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Traders' choice between limit and market orders: evidence from NYSE stocks[☆]

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Abstract

In this paper, we examine a trader's order choice between market and limit orders using a sample of orders submitted through NYSE SuperDot. We find that traders place more limit orders relative to market orders when: (1) the spread is large, (2) the order size is large, and (3) they expect high transitory price volatility. A rise in informational volatility appears neither to increase nor decrease the placement of limit orders. We also find that a rise in lagged price volatility decreases the size of spread, which is driven by the increase in the placement of limit orders.

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1. Introduction

When making a trading decision, traders can choose to post limit orders and supply liquidity to the market, or place market orders and consume liquidity. The key differences between the two types of orders are the probability of execution and

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the price at which each is to be executed. While limit orders are stored in a limit-order book to await execution, market orders are executed with certainty at the posted prices in the market. Thus, traders face the following dilemma when making a decision about which type of order to choose. With a limit order, if a trade occurs, the trader will execute it at a price more favorable than that of a market order. However, there is a risk that the limit order will not be executed. Furthermore, because the limit-order prices are fixed, the trader faces an adverse selection risk due to the arrival of new information. Limit-order traders are more likely to be executed at a loss when their orders are mispriced than when they are not. The tradeoff between the execution probability, the transaction price, and the risk of adverse selection should play a key role in a trader's decision as to which type of order to use.

Several papers have empirically examined traders' order choice. [Keim and Madhavan \(1995\)](#) provide evidence related to the institutional trader's choice of order type. They show that liquidity traders such as indexers are likely to use market orders, but that informed traders whose information value decays slowly tend to use limit orders. [Biais et al. \(1995\)](#) examine the interaction between the order book and order flow in the Paris Bourse. They show that traders place limit orders when the bid–ask spread is large and the order book is thin. [Harris and Hasbrouck \(1996\)](#) compare the performance of market and limit orders submitted through the NYSE SuperDot. They show that limit orders placed at or better than the prevailing quote perform better than market orders. [Chung et al. \(1999\)](#) examine the intraday variation in spreads established by limit-order traders and show that more investors enter limit orders when the spread is wide. Other recent papers that have documented how limit-order trading reacts to market conditions include [Hollifield et al. \(1999\)](#), who show that changes in the relative profitability of limit and market orders are important for explaining the empirical variation in order submission rates in the Stockholm Stock Exchange; [Goldstein and Kavajecz \(2000\)](#), who find dramatic shifts in traders' willingness to place limit orders during extreme market movements in the NYSE; [Sandas \(2000\)](#), who shows that the depth in the limit-order book is time-varying in the Stockholm Stock Exchange; and [Hollifield et al. \(2001\)](#), who analyze the costs and benefits of providing and using liquidity in the Vancouver Stock Exchange.

Motivated by several theoretical papers, we focus on the impact of price volatility on traders' order choice.¹ [Foucault \(1999\)](#) provides a model of price formation and order placement decisions in a dynamic limit-order market. His main finding is that the price volatility is a main determinant of the mix between market and limit orders. When the asset volatility increases, market-order trading becomes more costly as limit-order traders ask for a larger compensation for the risk of being picked off in markets with high volatility. As a result, more traders find it optimal to submit limit

¹Cohen et al. (1981), Glosten (1994), Harris (1994), Kumar and Seppi (1994), Chakravarty and Holden (1996), Seppi (1997), Parlour (1998), Parlour and Seppi (1998), Viswanathan and Wang (1998), and Foucault (1999) develop equilibrium models of the limit-order book and examine the various aspects of limit-order trading.

orders. An implication of his model is that the proportion of limit orders in the order flow increases with the price volatility.

Handa and Schwartz (1996) and Handa et al. (1998) model the choice between limit and market orders and show that the choice depends on the trader's belief about the probability of adverse selection. That is, the trader's decision depends on whether his transaction is being executed against an informed or an uninformed trader. Handa and Schwartz (1996) show that transitory volatility attracts limit orders more than market orders as the gains from supplying liquidity exceed the potential loss from trading with informed traders.²

We examine the impact of price volatility on the order flow using the New York Stock Exchange's TORQ dataset. Consistent with the predictions of theoretical limit-order trading models, we find that a rise in price volatility is followed by an increase in the placement of limit orders. We note that the attractiveness of limit orders relative to market orders should be greater when the spread is large. This is because traders are more willing to supply liquidity when the price of liquidity is high. Thus, the impact of volatility on order flow might in fact capture the effect of spread if higher volatility is associated with larger spread. We examine the effect of volatility controlling for the size of spread, and still find that more limit orders follow a rise in price volatility, which suggests that the effect of volatility on order flow is distinct from the effect of spread on order flow.

It is also important to distinguish between volatility arising from noise or liquidity trading and volatility arising from information, as they can have a different impact on order flow. According to Handa and Schwartz (1996), an increase in transitory volatility attracts more limit orders. In their framework, a rise in volatility due to informed trading should discourage the placement of limit orders, as the risk of being picked off by informed traders increases and thus the potential loss from trading with them also increases. In contrast, according to Foucault (1999), more traders find it optimal to submit limit orders, even when the risk of being picked off by informed traders increases. Thus, his model predicts an increase in the placement of limit orders following a rise in information-driven volatility. To test the two competing predictions, we decompose the price volatility into that arising from noise and that arising from information. The result shows that more limit orders than market orders are placed when transitory volatility rises. However, the impact of informational volatility on order flow is indeterminate, a finding that supports neither Handa and Schwartz's nor Foucault's arguments.

Finally, we examine the dynamic relation between spread and volatility and find that spread tends to be tight after high volatility and large after low volatility. This is

²Foucault (1999) and Handa and Schwartz (1996) develop models of liquidity provision in a pure limit-order market with a specialist playing no roles. Seppi (1997) develops a model of liquidity provision in which a specialist with market power competes against a competitive limit-order book. He finds that a hybrid specialist/limit-order market such as the NYSE provides better liquidity to small retail and institutional trades, but a pure limit-order market such as the Paris Bourse offer better liquidity on mid-size orders. However, his model does not explicitly consider the impact of transitory component of prices on liquidity provision.

consistent with the view that high volatility encourages the placement of limit orders, which in turn leads to tight spread.

The paper proceeds as follows. Section 2 develops hypotheses concerning the relation between spread, price volatility, and order flow. Section 3 describes the data used. Section 4 presents empirical results. Finally, Section 5 concludes the paper.

2. Spread, volatility, and traders' order choice

The two most important variables that affect traders' choice between market and limit orders are probably spread and price volatility. The attractiveness of limit orders relative to market orders is greater when the spread is large. This is because traders are more willing to provide liquidity when the price of supplying liquidity is high. Using the data on the Paris Bourse, [Biais et al. \(1995\)](#) find that the conditional probability that investors place limit orders rather than hitting the quotes (i.e., placing market orders) is larger when the spread is large, but they hit the quotes when the spread is tight. In other words, traders provide liquidity when its price is high but consume it when it is plentiful. [Chung et al. \(1999\)](#) also find that in the NYSE, more investors enter limit orders when the spread is wide, and more investors hit the quotes when the spread is tight.

