval after a large time interval is quite high (128.5). Previous empirical research has argued that intraday patterns (and in particular U-shaped patterns) in the trading activity could reflect clustering as in Admati and Pfleiderer (1988). Our analysis of the time interval between events provides an alternative way of documenting clustering.

To test the significance of this difference in conditional interarrival times we conduct likelihood ratio tests. The conditional average interarrival times we compute are the maximum likelihood estimates of Poisson processes with changing parameters: in state  $s$  the distribution of the time interval until the next event is exponential with parameter  $\theta(s)$ . In the present case, the state is whether the last time interval was long or short. The estimate of the parameter is the empirical average time interval until the next event in state  $s$ . The statistic we use is the ratio of the unconstrained likelihood of the observations to the likelihood under the constraint that parameters are equal across states. This ratio asymptotically follows a  $\chi^2$  distribution, with  $S - 1$  degrees of freedom, where  $S$  is the number of states. The  $\chi^2$   $p$ -values and number of degrees of freedom are given in the last column of Table VI. Equality of conditional expected time intervals is strongly rejected.

Our results could simply capture intraday patterns, however. During inactive periods (as around lunch time), time intervals are repeatedly long, whereas during active trading periods (as between 10:00 and 11:00), time intervals are repeatedly short. To control for this effect we compute the expected time interval after a long or a short time interval, for each of the seven trading hours of the day. We find that the result is robust. For each trading hour, the expected time interval until the next event is lower after a short time interval than after a large one.<sup>41</sup>

<sup>41</sup> The expected waiting time after large and small time intervals are 71.8 seconds versus 49.5 seconds between 10:00 A.M. and 11:00 A.M., 104.1 seconds versus 68.7 seconds between 11:00 A.M. and 12:00 noon, 163.2 seconds versus 99.4 seconds between 12:00 noon and 1:00 P.M., 247.5 seconds versus 145.4 seconds between 1:00 P.M. and 2:00 P.M., 193.0 seconds versus 109.6 seconds between

In order to investigate the implications of the two other theories, i.e., asymmetric information and priority, we analyze in the following subsections the impact of i) the bid-ask spread and ii) the type of the last event, on the time interval until the next event.

*A. The Average Time Interval between Two Orders or Trades, Conditional on the Bid-Ask Spread*

Table VI relates the average time interval between two orders or trades to the size of the spread just after the first event. For each stock, we compute the time-series quartiles of the distribution of the spread. We use these statistics to sort the observations into four categories: large spread, medium-large spread, medium-small spread, or small spread. The average time interval is lowest when the spread is very large (77.4 seconds). The  $\chi^2$  test strongly rejects equality of the four average time intervals.

When the spread is large, new orders within the quotes occur relatively more quickly than other types of orders. This provides additional evidence against the hypothesis that random order placement mechanically results in frequent orders within the spread when the latter is large. Rather, our results point to the following interpretation. When the spread is large (after large liquidity shocks), traders quickly place orders within the best quotes to supply liquidity at relatively advantageous prices and to obtain time priority. In this case the following behavior is observed for the bid-ask spread: after transient increases, the spread rapidly reverts to its original level.

*B. The Distribution of the Time Interval between Two Orders or Trades, Conditional on the Nature of the First Event*

Table VI also reports the average waiting time until the next event, after each of the 15 categories of events or trades defined in the previous section.

The shortest average time interval (approximately 68.5 seconds) is after market sell orders. The time interval after market buy orders is also relatively small (80.5 seconds). After a market sell (buy) order the ask (bid) is unusually low (high). The competing traders who monitor the market, quickly seize this opportunity to trade at a favorable price.

The second lowest expected time interval is after large trades (72.8 after large purchases, 70.5 after large sales). This may be because large trades are reactions to strong informational signals (or are themselves strong informational signals) calling for quick reaction from the market. The association between high trading frequency and the likelihood of insider trading is consistent with Easley and O'Hara (1992).

The short time interval after large trades might reflect that i) large trades widen the spread and ii) the market reacts quickly to large spreads. To determine if such "spurious correlation" is driving our results, we compute the

2:00 P.M. and 3:00 P.M., 120.7 seconds versus 58.9 seconds between 3:00 P.M. and 4:00 P.M., and 100.7 seconds versus 58.3 seconds between 4:00 P.M. and 5:00 P.M.

Table VI  
Expected Time Interval Until the Next Order or Trade

For the 19 trading days in the period between October 29 and November 26, 1991, for the stocks included in the CAC 40 index at that time, Table VI reports the average waiting time (in seconds) until the next event (order or trade) conditioning on:

- the type of the last event,
- or whether, after the last event, the bid-ask spread was below its time-series 1st quartile, between the 1st quartile and the median, between the median and the 3rd quartile, or above the 3rd quartile.
- or whether the last time interval between 2 events was larger or smaller than its time-series median.

