# Limit Orders, Depth, and Volatility

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## Abstract

We investigate the role of limit orders in the liquidity provision in the Hong Kong stock market, which is based on a computerized limit-order trading system. Consistent with Handa and Schwartz (1996), results show that market depth rises subsequent to an increase in transitory volatility, and transitory volatility declines subsequent to an increase in market depth. We also examine how transitory volatility affects the mix between limit orders and market orders. When transitory volatility arises from the ask (bid) side, investors will submit more limit sell (buy) orders than market sell (buy) orders. This result is consistent with the existence of limit-order traders who enter the market and place orders when liquidity is needed.

JEL **Classification Numbers**: G10, G12, G13

**Keywords**: limit orders, market orders, depth, volatility, and liquidity traders.

Interest in limit-order trading has grown rapidly in recent years as it plays a vital role in the liquidity provision in the world's stock exchanges of different market architectures. In an order-driven market, such as the Paris Bourse or the Tokyo Stock Exchange, all liquidity is provided by limit orders submitted by natural buyers and sellers.[1] In a specialist market, such as the New York Stock Exchange (NYSE), a substantial amount of the liquidity is supplied by public limit orders. For example, Harris and Hasbrouck (1996) document that 54% of SuperDot orders are limit orders, and Ross, Shapiro, and Smith (1996) report that limit orders account for 65% (75%) of all executed orders (executed shares). Even in a dealership market, such as the NASDAQ or London's SEAQ International, some forms of limit-order trading have been introduced in recent years.[2]

Although limit-order trading is of paramount importance, it was not until recently that researchers began to investigate in depth the role of limit-order trading in the market microstructure. On the theory side, Glosten (1994), Kumar and Seppi (1994), Chakravarty and Holden (1995), Handa and Schwartz (1996), Parlour and Seppi (1997), Foucault (1997), Handa, Schwartz and Tiwari (1998), and Viswanathan and Wang (1998) develop equilibrium models of the limit order book. On the empirical side, several studies examine the role of limit order books in supplementing the liquidity provided by the specialists in the NYSE.[3] Although many stock exchanges around the world are based on pure limit order books, very few empirical papers investigate the role of limit-order traders in an order-driven market without any designated market maker. One notable exception is Biais, Hillion, and Spatt (1995), who study the computerized limit-order market of the Pairs Bourse, investigating the dynamics of the order flow and order book.

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[1] See Lehmann and Modest (1994) and Hamao and Hasbrouck (1995) for the Tokyo Stock Exchange, and Biais, Hillion, and Spatt (1995) for the Paris Bourse.
[2] NASDAQ market makers are now required to display customer limit orders. The London market uses an electronic order book for smaller orders while large orders are still routed through a dealership mechanism.
[3] Harris and Hasbrouck (1996) compare the performance of market and limit orders submitted through the NYSE SuperDot. Greene (1996) develops a methodology for inferring limit-order executions from transactions and quote data. Kavajecz (1999) partitions quoted depth into the specialist's contribution and the limit order book's contribution. Chung, Van Ness, and Van Ness (1999) examine the intraday variation in spreads established by limit-order traders.

The objective of this paper is to extend the analysis of the role of limit-order trading in liquidity provision in a pure order-driven market. While Biais, Hillion, and Spatt (1995) examine the intertwined dynamics of the order flow and order book, we focus on the interaction between short-term volatility and order flow composition. The study is motivated by Handa and Schwartz (1996), Foucault (1997), and Handa, Schwartz, and Tiwari (1998) who model the choice of investors in placing limit orders and market orders in a pure order-driven market. There is no designated market maker who is obligated to provide liquidity to the market. Instead, the suppliers of liquidity are the natural buyers and sellers themselves who choose to place limit orders. At the same time, these buyers and sellers could also trade via market orders and consume liquidity in the market. The choice between limit and market orders depends on the investor's beliefs about the probability of his or her limit order executing against an informed or a liquidity trader. When there is temporary price movement due to liquidity shocks, this will attract public traders to submit limit orders rather than market orders, as the net gain from supplying liquidity instead of consuming liquidity is greater than the risk of being picked off by informed traders. Therefore, Handa and Schwartz (1996) and Foucault (1997) argue that in an order driven market, transitory volatility affects the profitability and choice of investors in placing limit and market orders.