Regarding the consequences of volatility on limit-order placement, the intuition is not as straightforward as it is for spread. On the one hand, a rise in volatility leads to an increase in limit-order placement. This is because, all other things being equal, the greater the volatility, the greater the probability of a limit order being executed. However, this argument is unsatisfactory as it assumes that volatility reflects only noise in prices and is unrelated to public or private information flows about fundamental values. One must therefore take into account the fractions of volatility corresponding to information flows and the adverse selection argument, first made by [Copeland and Galai \(1983\)](#) and related to [Kyle \(1995\)](#) and [Glosten and Milgrom \(1985\)](#).

Consider a world where transaction prices move solely in response to information. In this world, the placement of limit orders is clearly unattractive because they have option features.³ A trader who submits a limit buy (sell) order provides the market with a free put (call) option. When the underlying value of the asset moves against the trader who submits a limit order, the limit order will be executed and the trader loses. When the value of an asset moves in favor of the trader, a limit order will never be executed. For instance, consider a trader who submits a limit sell order at \$30. If information moves the underlying value of the stock to \$31, the limit sell order will be executed. Thus, the trader loses a dollar. If information moves the underlying value of the stock to \$29, then the limit sell order will never be executed. Therefore, the higher the volatility arising from information flows, the less attractive are limit orders.

³[Copeland and Galai \(1983\)](#) are the first to note the option characteristic of limit orders.

Handa and Schwartz (1996) examine the rationale and profitability of limit-order trading. In their model, traders' choice depends on the probability that the limit order is executed against an informed or a liquidity trader. While executing limit orders against a liquidity trader is profitable, executing orders against an informed trader is undesirable. The liquidity-driven price volatility will attract public traders to submit limit orders rather than market orders. This is because the gains from supplying liquidity increase as transitory volatility increases. By testing the prediction of Handa and Schwartz (1996) using data from the Stock Exchange of Hong Kong, Ahn et al. (2000) find that investors submit more limit sell (buy) orders than market sell (buy) orders if volatility arises from the ask (bid) side. However, they implicitly assume that their measure of price volatility is transitory and do not separate the fraction of volatility corresponding to information flows.

Another important prediction of Handa and Schwartz (1996), which has not been tested, is that a rise in volatility due to informed trading discourages the placement of limit orders. This is because the risk of being bagged by informed traders and thus potential losses increases. Foucault (1999), however, predicts just the opposite. Using a game-theoretic argument, he shows that more traders find it optimal to submit limit orders, even when the risk of adverse selection increases. When the volatility due to informed trading increases, limit-order traders are more exposed to the risk of being picked off by informed traders. For this reason, traders post quotes that are less attractive, which increases the cost of trading. Thus, market-order trading is more costly and so more traders find it optimal to carry their trades using limit orders. This effect of volatility has the implication that the proportion of limit orders in the order flow is positively related to asset volatility. However, in Foucault's model, there are no "noise traders" that trigger transitory volatility, and the model does not predict the impact of transitory volatility on order flows.⁴

In sum, Handa and Schwartz predict that traders will submit more limit orders relative to market orders when they expect a rise in transitory volatility. When they expect a rise in information-driven volatility, they will submit less limit orders than market orders. However, Foucault predicts that traders will submit more limit orders following a rise in information-driven volatility. We will test these predictions in the following sections.

3. Data

We obtain data from the NYSE's trades, orders, reports, and quotes (TORQ) dataset.⁵ It contains records of transactions, orders, and quotes for a sample of 144 NYSE-listed stocks over the three-month period from November 1, 1990 to January 31, 1991. The transaction data include the date and time of the transaction, the transaction price, and the number of shares traded. The order data contain the date and time of order submission, the type of order, and the number of shares submitted.

⁴In his model, heterogeneity of reservation prices for a given asset value generates trading.

⁵See Hasbrouck (1992) for the details of using the TORQ dataset.

The quote data provide information on the date and time of each quote, the bid price, and the ask price.

Among the 144 stocks recorded in the TORQ dataset, we examine the 30 stocks that have the highest frequency of orders submitted during the sample period. The total number of orders submitted for the sample stocks is 842,124 for a number of shares exceeding 1,686 million. Table 1 shows the list of stocks included in the sample and the number of orders submitted for each stock.

Table 1

Frequency distribution of orders by order type for the 30 stocks of the TORQ dataset with the highest frequency of orders

This table presents the frequency distribution of orders by order type. The sample consists of the 30 stocks with the highest frequency of orders from the TORQ dataset. “Number of orders” is the total number of orders submitted during the period from November 1, 1990 to January 31, 1991. Order types consist of “Market order,” “Limit order,” and “Others.” “Others” includes stop, stop limit, market at close, and limit or better order.

Ticker	Number of orders	Order type		
		Market order (%)	Limit order (%)	Others (%)
T	102,736	50.4	45.8	3.7
MO	93,594	45.3	47.2	7.5
GE	86,937	43.3	50.3	6.4
IBM	86,889	44.9	47.0	8.1
BA	69,503	43.7	51.8	4.5
XON	46,679	55.1	39.4	5.5
FNM	36,514	30.7	66.3	3.0
GLX	36,424	32.8	62.2	5.0
FPL	28,276	45.1	51.8	3.2
SLB	22,885	50.4	44.6	5.0
AMD	22,701	29.2	66.6	4.2
DI	19,375	43.0	53.0	4.0
CUE	15,497	28.7	66.8	4.5
FDX	13,403	46.0	44.8	9.2
POM	13,189	38.9	59.0	2.1
CL	12,885	48.1	46.4	5.5
CAL	12,269	15.8	81.4	2.9
WBN	11,902	18.7	77.7	3.5
HAN	11,591	39.3	56.4	4.3
CMY	10,933	47.0	48.5	4.5
CPC	10,887	57.0	38.0	5.0
KR	9,851	43.7	52.1	4.3
EMC	9,361	24.8	68.3	6.9
CYR	9,299	44.7	47.4	8.0
AL	9,127	48.0	48.1	3.9
NSP	8,692	60.7	34.1	5.1
TEK	8,109	48.5	43.8	7.7
SNT	8,030	63.8	29.8	6.4
PCO	7,300	49.2	45.8	5.1
FBO	7,286	54.3	40.7	4.9
Total	842,124	43.7	50.9	5.4

Orders can be classified into two categories based on the time horizon over which each is valid, the day order, and the good-till-canceled order. For each category, there are six types of orders depending on the conditions attached. They are: market order, limit order, stop order, stop limit order, market at close order, and limit or better order. Of the total number of orders submitted, day orders account for 85.6%. Limit orders and market orders are more or less evenly distributed, accounting for 50.9% and 43.7%, respectively. However, the total number of shares submitted is vastly different for limit orders and market orders. Limit orders represent 77.4% of the total number of shares submitted, which suggests that limit orders are generally much larger than market orders.