The conditional averages are computed after pooling all stocks in the sample. However, the quartiles used to determine the conditioning variables are computed on a stock by stock basis.

Conditioning Variable	Expected Time	$\chi^2$ Test
Unconditional	98.04	
Large spread	77.361	$\chi^2 = 4,557.08$ $p = 0.00$ d.f. = 3
Large medium spread	99.733	
Small medium spread	107.133	
Small spread	107.643	
Large previous time interval	128.49	$\chi^2 = 24,326.19$ $p = 0.00$ d.f. = 1
Small previous time interval	68.249	
Large buy	72.8	$\chi^2 = 31,890$ $p = 0.00$ d.f. = 14
Market buy	80.5	
Small buy	107.6	
New bid within	93	
New bid at	92.8	
New bid below	98.6	
Cancel bid	82.5	
Large sell	70.5	
Market sell	68.5	
Small sell	105.6	
New ask within	104	
New ask at	114.3	
New ask above	100.9	
Cancel ask	73.6	
Application	112.9	

average time interval, conditioning jointly on the size of the spread and the type of the last event. We find that our results are robust, i.e., the expected time interval is lower after large trades than after other trades (except market orders) whether the spread is large or not.

Again, the  $\chi^2$  test strongly rejects equality across conditional averages.

C. The Distribution of the Time Interval between Specific Sequences of Events

Table VII reports the average time interval between two specific orders or trades. Cancellations follow each other quickly (the average time interval

**Table VII**  
**Mean Time Between Two Specific Events**

For the 19 trading days in the period between October 29 and November 26, 1991, for the stocks included in the CAC 40 index at that time, Table VII reports the average waiting time (in seconds) between two events (orders or trades). The averages are computed after pooling all stocks in the sample.

Sequence of Events	Average Time
Large buy (sell), large buy (sell)	67.1
Small buy (sell), small buy (sell)	95.2
Market sell (buy), market buy (sell)	73.1
New ask (bid) within, new ask (bid) within	86
Large spread, new ask or bid within	74.6
Cancel bid (ask), cancel bid (ask)	55.5
Market buy (sell), cancel bid (ask)	66.25
Unconditional	98.04

between such events is 55.5) reflecting investors' concerns about adverse execution.

The mean time interval between two large trades is also rather small (67.1 seconds). As discussed above (Section III.C), this suggests that the reason why large trades tend to follow each other is not order splitting. Rather, the short time interval between large trades could reflect imitation (Sarkar (1990)), similar but successive reactions by different agents to the same events, or the association between large trades, private information, and high trading frequency, see Easley and O'Hara (1987) and (1992). In contrast, small trades follow each other more slowly (95.2 seconds). So persistence in small trades could in part reflect order splitting.

Market buy (sell) orders following market sell (buy) orders do so relatively quickly (73.1 seconds). As discussed in the previous section, market buy orders following market sell orders take advantage of the unusually small spread and low ask price, provide liquidity to the first market order, and restore the prior state of the book. That such orders are placed very quickly in the book suggests that agents monitor the book and quickly provide liquidity when it is needed and are rewarded by attractive price and priority conditions.

Cancellations on the ask (bid) side following market sell (buy) orders do so relatively quickly too. The average time interval between such events is 66.25. We noted in the previous section that such sequences of orders occur because investors (i) place market orders to test if there exist hidden quantities at the best quotes and then (ii) cancel the amount that was not filled to avoid further adverse execution. That those cancellations occur quickly reflects the concern of investors about such adverse executions.

New orders within the quotes following new orders within the quotes take place rather quickly (86 seconds). This reflects that competing traders under-



cutting each other do so quickly to gain time as well as price priority. This is consistent with Bernhardt and Hughson (1993a), who analyze the first mover advantage to liquidity suppliers in presence of price discreteness and time priority. Also, traders are eager to post their orders quickly, before the other side of the market hits the quote offered by this side of the market.

Another similar piece of evidence is the finding that new orders within the quotes are placed quickly when the spread is large. In this case, the average time interval is 74.6 seconds. This is consistent with our previous remarks that i) increases in the spread are likely to be transient liquidity events, and ii) competing traders quickly place orders when the spread is large.

## **V. Comparison of the Paris Bourse with Other Limit Order Markets**

The Paris Bourse, the NYSE, and the Tokyo Stock Exchange rely (at least partially) on limit orders for the supply of liquidity. Our analysis of the Paris Bourse provides some insights about the supply of liquidity in limit order markets consistent with results obtained for the NYSE and the Tokyo Stock Exchange. For example, using Table IX in Harris and Hasbrouck (1992) the empirical frequencies of different types of orders conditional on the size of the spread can be computed. Comparing these frequencies to those we obtained for the Paris Bourse shows that in both markets limit orders within the quotes are relatively more frequent when the spread is large, while limit orders matching the quotes are relatively more frequent when the spread is tight. Another feature common to the NYSE, the Paris Bourse, and the Tokyo Stock Exchange is that market orders can be “stopped” rather than immediately executed, either automatically as in Paris, or depending on the judgment of the specialist, as in Tokyo or New York. In the Paris Bourse, market orders stopped at the quotes often attract liquidity from the other side of the market (see, for example, Table IV and its discussion in Section III.C). For the NYSE, Harris and Hasbrouck (1992) find that market orders are often stopped by the specialist and executed inside the quotes. For the Tokyo Stock Exchange, Hamao and Hasbrouck (1995) show similarly that orders are often stopped by the *saitori*.