In this paper, we examine the empirical relations between the transitory volatility and the order flow in a pure order-driven market. First, we investigate the dynamic relation between the transitory volatility and the market depth. According to Handa and Schwartz (1996), when there is a paucity of limit orders so that there is an increase in short-term price fluctuation, investors will find it more profitable to place limit orders. Such an influx of limit orders provides liquidity to the market, so that short-term volatility will decline. Second, we study how the transitory volatility affects the mix of limit and market orders. In particular, since the transitory volatility could arise from either the bid or the ask side, we examine whether they have different impacts on the buyers and sellers in their order placement strategies.

We perform an empirical analysis on the electronic limit order books of the Hong Kong stock market. Consistent with Handa and Schwartz (1996), results show that a rise in transitory volatility is followed by an increase in market depth, and a rise in market depth is followed by a decrease in transitory volatility. We also find that an increase in transitory volatility affects the order flow composition. However, it is important to distinguish between volatility arising from the bid side and the ask side, as they have different impacts on the buy and sell order flows. Evidence indicates that more limit buy orders than market buy orders are placed if the transitory volatility arises from the bid side, and that more limit sell orders than market sell orders are placed if the transitory volatility arises from the ask side. These results are consistent with the existence of liquidity providers who enter the market and place limit orders on either the bid or the ask side, depending on which side will earn profits for the liquidity provision.

Critics of an order-driven trading system without market makers often argue that traders can be reluctant to enter orders into the system in a volatile market environment, since trading via limit orders is costly when the adverse selection problem is severe. Contrary to this view, the evidence presented in our study indicates that there exists a sufficient number of potential liquidity suppliers who are ready to step in by placing limit orders when liquidity is most needed. The evidence is consistent with the view that an order-driven trading mechanism without the presence of market makers can be viable and self-sustaining.

The paper proceeds as follows. Section I develops hypotheses on the dynamic relation between transitory volatility and order flows. Section II describes the trading mechanism of the Hong Kong stock market and the data used. Section III describes the empirical methodology and construction of variables. Section IV presents empirical results, and Section V concludes the paper.

## I. Limit-Order Trading in a Pure Order-Driven Market

In a pure order-driven market, there is no designated market maker who has the obligation to provide liquidity to the market. Investors can choose to post limit orders or market orders. While limit orders are stored in a limit-order book awaiting future execution, market orders are executed with certainty at the posted prices in the market. Traders face the following dilemma. With a limit order, if a trade occurs, the investor will execute it at a more favorable price than a market order. On the other hand, there is the danger of the order not being executed. Furthermore, because the limit order prices are fixed, the investor faces an adverse selection risk due to the arrival of informed traders.

In Glosten's (1994) framework, traders can be broadly classified into two groups according to their attitude on immediacy: the "patient" traders who can postpone their trading and the "urgent" traders who need to trade immediately. The "patient" traders place limit orders and supply liquidity to the market, while the "urgent" traders place market orders and consume liquidity. According to Glosten (1994), informed investors are more likely to be urgent rather than patient traders. There are at least two reasons. First, the value of private information depreciates as time lapses, so an informed trader favors an immediate execution over waiting. Second, competition among the informed traders makes choosing a limit order an inferior strategy. For example, suppose informed investor A submits a limit buy order while another competing informed investor B undercuts the price by submitting a market buy order. If investor B's market buy order consumes all the limit sell orders at the best ask price, the chance that investor A's limit buy order is executed will be reduced. Given the existence of informed traders in the market, Glosten (1994) argues that the "patient" trader will not choose to place a limit order unless the expected gain from transacting with a liquidity trader exceeds the expected loss from transaction with an informed trader.