We restrict our sample for analysis to day market and day limit orders. We analyze only standard day orders since our focus is on how traders choose between market and limit orders on any given trading day.⁶ Our day order sample consists of 661,033 orders, of which 49.8% are market orders and 50.2% are limit orders. The total number of shares in the sample is 1,491 million, of which 82.5% are traded through limit orders and the remaining 17.5% through market orders. The average sizes of the market orders and limit orders are 776 and 3,630 shares, respectively. Orders for less than 1,000 shares account for 54.9% of the total number of orders submitted, but they represent only 7.4% of the total number of shares traded. Orders for 10,000 shares or more account for only 5.7% of the total number of orders submitted, but they account for as much as 46.5% of the total number of shares traded. The sample period covers 63 trading days among which there are two days when the market opening was delayed and one day when the market closed earlier than usual.⁷ Among the 30 sample stocks, the median of the total number of orders for the 63 days is 9,750, and the average number of orders per day per stock is 107.

4. Empirical analysis

4.1. *Intraday variation of market and limit orders*

In our empirical analysis, we will test the theoretical predictions of limit-order trading models regarding the interaction between price volatility, spread, and order flow. However, the theoretical models do not guide us in choosing the length of the time interval in the measurement of variables concerned. We conduct the empirical analysis based on 30-min intervals. We examine later the sensitivity of our results to the choice of time intervals.

Each day, trading hours will be partitioned into thirteen 30-min intervals and one batch auction period. We do not include an overnight interval in our analysis since all orders included in our sample are day orders and there are no good-till-canceled orders.

⁶There are 38,677 nonstandard market orders that are excluded from our sample. These are the orders to which some specific conditions are attached, such as a special settlement.

⁷The market's opening was delayed on November 23, 1990 and on December 27, 1990. The market closed earlier on December 24, 1990.

Fig. 1 shows the intraday frequency of newly submitted orders by 30-min intervals. The intraday order frequency is V-shaped for both market and limit orders. Clearly, the first 30-min time interval after the market opens has the highest frequency of order submissions, and the frequency of order submissions decreases monotonically until the interval of 13:00–13:30 at which time it bottoms out for the day. It then marks an increasing trend until the market closes. Our intraday pattern of order frequency is similar to the results reported by Biais et al. (1995) for the Paris Bourse and to the results reported by Harris and Hasbrouck (1996) for the NYSE.

Although the intraday order frequency is V-shaped for both market and limit orders, the relative proportion of limit orders to the total number of orders submitted shows a very different pattern. While not reported, the intraday pattern of the relative proportion of limit orders decreases monotonically throughout the day once the trading starts. Limit orders account for 56.2% of all orders submitted during the first 30 min after the market opens, the highest such proportion for the entire day. The proportion of limit-order submissions declines throughout the day until it reaches 42.9% during the last 30 min before the market closes, its lowest point of the day. Traders are less likely to submit limit orders when there is little time left until the market closes.

We also compute the mean proportion of limit orders at different times of the day by order size to see whether the size of order has any relation to the choice of order. We partition orders submitted during each trading day into two subgroups by the median of order size and compute the mean proportion of limit orders for each of the

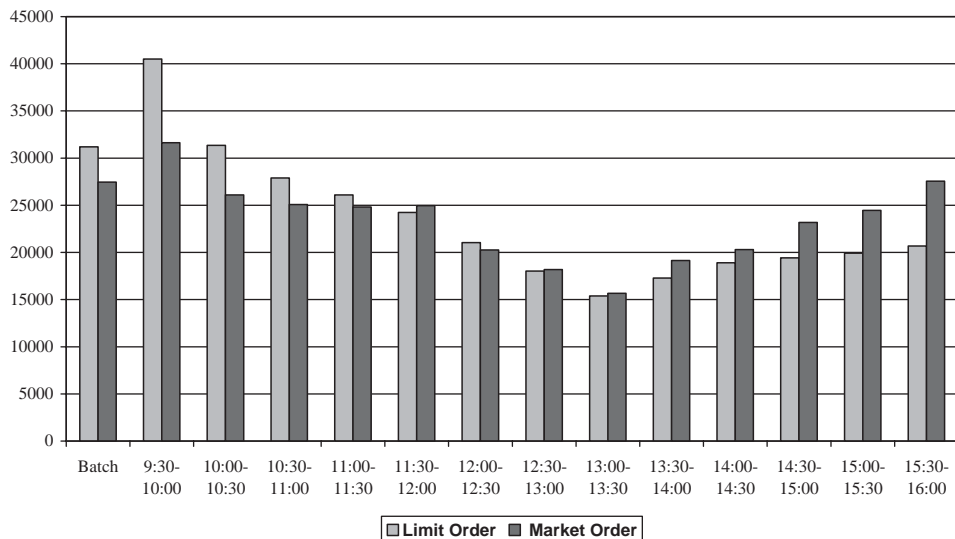


Fig. 1. Intraday frequency of limit and market orders. This graph depicts the average number of orders submitted during the 30-min intervals of each trading day for the 63 trading days from November 1, 1990 to January 31, 1991. The sample consists of standard day orders for the 30 stocks with the highest frequency of orders from the TORQ dataset.

30-min time intervals and for the batch auction. We repeat the procedure for each stock and for each trading day, and average the limit-order proportions across the 30 stocks and across the 63 trading days at different times of the day. Fig. 2 presents the results. What is immediately obvious from Fig. 2 is that limit orders are more likely to be large orders. Throughout the trading day, the mean proportion of limit orders ranges from 66% to 79% when the size of order is large. However, when the size of order is small, it is between 28% and 36%. Put differently, if the size of order is large, traders are more than twice as likely to submit limit orders than market orders. Our evidence underscores the importance of controlling the size of order when one examines the order flow and its relation to other microstructure variables.

4.2. The impact of volatility on the choice of market and limit orders

Theories of limit-order trading predict that a trader is more likely to submit limit orders when he expects high price volatility. We need to measure the expected volatility to validate this claim. If we measure the volatility for the same 30-min interval during which the limit-order proportion is measured, what we have is the ex-post volatility. The volatility should be measured ex-ante to reflect a trader's expectation with regard to future price volatility. However, as it is difficult to formulate a model that measures ex-ante volatility in practice, we use the price volatility for the lagged period as a proxy for an ex ante volatility. By doing so, we

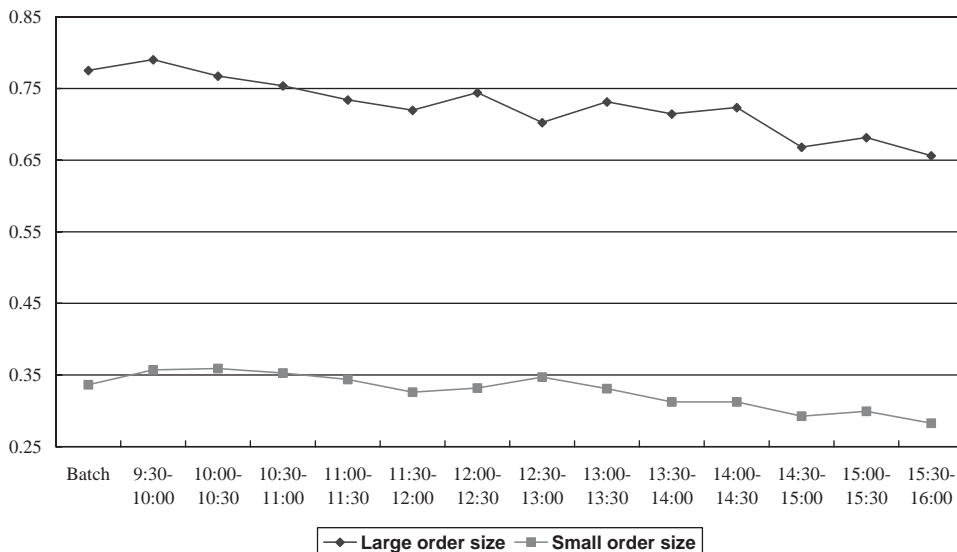


Fig. 2. Mean proportion of limit orders at different times of the day by order size. This graph depicts the mean proportion of limit orders at different times of the day by order size. The sample consists of standard day orders for the 30 stocks with the highest frequency of orders from the TORQ dataset. All orders submitted during each trading day are partitioned into two groups by the median of the order size. Limit-order proportions for each of the 30-min intervals are computed for the two groups and are averaged across the 63 trading days from November 1, 1990 to January 31, 1991, and across the 30 stocks.