These results suggest the existence of potential liquidity supply, not available within the limit order book. The following interpretation can be offered. For example, some agents who are willing to buy or sell do not place their orders in the book immediately, perhaps because they are afraid of adverse execution or are reluctant to reveal their willingness to trade. Instead, they monitor the market, waiting for favorable opportunities to hit the quotes or place orders. Such opportunities arise when the spread is large or market orders have been stopped.

We also find that the order flow exhibits a large degree of positive serial correlation. This is consistent with positive autocorrelation in trade direction observed for the NYSE and the TSE (see Hasbrouck (1988) and Hamao and Hasbrouck (1995)). Hamao and Hasbrouck (1995) note that in New York this positive autocorrelation could reflect the intervention of the specialist or the discreteness of the pricing grid. But they also note that the intervention of the

specialist cannot be the only factor, since positive autocorrelation is also observed in Tokyo where there is no specialist in charge of enforcing price continuity. Our results confirm this. Also, strong positive autocorrelation is observed in Paris for stocks for which the pricing grid is much tighter than in New York. Consequently, discreteness cannot be the major cause of this phenomenon. In the previous sections, we offered alternative interpretations (e.g., order splitting and imitation) that could apply to New York and Tokyo as well as to Paris.

The Paris Bourse differs from the NYSE and the TSE in other respects, however. First, Paris is much more transparent than Tokyo and New York. In Paris the five best limit orders on each side of the book are widely disseminated. In New York only the bid-ask quotation is electronically disseminated to traders other than the specialist. In Tokyo, only the members' lead offices and the booth can observe the orders, and they are required not to disseminate this information. Second, in Paris execution is automated and depends on rules, while in Tokyo and New York execution is not automated, and is left (to some extent) to the discretion of the specialist. This results, in particular, in less strict enforcement of time priority in Tokyo and New York than in Paris. We expect therefore that the behaviors which we observe in Paris, and attribute to the quest for priority, should be less pervasive in Tokyo and New York.<sup>42</sup>

Finally, comparing our results and those of Hamao and Hasbrouck (1995) points to some ambiguity in the market reaction to large trades. We find that after large purchases (sales), cancellations on the ask (bid) side are frequent. In Tokyo, Hamao and Hasbrouck (1995) find that quotes tend to revert to their original locations after large trades. The ambiguity in the empirical results may reflect the ambiguity in the theoretical results in Glosten (1994). In the interpretation of his Proposition 3, Glosten notes that it is not necessarily the case that offers need to be cancelled after large purchases. Of course, the theoretical framework in Glosten (1994) is based upon a one-period model, whereas market data is generated in a dynamic world. Alternatively, different results may reflect that large trades are a stronger informational signal in Paris than in Tokyo. In Paris large trades are sure to execute and bear significant price impact, and thus express a strong eagerness to trade, while in Tokyo they are somewhat insured against the risk of large price impacts by the possibility that the *saitori* will stop them.

## **VI. Conclusion**

This article is an analysis of the order book and the order flow in the Paris Bourse. To perform this analysis, we use the rich information flow, also available in continuous time to market participants. We focus on the particular institutional features of the market, i.e., the limit order book, the strict en-

<sup>42</sup> Examples of such observed behaviors are that i) limit orders within the quotes are particularly frequent when the depth at the quotes is large, and that ii) when the spread is large, traders undercut each other by placing successive new limit orders within the quotes.

forcement of priority rules, and the treatment of market orders. We analyze the intertwined dynamics of the order flow and order book.

Our analysis delivers some insights on price formation and the supply of liquidity in a transparent, computerized, limit order book, and on the role of priority considerations in this setting. Our results are consistent with the presence of limit order traders monitoring the order book, competing to provide liquidity to the market when it is needed and rewarded, and quickly seizing favorable trading opportunities. Limit order traders tend to undercut one another *quickly* when providing liquidity, and to place orders within the quotes when the depth at the quotes is large, to gain time priority. We also document different ways in which bid and ask quotes impound the information content of large trades in a limit order market. For example, after a large sale (a negative informational signal), the bid quote is adjusted downward mechanically, because the large trade consumed the liquidity at the bid, whereas the ask quote is frequently lowered next, as the market adjusts its expectations downward.

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