Like many other limit-order trading models, Glosten (1994) does not allow traders to choose between market and limit orders. For this reason, these models cannot derive implications regarding the determinants of order flow composition. Foucault (1997) explicitly incorporates an investor's decision to trade via limit order or market order, and develops a model in which the mix between market and limit orders can be characterized in equilibrium. He finds that the volatility of the asset is a main determinant of the mix between market and limit orders. When the asset volatility increases, the probability of being picked off by informed investors and the potential losses to them are larger. Limit order traders have to post higher ask prices and lower bid prices relative to their reservation prices in markets with high volatility. But in this case, market orders become less attractive. Consequently, more traders use limit orders instead of market orders when the asset volatility is high.

Handa and Schwartz (1996) also examine the rationale and profitability of limit order trading in a trading environment where investors could submit either limit order or market order. The choice depends on the probability that the limit order is executed against an informed or a liquidity trader. An important difference between informed trading and liquidity trading is that the former triggers permanent price changes, but the latter results in temporary price changes. While executing limit orders against the liquidity-driven price changes is profitable, executing the orders against permanent price changes is undesirable. By endogenizing the decision to trade via market or limit order, Handa and Schwartz (1996) illustrate the ecological nature of the pure-order driven market where the supply of, and demand for, liquidity can be in natural balance. Suppose there is a paucity of limit orders. An increase in liquidity trading will cause a temporary order imbalance and lead to short-term fluctuation in transaction prices. The liquidity-driven price volatility will attract public traders to submit limit orders rather than market orders, as the gains from supplying liquidity can more than offset the potential loss from trading with informed traders. This influx of limit orders will continue until short-term volatility decreases and limit-order trading is no longer profitable. In turn, a decrease in volatility results in fewer limit orders, which causes temporary order imbalance. These considerations lead to the following two hypotheses:

*Hypothesis 1: An increase (a decrease) in short-term price volatility is followed by an increase (a decrease) in the placement of limit orders relative to market orders, so that the market depth will increase (decrease) subsequently.*

*Hypothesis 2: An increase (a decrease) in market depth is followed by a decrease (an increase) in short-term price volatility.*

## II. Description of the Market and the Dataset

*A. The Open Limit-Order System of the Stock Exchange of Hong Kong*

The Stock Exchange of Hong Kong (SEHK) is a good example of a pure order-driven market. In the absence of designated market makers, security prices are determined by the buy and sell orders submitted by public investors. Trading is conducted through terminals in the trading hall of the Exchange and through terminals at the members' office. Orders are placed through brokers and are consolidated into the electronic limit-order book and executed through an automated trading system, known as the Automatic Order Matching and Execution System (AMS).[4] While an investor could place a market order or a limit order to the broker, the trading system only accepts limit orders. Thus, the broker submits the customer's market order in the form of a limit order that matches the best price on the other side of the book. Investors are allowed to cancel or decrease orders at any time prior to matching, but they cannot enlarge the order already submitted. Trading is conducted on weekdays excluding public holidays and is carried out on the exchange floor in two sessions each day, from 10:00 to 12:30 and from 14:30 to 15:55.

Orders in automatch stocks are executed on a strict price and time priority basis. Orders are matched following the sequence in which they are entered into the AMS, based on the best price. An order entered into the system at an earlier time must be executed in full before the execution of an order entered at a later time at the same price. An order with a price equal to the best opposite order is matched with opposite orders at the best price queue residing in the system, one by one, according to time priority. The queue position in the system is maintained until whichever occurs first: the order is completely filled, the order is cancelled, or the trading day ends, at which point all orders are purged from the AMS.