implicitly assume that the trader's expectation concerning future price volatility is based on the price volatility he observes during the period immediately prior to the time he submits an order. In other words, we assume that traders form adaptive expectations based on past observations. In a rational expectation model, the typical adaptive expectation scheme is as follows, where η is called the coefficient of adaptation: $E(p_{t+1}) = E(p_t) + \eta(p_t - E(p_t))$. If η is equal to 1, then the adaptive scheme reduces to $E(p_{t+1}) = p_t$ and it corresponds to our case since $Var(E(p_{t+1})) = Var(p_t)$.

We measure the volatility during the time interval t by the high–low price ratio (i.e., highest price during time interval t –lowest price during time interval t)/((highest price + lowest price)/2). The return variance is the most popular measure of the volatility. However, we measure the volatility by the high–low price ratio since there are periods during which there is not a large enough number of transactions. This is particularly true for infrequently traded sample stocks.⁸ For each 30-min trading interval, we compute the volatility and the proportion of limit orders. Then we classify all volatility observations into four quartiles and compute the mean proportion of limit orders for four lagged volatility quartiles. We expect that observations in the first quartile of the lagged volatility induce a higher limit-order proportion than those in the lower quartiles.

Table 2 presents the results regarding the limit-order proportions for each quartile of the lagged volatility. “ t_{14} ” in the table is the t -statistic testing the null hypothesis that the mean proportions of both the first and the fourth quartile are the same. For 27 out of the 30 stocks, the first quartile has a higher proportion of limit orders. For 15 out of 27 stocks, the hypothesis of equal limit-order proportions is rejected at the 5% level or a lower level of significance. On average, the limit-order proportion of the first quartile is 51.5%, while it is 47.8% for the fourth quartile. A comparison between the first and third quartiles yields similar results to the comparison between the first and fourth quartiles. The hypothesis of an equal mean proportion of limit orders is rejected for 15 stocks at the 5% level or a lower level of significance. In all of those 15 stocks, the first quartile has a higher proportion than the third. Traders submit more limit orders when the price is more volatile, particularly for those stocks that have a higher frequency of orders submitted.⁹

We also examine how time variation in volatility affects the order flow. We compute the mean proportions of limit orders by the level of lagged volatility at different times of the day.¹⁰ Since we use lagged volatility as a measure of ex-ante

⁸For the volatility computation, we use only those trades executed on the NYSE. The median of the number of transactions per sample stock during the 63 trading days is 5,621. This translates into 89 trades per day. However, there are many periods during which no transactions occurred since transactions are clustered during a certain period of the day such as the beginning and the end of the day. This is particularly true for less actively traded stocks. For the periods during which there are no transactions, we consider the price volatility to be zero.

⁹In all tables, ticker symbols are presented in the order of frequency of orders (see Table 1). Thus, T is the stock that has the highest frequency of orders in our sample of 30 stocks. FBO is the stock that has the lowest frequency of orders in our sample of 30 stocks.

¹⁰The results are not reported but are available upon request.

Table 2

Mean proportion of limit orders by the level of lagged volatility

This table presents the mean proportion of limit orders by the level of lagged volatility during the 30-min intraday intervals. The proportion of limit orders and the lagged volatility are measured for 30-min intervals of each trading day for the 63 trading days from November 1, 1990 to January 31, 1991. Volatility is measured as the high-low ratio; i.e. (highest price – lowest price)/((highest price + lowest price)/2). The first (fourth) quartile includes the observations in the highest (lowest) 25% of the lagged volatility. + indicates the sample whose third quartile contains less than 25% of observations since volatility was measured at zero in more than 25% of all periods. ++ indicates the sample for which the volatility was measured at zero in more than 50% of all periods, and those are included in the fourth quartile. t_{ij} is the t -statistic that tests whether the mean proportions of limit orders of the i th and j th quartiles are the same. ** and * indicate significance at 1% and 5% levels, respectively.

Ticker	Mean proportion of limit orders for lagged volatility quartiles				t -value for paired mean		
	First quartile	Second quartile	Third quartile	Fourth quartile	t_{14}	t_{13}	t_{24}
T	0.429	0.384	0.354	0.375	4.19**	5.90**	0.73
MO	0.458	0.459	0.433	0.407	4.00**	2.27*	4.15**
GE	0.499	0.469	0.448	0.444	4.73**	4.32**	2.22
IBM	0.455	0.447	0.446	0.451	0.34	0.88	–0.40
BA	0.510	0.497	0.463	0.450	4.78**	3.83**	3.71**
XON	0.400	0.376	0.388	0.343	3.62**	0.82	2.06*
FNM	0.716	0.682	0.701	0.660	4.40**	1.21	1.55
GLX	0.619	0.576	0.578	0.570	2.96**	2.64**	0.31
FPL	0.479	0.388	0.397	0.377	4.75**	3.63**	0.55
SLB	0.475	0.484	0.428	0.424	2.79**	2.47**	3.41**
AMD++	0.523	0.609	—	0.524	–0.04	—	3.87**
DI	0.531	0.497	0.460	0.463	3.12**	3.29**	1.52
CUE+	0.525	0.497	0.506	0.494	1.17	0.44	0.10
FDX+	0.603	0.513	0.622	0.573	1.31	–0.71	–2.59**
POM	0.483	0.444	0.403	0.460	0.84	3.14**	–0.62
CL	0.585	0.542	0.484	0.537	1.87	4.31**	0.17
CAL+	0.647	0.667	0.621	0.637	0.35	0.60	1.20
WBN+	0.769	0.724	0.669	0.715	2.69**	3.54**	0.39
HAN	0.441	0.413	0.475	0.450	0.13	–0.64	–0.72
CMY+	0.526	0.447	0.535	0.458	2.53*	–0.29	–0.39
CPC	0.431	0.399	0.374	0.327	4.15**	2.21*	2.77**
KR+	0.494	0.411	0.525	0.481	0.47	–0.95	–2.41*
EMC+	0.665	0.641	0.592	0.622	1.56	2.63**	0.63
CYR+	0.551	0.573	0.458	0.465	3.23**	2.15*	3.83**
AL++	0.477	0.559	—	0.537	–2.22*	—	0.78
NSP+	0.297	0.251	0.299	0.347	–1.85	–0.05	–3.57**
TEK++	0.510	0.492	—	0.485	0.81	—	0.24
SNT+	0.362	0.358	0.239	0.331	1.22	2.89**	1.03
PCO+	0.545	0.460	0.580	0.516	1.06	–0.61	–1.78
FBO++	0.448	0.469	—	0.426	0.75	—	1.40
Average	0.515	0.491	0.480	0.478			

volatility, we lose the first 30-min time interval and present the results from the 10:00–10:30 time interval. The high-volatility observations are those in the first quartile of the lagged volatility and the low-volatility observations are those in the fourth quartile of the lagged volatility. We compute the limit-order proportions of each stock at different times of the day and average them across the 30 stocks and across the 63 trading days. As shown in Fig. 1, the ratio of limit orders relative to total orders is highest during the 10:00–10:30 interval and continues to decrease until the market closes for both volatility groups. Consistent with the results presented in Table 2, at all times of the trading day, the mean limit-order proportion is higher when the volatility is high. It ranges from 57% to 44% for the high-volatility group, but it ranges from 52% to 43% for the low-volatility group. Overall, the results show that traders are more likely to submit limit orders when they expect greater price volatility.

Chung et al. (1999) find that in the NYSE, more investors enter limit orders when the spread is wide, and more investors hit the quotes when the spread is tight. Thus, the impact of volatility on order flow might in fact capture the effect of spread if the increase in lagged volatility results in a larger spread. To examine the effect of spread and volatility on the choice of orders, we compute the limit-order proportions for four subgroups conditional on previous volatility being high or low, and spread being large or small. The high-volatility observations are those in the first quartile of the lagged volatility and the low-volatility observations are those in the fourth quartile of the lagged volatility. The large spread observations are the ones that belong to the top 50% in the spread size and the small spread observations are the ones that belong to the bottom 50% in the spread size. Table 3 presents the results. For most of the sample stocks, one cannot reject the hypothesis that the mean proportion of limit orders for large spreads is the same as that for small spreads. For the group of higher volatility, four stocks have significantly higher limit-order proportions for the large spread and two stocks have significantly higher limit-order proportions for the small spread. For the remaining 24 stocks, the limit-order proportions for the observations of the large spread and the small spread are not significantly different. The results are similar for the group of lower volatility. Six stocks have significantly higher limit-order proportions for the large spread. For the remaining 24 stocks, the limit-order proportions for the observations of the large spread and the small spread are not significantly different. These results seem to suggest that the effect of the spread on the likelihood of limit-order submission is indeterminate.

It is well known that spread and volatility change across time. To examine how time-variation in spread and volatility affects order flow, we compute the limit-order proportions for four groups conditional on previous volatility and spread at different times of day for each stock, and average them across the 30 stocks and across the 63 trading days. Fig. 3 presents the results. What is clear from the figure is that most of the time, the limit-order proportions are highest when volatility is high and spread is large, and that they are lowest when volatility is low and spread is small. It is also apparent that higher volatility is associated with higher proportions of limit orders. A comparison between high-volatility and low-volatility groups when the spread is

Table 3

Mean proportion of limit orders by spread size conditional on volatility

This table presents the mean proportion of limit orders by spread size conditional on volatility. The high-volatility observations are those in the first quartile of the lagged volatility and the low-volatility observations are those in the fourth quartile of the lagged volatility. The large spread observations are the ones that belong to the top 50% in the spread size and the small spread observations are the ones that belong to the bottom 50% in the spread size. The mean limit-order proportion, volatility, and spread size are measured for 30-min intervals of each trading day for the 63 trading days from November 1, 1990 to January 31, 1991. The *t*-statistic tests whether the mean limit-order proportions of the large spread and the small spread are the same. ** and * indicate significance at 1% and 5% levels, respectively.

Ticker	High volatility			Low volatility		
	Large spread	Small spread	<i>t</i> -value	Large spread	Small spread	<i>t</i> -value
T	0.413	0.444	−1.78	0.380	0.377	0.15
MO	0.449	0.467	−1.10	0.431	0.382	2.56**
GE	0.503	0.494	0.55	0.457	0.438	1.12
IBM	0.444	0.466	−1.63	0.461	0.446	0.90
BA	0.505	0.515	−0.58	0.447	0.458	−0.58
XON	0.406	0.394	0.55	0.355	0.332	0.96
FNM	0.705	0.727	−1.42	0.668	0.648	0.97
GLX	0.635	0.602	1.66	0.611	0.544	2.69**
FPL	0.451	0.507	1.92*	0.404	0.343	1.98*
SLB	0.461	0.485	−0.95	0.431	0.422	0.33
AMD	0.660	0.467	5.04**	0.576	0.505	2.69**
DI	0.508	0.556	−1.73	0.470	0.458	0.38
CUE	0.543	0.507	0.89	0.513	0.420	2.67**
FDX	0.620	0.579	1.21	0.560	0.570	−0.34
POM	0.510	0.455	1.47	0.444	0.473	−0.74
CL	0.546	0.622	−2.52**	0.534	0.524	0.25
CAL	0.721	0.608	2.63**	0.641	0.560	2.29**
WBN	0.773	0.764	0.36	0.713	0.673	1.16
HAN	0.503	0.390	3.09**	0.500	0.385	3.08**
CMY	0.580	0.471	2.76**	0.459	0.438	0.58
CPC	0.425	0.438	−0.42	0.253	0.346	−1.39
KR	0.509	0.477	0.78	0.458	0.460	−0.06
EMC	0.646	0.685	−1.11	0.573	0.556	0.39
CYR	0.548	0.552	−0.07	0.451	0.456	−0.14
AL	0.488	0.466	0.49	0.521	0.507	0.42
NSP	0.288	0.304	−0.42	0.296	0.335	−0.96
TEK	0.519	0.499	0.39	0.457	0.449	0.22
SNT	0.321	0.400	−2.05*	0.318	0.326	−0.22
PCO	0.548	0.540	0.21	0.497	0.492	0.13
FBO	0.428	0.467	−0.81	0.394	0.413	−0.54
Average	0.521	0.512		0.476	0.458	

large shows that the former has a higher frequency of limit orders for most of the 30-min trading intervals. A comparison between the two volatility groups when spread is low is even more revealing. For instance, during the 10:00–10:30 time interval, the mean proportion of limit orders is 56% when volatility is large, while the same figure