[4] Most of the orders are executed through the AMS, although a few orders are manually matched through brokers. During the one-year period between July 1996 and June 1997, automatched trades accounted for 96.4% of all transactions of the 33 Hang Seng Index component stocks in our sample.

The order-and-trade information is disseminated to the public on a real-time basis using an electronic screen. All brokers are directly connected to the AMS system. Investors can obtain information in real time through the Teletext system, a support system of the Exchange. The AMS displays the best five bid-and-ask prices, along with the broker identity (broker code) of those who submit orders at the respective bid/ask prices being shown, and the number of shares demanded or offered at each of the five bid-and-ask queues.

The trading mechanism of the SEHK is similar to the electronic limit-order market modeled by Glosten (1994). First, the market is fully centralized and computerized. The information regarding the limit-order book (up to the best five queues) is immediately available to all market participants through the electronic screen. This transparency is not available in some other limit-order markets in the world.[5] For example, in the Tokyo Stock Exchange, only the members' lead offices can observe the orders, and they are not allowed to disseminate this information. In the NYSE, only the bid-ask quotation is electronically disseminated to traders. In the Paris Bourse, orders can be hidden (Biais, Hillion, and Spatt (1995)). There are no such hidden limit orders in the SEHK. Second, execution of a trade against the limit order book occurs in a "discriminatory" fashion. That is, if the size of the market order is large enough to consume several limit orders at different prices, each limit order is executed at its own limit price.

*B. Data*

We obtain our data from the Trade Record and the Bid and Ask Record, both provided by the SEHK. The Trade Record includes all transaction price-and-volume records with a time stamp recorded to the nearest second. The Bid and Ask Record contains information on limit-order prices and order

[5] However, there is no consensus on the relation between transparency and liquidity. See O'Hara (1995) for discussion.

quantity. It tracks the number of orders in the same queue and records up to five queues at every 30-second interval.

We focus on the 33 component stocks in the Hang Seng Index (HSI) between July 1996 and June 1997. The 33 HSI component stocks are the most actively traded and provide a reasonable representation of the market, since they account for about 70% of the total market capitalization. Limiting our analysis to the most actively traded stocks in the market guarantees that there are enough observations necessary for our intraday time-series analysis.

Table 1 describes some of the characteristics of our sample firms. The average (median) number of trades per stock per day in our sample is 387 (346), suggesting a high level of trading activity in our sample stocks.[6] The average (median) dollar spread is $HK0.12 ($HK0.07). For most of the stocks in our sample, the average dollar spread is about one tick size. The average (median) percentage spread is 0.47% (0.39%) during the sample period, which is comparable to that of most liquid stocks in the U.S. For example, Angel (1997) reports that the median bid-ask percentage spread is 0.32% for the Dow Jones Industrial Average index stocks.

Figure 1 shows the average levels of quoted depth and volatility at each 15-minute interval of the trading day. The statistics are expressed as percentage deviations from their respective full-day averages. The figure shows a U-shaped pattern in volatility as reported in previous studies. The quoted depth follows a reverse U-shaped pattern. This depth pattern is consistent with those of the NYSE documented by Lee, Mucklow, and Ready (1993) and those of the Paris Bourse by Biais, Hillion, and Spatt (1995). Overall, Figure 1 underscores the importance of controlling the time-of-the-day effect in investigating the relation between volatility and depth.

[6] The average (median) number of trades per stock per day for the CAC 40 index stocks reported in Biais et al. (1995) is 149 (114).

## III. Empirical Methodology

*A. Time Intervals*

In our empirical analysis, we will test the theoretical prediction of Handa and Schwartz (1996) regarding the interaction between short-term price volatility and order flow. However, the theory does not guide us in choosing the length of the time interval in the measurement of volatility. On the one hand, since we are interested in short-term price fluctuation caused by order imbalance, the time interval should not be too long, otherwise the volatility we measure is likely to be permanent rather than temporary. On the other hand, the time interval should not be too short, or else there are not enough transactions that trigger price fluctuation. With these considerations, the empirical analysis is conducted based on 15-minute intervals.

Each day, trading hours will be partitioned into fifteen 15-minute intervals, and one 10-minute interval. This is because the SEHK is open from 10:00 to 12:30 and from 14:30 to 15:55, so that the last measurement interval is 10 minutes long. We do not include an overnight interval in our analysis, since all orders in the limit-order book are purged at the end of each daily session. In other words, all limit orders in the SEHK are "day" orders and there are no "good till canceled" orders.

*B. Short-Term Price Volatility*

We compute short-term price volatility ($RISK_t$) 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. This price volatility measure differs from the conventional variance measure $(\frac{1}{N}\sum_{i=1}^{N}(R_{i,t}-\overline{R})^2)$ in a couple of ways. First, in computing $RISK_t$, we do not subtract the mean return from $R_i$. Implicitly, we assume that the mean return is zero, which is quite reasonable considering 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. Nevertheless, our short-term price volatility measure will be positively related to the total number of transactions. We will therefore have to control for the impact of the total number of transactions in our empirical analysis. In addition, we perform robustness test based on an alternative measure of price volatility, which we will discuss in Section IV.D.

We further decompose the transitory volatility into upside and downside measures. The upside volatility ( $RISK_t^+$ ) is computed based on positive return observations $\sum_{R_{i,t}>0} R_{i,t}^2$ , while the downside volatility ( $RISK_t^-$ ) is based on negative return observations $\sum_{R_{i,t}<0} R_{i,t}^2$ . When there is a paucity of limit orders on the ask (bid) side, the temporary order imbalance results in upside (downside) volatility, and this will encourage public traders to place more limit sell (buy) orders.

C. *Market Depth and Order Flow*

Throughout the empirical analysis, we measure the depth, order flow and trading activity based on the number, instead of the size, of orders and transactions. This is motivated by Jones, Kaul and Lipson (1994) who show that the number of transactions, not the share volume, is a major determinant of price volatility. We compile the market depth ($DEPTH_t$) based on the total number of limit orders posted at the bid and ask prices at the end of time interval t. Since the electronic order books in the SEHK record the outstanding limit orders at the best five quotes, we can compile the market depth at any of these five quotes. In addition, we compute the depth at the bid and ask quotes respectively ( $DEPTH_t^{bid}$ and $DEPTH_t^{ask}$ ).

We also calculate the change of market depth for the interval t ($\Delta DEPTH_t$). There is an interesting interpretation for the variable $\Delta DEPTH_t$. Suppose we define $NPLO_t$ as the number of newly placed limit orders during time interval t [7], and $NLOE_t$ as the number of limit orders that are executed during the interval t. Then by definition,

$$DEPTH_t = DEPTH_{t-1} + NPLO_t - NLOE_t \,. \tag{1}$$

Since market orders must be executed against limit orders, and if we define $NTRADE_t$ as the number of trades (which is also the number of market orders) during time interval t, then $NLOE_t = NTRADE_t$. We can rewrite equation (1) as:

$$\Delta DEPTH_t = NPLO_t - NTRADE_t \,. \tag{2}$$

The variable $\Delta DEPTH_t$ provides us information on the order flow composition, that is, the difference between the number of newly placed limit orders and market orders during time interval t. We will focus on this variable when we examine the relation between transitory volatility and order flow composition.