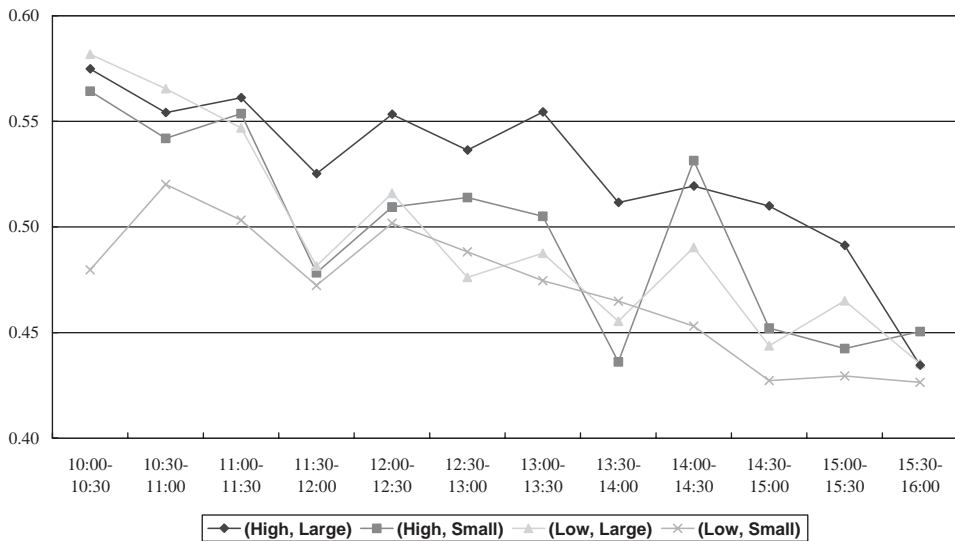


Fig. 3. Mean proportion of limit orders at different times of the day by levels of lagged volatility and spread. This graph depicts the mean proportion of limit orders at different times of the day by levels of lagged volatility and spread. The sample consists of standard day orders for the 30 stocks with the highest frequency of orders from the TORQ dataset. Limit-order proportions for each of the 30-min intervals are computed for the four subgroups of the sample conditional on lagged volatility being high or low, and spread being large or small. Then they are averaged across the 63 trading days from November 1, 1990 to January 31, 1991, and across the 30 stocks. (A,B) represents the mean proportion of limit orders when the volatility is A (high or low) and the spread is B (large or small).

is only 48% when volatility is low. For other time intervals, the high-volatility group is also associated with higher proportions of limit orders. Overall, the evidence suggests that the impact of volatility on the placement of limit orders is not driven by the spread.

4.3. Limit orders, informational volatility, and transitory volatility

The previous section documents that higher volatility induces the placement of limit orders and that the effect is not due to an increase in spread. The intuition underlying this result is that, all other things being equal, the greater the volatility, the greater the probability that a given limit order will be executed, which provides traders with incentives to place unaggressively priced limit orders in a volatile market. However, this line of reasoning presumes that stock price changes reflect only noise, and are unrelated to information flows about fundamental values. To the extent that higher volatility reflects increased information flows, so the risk of being bagged by informed traders increases, limit-order placement will be less attractive. To investigate how the “informational” and “noise” components of price changes

affect limit-order placement, we decompose the transaction price into an implicit efficient price reflecting fundamental values and a noisy price that drives the transaction price away from the implicit efficient price. Specifically, we model security price as follows:

$$p_t = m_t + s_t, \quad s_t \approx N(0, \sigma_s^2),$$

$$m_t = m_{t-1} + w_t, \quad w_t \approx N(0, \sigma_w^2), \quad (1)$$

where p_t is the transaction price at time t that is actually observed; m_t is the random-walk term that has the interpretation of implicit efficient price; w_t is the unforecastable increment arising from updates to the conditional expectation of the stock's terminal value; and s_t is the stationary component that can be viewed as a residual driving the transaction price away from the implicit efficient price. s_t and w_t are assumed to be uncorrelated variables with zero means and constant variances. The model is known as a random pricing error model and is typically applied to macroeconomic time series (Hasbrouck, 1996). The model only makes use of transaction prices, ignoring the information contained quote or transaction volume data. For the sake of ease of model estimation, we use the most simplistic model in the present paper. We leave the estimation of a more realistic model that incorporates information contained in the transaction volume and quote data for future study. The model can be represented in the framework of state space model and can be recursively estimated by means of the Kalman filter. The implicit efficient price (the state variable) is not directly observable and its movements are assumed to be governed by a random-walk process.

We estimate the model using transaction prices of all 63 trading days for each stock and decompose them into efficient prices and noisy prices. We measure the informational (transitory) volatility by the high–low ratio of efficient (noisy) prices during each 30-min trading interval. An alternative way to measure informational and transitory volatilities would be to estimate σ_w^2 and σ_s^2 for each interval. However, this approach is difficult to implement due to the small number of observations during each interval. We partition the sample into four groups according to the medians of informational and transitory volatilities; i.e.: (1) high informational volatility and high transitory volatility (group 1), (2) high informational volatility and low transitory volatility (group 2), (3) low informational volatility and high transitory volatility (group 3), and (4) low informational volatility and low transitory volatility (group 4). Fig. 4 presents the mean proportions of limit orders at different times of the day for the four groups.

According to Handa and Schwartz (1996), an increase in transitory volatility will induce new limit orders and an increase in informational volatility will discourage the new placement of limit orders. Thus, we expect that the mean proportion of limit orders of group 3 is higher than that of group 2. The results indeed show that the mean proportion of limit orders is higher for group 3 than for group 2 at all times with the exception of the 10:00–10:30 time interval. Further, when controlling the informational volatility, the high transitory volatility group has higher limit-order

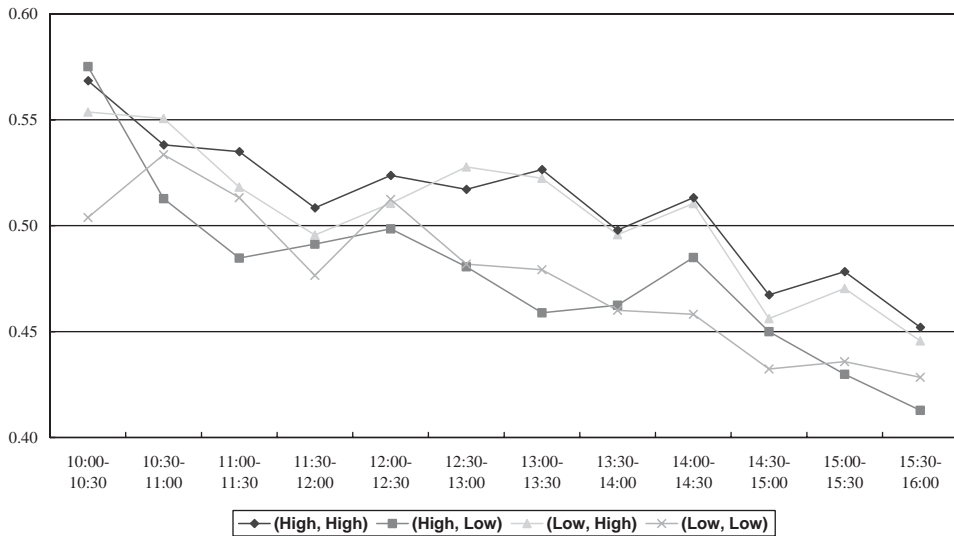


Fig. 4. Mean proportion of limit orders at different times of the day by levels of informational and transitory volatilities. This graph depicts the mean proportion of limit orders at different times of the day by levels of informational and transitory volatilities. The sample consists of standard day orders for the 30 stocks with the highest frequency of orders from the TORQ dataset. Limit-order proportions for each of the 30-min intervals are computed for the four subgroups of the sample conditional on informational volatility being high or low, and transitory volatility being high or low. Then they are averaged across the 63 trading days from November 1, 1990 to January 31, 1991, and across the 30 stocks. (A,B) represents the mean proportion of limit orders when the informational volatility is A (high or low) and the transitory volatility is B (high or low).

proportions. For instance, a comparison of groups 1 and 2 shows that the mean proportion of limit orders is higher for the high transitory volatility group (group 1) than for the low-volatility group (group 2) at all times with the exception of the 10:00–10:30 time interval. When informational volatility is low, a comparison of groups 3 and 4 indicates that higher transitory volatility is always associated with higher proportions of limit orders. However, when controlling the transitory volatility, the high informational volatility group does not necessarily have lower limit-order proportions. A comparison of groups 1 and 3, or of groups 2 and 4, shows few differences in the mean proportions of limit orders between the two groups.