We also construct variables for the mix between the newly placed limit orders and market orders for the buy and sell sides, respectively. By definition, the number of market buy orders ($NTRADE_t^{buy}$) during time interval t is equal to the number of limit sell orders executed during the same interval ($NLOE_t^{sell}$). We can obtain the number of newly placed limit sell orders during time interval t ($NPLO_t^{sell}$) by adding $NTRADE_t^{buy}$ to the change of depth at the ask ($\Delta DEPTH_t^{ask}$). If we define $DIFF_t^{sell}$ as the difference between the number of newly placed limit sell orders ($NPLO_t^{sell}$) and market sell orders ($NTRADE_t^{sell}$) during time interval t, it could be computed as:

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[7] Since some limit orders are cancelled without being executed, $NPLO_t$ is more accurately defined as the net number of newly placed limit orders (i.e., number of newly placed limit orders minus the number of cancelled limit orders).

$$\mathrm{DIFF}_t^{sell} = \Delta\mathrm{DEPTH}_t^{ask} + \mathrm{NTRADE}_t^{buy} - \mathrm{NTRADE}_t^{sell}. \tag{3}$$

Similarly, by definition, the number of market sell orders during time interval t ($\mathrm{NTRADE}_t^{sell}$) is equal to the number of limit buy orders executed during the same interval ($\mathrm{NLOE}_t^{buy}$). We can obtain the number of newly placed limit buy orders during time interval t ($\mathrm{NPLO}_t^{buy}$) by adding $\mathrm{NTRADE}_t^{sell}$ to the change of depth at the bid ($\Delta\mathrm{DEPTH}_t^{bid}$). If we define $\mathrm{DIFF}_t^{buy}$ as the difference between the number of newly placed limit buy orders ($\mathrm{NPLO}_t^{buy}$) and market buy orders ($\mathrm{NTRADE}_t^{buy}$) during time interval t, it could be computed as:

$$\mathrm{DIFF}_t^{buy} = \Delta\mathrm{DEPTH}_t^{bid} + \mathrm{NTRADE}_t^{sell} - \mathrm{NTRADE}_t^{buy}. \tag{4}$$

In the empirical analysis, we will relate $\mathrm{DIFF}_t^{sell}$ and $\mathrm{DIFF}_t^{buy}$ to the volatility arising from the ask and bid sides ($\mathrm{RISK}_t^-$ and $\mathrm{RISK}_t^-$). The hypothesis is that if transitory volatility arises from the ask (bid) side at time t-1, this will encourage public traders to place limit sell (buy) orders rather than market sell (buy) orders at time t, so that $\mathrm{DIFF}_t^{sell}$ ($\mathrm{DIFF}_t^{buy}$) will increase.

## IV. Empirical Results

*A. Impacts of Transitory Volatility on Market Depth*

To examine the effect of transitory volatility on subsequent market depth, we first estimate the following regression for each stock:

$$DEPTH_t = \alpha_1 + \beta_1 RISK_{t-1} + \theta_1 NTRADE_t + \sum_{k=1}^{14} \gamma_k TIME_{k,t} + \rho_1 DEPTH_{t-1} + \varepsilon_t \tag{5}$$

where $DEPTH_t$ is the market depth (number of outstanding limit orders) at the end of time interval t, $RISK_{t-1}$ is the transitory volatility during time interval t-1, $NTRADE_t$ is the number of trades during time interval t, $TIME_{k,t}$ is an intraday dummy variable that takes the value of one if interval t belongs to the time interval k, and zero otherwise. The inclusion of $TIME_{k,t}$ and $DEPTH_{t-1}$ on the right-hand side is to control for intraday variation and autocorrelation in the market depth. Although there are sixteen intraday time intervals every day, we only have fifteen intraday observations because we use $DEPTH_{t-1}$ as an explanatory variable. Since we do not assign a dummy variable for one of the time intervals to avoid multicollinearity, we have only fourteen intraday dummy variables.

We estimate Equation (5) for each stock using Generalized Method of Moments (GMM) and obtain t-statistics that are robust to heteroskedasticity and autocorrelation (Newey and West (1987)). We use different measures of market depth as the dependent variable, including the total number of limit orders in the best five queues, in the best queue, and in the second through fifth queues.