4.4. Regression analysis

We use the following regression model to formally test the hypothesis that transitory volatility increases the placement of limit orders, while informational volatility decreases volatility. All variables used in the regression are measured for

30-min intervals in each trading day. The regression model is

$$Prop_t = \alpha + \sum_{k=1}^4 \beta_k Dum_{k,t} + \sum_{k=1}^{11} \gamma_k Time_{k,t} + \theta Spread_t + \delta Size_t + \varepsilon_t,$$

$$\text{and } \sum_{k=1}^4 \beta_k = 0. \quad (2)$$

The dependent variable, $Prop_t$, is the proportion of limit orders out of all day orders submitted during time interval t . $Time_{k,t}$ represents a time dummy variable that takes the value of one if time t belongs to the intraday interval k , and zero otherwise. $Time_{k,t}$ controls for the time-of-the-day effect of the limit-order proportions documented in the previous section. As each trading day lasts for six and one-half hours, there are thirteen 30-min intervals in one single trading day. Although there are 13 intraday intervals each trading day, we only have 12 intraday observations because we use the lagged volatility to measure the levels of informational and transitory volatilities. Since we do not assign a dummy variable for one of the time intervals to avoid perfect multicollinearity, we have only 11 intraday dummy variables.

$Spread_t$ is the average bid–ask spread (expressed in terms of percentage) during the intraday interval t . It is computed for every quote posted on the NYSE, and it is averaged over all quotes. We expect the coefficient on spread variable to be positive. $Size_t$ is the average number of shares per order submitted during the 30-min intraday interval t . We include the order size variable in the regression model to capture the effect of other factors that are not addressed by our hypothesis. As shown in Fig. 2, limit orders are generally much larger than market orders. Harris and Hasbrouck (1996) provide similar findings and argue that “any meaningful comparative analysis between market and limit orders must take this into account.” Given the findings shown in Fig. 2, we expect the coefficient for the size variable to be positive.

$Dum_{k,t}$ ($k = 1, 2, 3$, and 4) is a dummy variable that takes the value of one if informational volatility is high and transitory volatility is high ($k = 1$), if informational volatility is high and transitory volatility is low ($k = 2$), if informational volatility is low and transitory volatility is high ($k = 3$), and if informational volatility is low and transitory volatility is low ($k = 4$); and zero otherwise. To prevent perfect multicollinearity, we impose a restriction such that the sum of dummy coefficients is zero. The coefficient on each dummy variable measures the difference from the average level of volatility. We expect the coefficient on Dum_3 to be positive and greater than the coefficient on Dum_2 since transitory volatility leads to higher proportions of limit orders and informational volatility leads to lower proportions of limit orders.

We pool together all observations of the 30 sample stocks and run a pooled regression. Table 4 presents the results. The coefficient estimates of time dummy variables decrease monotonically as trading continues, which indicates that a trader is more likely to place a limit order when there is more time left until the market closes. Consistent with our prediction, spread and size variables are all positive and highly significant, confirming that higher spreads attract more limit orders and that larger orders are more likely to be limit orders. Our evidence that order size is a

Table 4

Pooled regression of the proportion of limit orders on dummy variables that measure the level of transitory and informational volatility

This table presents the regression results estimated for the 30 stocks from the TORQ dataset with the highest frequency of orders. The regression model is

$$Prop_t = \alpha + \sum_{k=1}^4 \beta_k Dum_{k,t} + \sum_{k=1}^{11} \gamma_k Time_{k,t} + \theta Spread_t + \delta Size_t + \varepsilon_t, \text{ and } \sum_{k=1}^4 \beta_k = 0,$$

where the dependent variable, $Prop_t$, is the proportion of limit orders out of all day orders submitted during the 30-min intraday interval t ; $Time_{k,t}$ represents a time dummy variable that takes the value of one if time t belongs to the 30-min intraday interval k , and zero otherwise; $Spread_t$ is the average bid–ask spread (expressed in terms of percentage) during the 30-min intraday interval t ; and $Size_t$ is the average number of shares per order submitted during the 30-min intraday interval t . $Dum_{k,t}$ ($k = 1, 2, 3$, and 4) is a dummy variable that takes the value of one if informational volatility is high and transitory volatility is high ($k = 1$), if informational volatility is high and transitory volatility is low ($k = 2$), if informational volatility is low and transitory volatility is high ($k = 3$), and if informational volatility is low and transitory volatility is low ($k = 4$); and zero otherwise. ** and * indicate significance at 1% and 5% levels, respectively.

Variables	Estimates	<i>t</i> -statistic
Intercept	0.4568	71.61**
Dummy variables for volatility level		
High informational volatility, High transitory volatility (β_1)	0.0083	2.87**
High informational volatility, Low transitory volatility (β_2)	−0.0070	−1.62
Low informational volatility, High transitory volatility (β_3)	0.0133	3.06**
Low informational volatility, Low transitory volatility (β_4)	−0.0145	−5.03**
Dummy variables for intraday time interval		
Spread (θ)	Highly significant	
Size (δ)	4.2139	23.37**
	0.3060	45.03**
Hypotheses		<i>F</i> -statistic
$\beta_2 = \beta_3$		7.16**
$\beta_1 = \beta_2$		6.41**
$\beta_3 = \beta_4$		21.42**
$\beta_1 = \beta_3$		0.67
$\beta_2 = \beta_4$		1.51
Adjusted R^2		0.1441

significant determinant of order type is quite different from the findings of Keim and Madhavan (1995). However, the different results are not necessarily contradictory since our sample consists of orders from both individual and institutional traders but their sample is concerned exclusively with institutional traders.¹¹

The parameters of our major interest are $\beta_1, \beta_2, \beta_3$, and β_4 . As expected, the estimate of β_3 is significantly positive at the 1% level, but the estimate of β_2 is

¹¹ The mean and median of order size for our sample were 2,210.4 and 950 shares, respectively. The median order size of the sample used by Keim and Madhavan was 4,800 shares.

significantly negative at the 10% level. The hypothesis of equal coefficients between β_2 and β_3 is strongly rejected. The results show that traders place more limit orders as opposed to market orders when transitory volatility is high and informational volatility is low. Further, the estimates of β_1 and β_2 are significantly positive and negative at the 1% and 10% levels, respectively. This result indicates that when controlling for the level of informational volatility (a high level of informational volatility), higher transitory volatility attracts more limit orders than lower transitory volatility does. The null hypothesis of equal coefficients is again strongly rejected. The result is even stronger when one compares the estimates of β_3 and β_4 . Again, controlling for the level of informational volatility (a low level of informational volatility), high transitory volatility is associated with high proportions of limit orders. However, once the level of transitory volatility is controlled, the level of informational volatility matters little. One cannot reject the null hypothesis of equal coefficients between β_1 and β_3 , and between β_2 and β_4 . In sum, the regression results are consistent with the view that what matters to the order choice of a trader are temporary price fluctuations, and that a trader will place a limit order when he expects greater transitory price volatility.

The finding that an increase in expected volatility attracts a new placement of limit orders is not new in the literature. Ahn et al. (2000) examine the dynamic relations between volatility and order composition and find that a rise in volatility is followed by an increase in the placement of limit orders. A distinct contribution of our paper is that while previous work has examined the interaction between order flow and total volatility, we decompose total volatility into transitory volatility and informational volatility. We explicitly show that it is an increase in transitory fractions of volatility that attracts limit-order submissions. To the best of our knowledge, this is a new finding.

It is interesting to note that an increase in informational volatility has little effect on the placement of limit orders. To the extent that adverse selection risk is enhanced as informational volatility goes up, limit-order placement would be less attractive. One reason why we don't find a significant relation between informational volatility and limit-order placement is that our measure of informational volatility is imprecise. However, it is also possible that some informed traders might prefer limit orders, so that the net effect of an increase in informational volatility on limit-order placement is indeterminate. Easley and O'Hara (1987) show that "informed traders prefer to trade larger amounts at any given price." As shown in Fig. 2, we find that the size of order tends to be larger with limit orders. To the extent that large traders tend to be better informed than small traders (Easley and O'Hara, 1987), large limit orders are likely to be placed by better informed traders.¹² Finally, Foucault (1999) argues that limit-order traders ask for a larger compensation for the

¹²However, in Glosten's (1994) framework, informed traders are more likely to use market orders. In Glosten (1994), traders can be classified into two groups according to their attitude regarding immediacy: the "patient" traders and the "urgent" traders. The "patient" traders place limit orders and supply liquidity to the market, while the "urgent" traders place market orders and consume liquidity. He argues that informed investors are more likely to be urgent traders than patient traders.

risk of being picked off by informed traders in markets with high volatility, which means that market-order trading is more costly. Thus, more traders find it optimal to carry their trades using limit orders, which suggests that high informational volatility does not necessarily decrease limit-order submissions.

4.5. *The impact of volatility on spreads*

There is quite a bit of cross sectional evidence that high volatility breeds a large spread. In the previous section, we documented that high lagged volatility encourages the placement of limit orders, which suggests that spread is likely to tighten in the next period. In this section, we investigate the impact of lagged volatility on spreads.

We compute the mean spread at different times of the day by levels of lagged volatility but do not report the results.¹³ The high-volatility observations are those in the first quartile of the lagged volatility, and the low-volatility observations are those in the fourth quartile of the lagged volatility. During the 10:00–10:30 time interval, the mean spread is 1.32% when lagged volatility is low, while it is only 0.93% when lagged volatility is high. This evidence is consistent with the view that the volatility increase in the previous period induces the placement of new limit orders, which in turn decreases the spread. The difference between the spreads is the highest during the 10:00–10:30 interval and continues to decrease until the time interval of 13:00–13:30 at which point there is little difference (0.006%) between the two groups. During the 13:30–14:00, 14:00–14:30, and 14:30–15:00 intervals, the spread of high volatility becomes larger than that of low volatility. However, the differences are less than 0.10%. During the last one hour of trading, the spread of high volatility again becomes smaller than that of low volatility. It is interesting to note that the differences between the spreads of the two volatility groups are generally bigger after the market opens and before the market closes—those trading periods when the volatilities are higher than at other trading times of the day. Overall, the evidence is consistent with our prediction that higher lagged volatility is likely to tighten spread.

4.6. *Sensitivity tests*

4.6.1. *Alternative measures of volatility*

We examine the sensitivity of our results to the choice of different measures of volatility. One alternative measure is the absolute return, or $|R_t| = |(P_t/P_{t-1}) - 1|$, where R_t is the return of the stock from interval $t - 1$ to t , and P_{t-1} and P_t are the last transaction prices at intervals $t - 1$ and t . However, the drawback of the absolute return is that it might not be able to detect transitory price volatility.¹⁴ We

¹³The results are available upon request.

¹⁴Suppose there are only two trades within the interval—the first one is on an up-tick and the second one is on a down-tick. The return (or absolute return) during the interval is equal to zero. Based on the absolute return measure, one would infer that the transitory volatility is zero and that there would be no effect on the liquidity provision. But since the transactions bounce between the bid and ask prices, it is likely that they are liquidity-driven and should induce an increase in the placement of limit orders.

also compute short-term price volatility in the time interval t as $\sum_{i=1}^N R_{i,t}^2$, where $R_{i,t}$ is the return of the i th transaction during time interval t , and N is the total number of transactions within the interval.¹⁵ This price volatility measure differs from the conventional variance measure in a couple of ways. First, we do not subtract the mean return from R_i as we assume that the mean return is zero. This assumption is quite reasonable given that the average return within the intraday interval is close to zero. Second, we do not divide the sum of squared returns by the total number of observations. This is because we would like to measure the cumulative price fluctuation within the interval, rather than the average price fluctuation for each transaction. For all measures of volatility, we find similar results.

4.6.2. Alternative measures of time intervals

All our empirical results are based on 30-min intervals to measure the return volatility and the mean frequency of limit orders. We replicate the empirical analysis using 15-min intervals. The results are qualitatively similar.

5. Conclusion

This paper examines a trader's order choice between market and limit orders using a sample of orders submitted through NYSE SuperDot. We find that traders place more limit orders relative to market orders when: (1) the spread is large, (2) the order size is large, and (3) they expect high transitory price volatility. We also find that a rise in lagged price volatility decreases the size of spread, which appears to be driven by the increase in the placement of limit orders.

Our results are closely related to some recent empirical studies. [Biais et al. \(1995\)](#) find that in the Paris Bourse, a thin order book attracts orders and a thick book results in trades. [Chung et al. \(1999\)](#) find that in the NYSE, more investors enter limit orders when the spread is wide, and more investors hit the quotes when the spread is tight. [Ahn et al. \(2000\)](#) show that when there is a paucity of limit sell (buy) orders so that there is an increase in upside (downside) volatility, potential sellers (buyers) will submit limit sell (buy) orders instead of market sell (buy) orders. A distinct contribution of our paper is that we illustrate that it is important to distinguish between transitory volatility and informational volatility. A rise in transitory volatility induces a new placement of limit orders. A rise in informational volatility appears neither to increase nor decrease the placement of limit orders relative to market orders.

It is somewhat surprising that an increase in informational volatility has little effect on the placement of limit orders. To the extent that adverse selection risk is enhanced as informational volatility goes up, limit-order placement would be less attractive. One reason why we don't find a significant relation between informational volatility and limit-order placement is that our measure of informational volatility could be imprecise. A better measure of informational volatility might result in a

¹⁵ [Ahn et al. \(2000\)](#) use this measure of volatility in their analysis of limit-order trading of the Stock Exchange of Hong Kong.

different conclusion. Alternatively, the reason for what we find could be that adverse selection may be less important than what researchers think.

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