We report the regression results in Table 2, which contains the cross-sectional means of the estimates and t-statistics, and the number of stocks (out of 33 stocks) that have significantly positive and negative estimates at the 10 percent level, respectively. For brevity, we do not report the estimates of $\gamma_k$. However, it should be noted that these coefficients are significantly different from zero, indicating the importance of controlling the time-of-day effect in the market depth.

Theoretically, there are mixed effects of the number of trades on market depth. On the one hand, since the transactions consume the liquidity available in the market, there is a mechanical relation such that an increase in trading volume drives down the market depth. Lee, Mucklow, and Ready (1993) present empirical evidence that the depth and volume are negatively correlated. On the other hand, higher trading activity may capture market interest and induce public investors to supply more liquidity to the market. Admati and Pfleiderer (1988) show that in equilibrium, discretionary liquidity traders have incentives to trade together, so that an increase in trading volume attracts more liquidity trading. Chung, Van Ness, and Van Ness (1999) argue that since investors place more limit orders when the probability of order execution is high, which in turn is an increasing function of the intensity of trading activity, the number of limit orders increases with trading volume. Therefore, the coefficient $\theta_1$ could be either positive or negative. Empirical results in Table 2 show that the first effect dominates the second effect, as DEPTH is significantly and negatively related to NTRADE. The average estimate of $\theta_1$ is -0.2345 (average t-value is -9.16) when the dependent variable is the total depth in all five queues, and is -0.1553 (average t-value is -9.11) when the dependent variable is the depth in the best queue.

The focus of our interest in regression (5) is the coefficient $\beta_1$, which measures the impact of transitory volatility on subsequent market depth. We find that a rise in transitory volatility generally leads to an increase in market depth. When DEPTH is defined as the depth in the best queue, the average estimate of $\beta_1$ is 0.0022 (average t-value = 4.24). When DEPTH is defined as the depth in the second through fifth queues, the average estimate of $\beta_1$ is 0.0025 (average t-value = 3.76). These results support the notion that an increase in transitory volatility is followed by an increase in market depth.[8]

*B. Impacts of Transitory Volatility on Order Flow Composition*

The above results are consistent with the conjecture that an increase in liquidity-driven price volatility encourages more investors to supply liquidity. But according to our hypothesis, an increase in transitory volatility not only causes the market depth to increase, but it also affects the order flow composition, as investors will be encouraged to submit limit orders rather than market orders. To shed light on this issue, we estimate the following regression model for each of the 33 stocks in our sample:

[8] Since Chung, Van Ness, and Van Ness (1999) find that lagged spread affects the placement of limit orders, we have also modified equation (5) by including the spread at time t-1 as an explanatory variable. Results, which are qualitatively similar, are not reported here.

$$\Delta DEPTH_t = \alpha_1 + \beta_1 RISK_{t-1} + \sum_{k=1}^{13} \gamma_k TIME_{k,t} + \rho_1 \Delta DEPTH_{t-1} + \varepsilon_t , \qquad (6)$$

where $\Delta DEPTH_t$ is the change of depth from time t-1 to t. The reason that we have one fewer intraday dummy variable in equation (6) than in equation (5) is that we lose one more observation per day as we use the change of market depth instead of the level. Unlike equation (5), we do not include $NTRADE_t$ as an explanatory variable. This is because implicit in the calculation of $\Delta DEPTH_t$ , $NTRADE_t$ is subtracted from the depth at time t-1 and is already taken into consideration. Following our discussion in Section III, $\Delta DEPTH_t$ is a measure of order flow composition, as it equals the difference between the number of newly placed limit orders and market orders submitted during time interval t. According to our hypothesis, an increase in transitory volatility induces investors to submit more limit orders instead of market orders. Therefore, we predict that $\Delta DEPTH_t$ is positively related to $RISK_{t-1}$.

Table 3 reports the estimates for regression (6). It is noted that the variable $\Delta DEPTH_t$ is negatively autocorrelated. For example, when we compute $\Delta DEPTH_t$ based on all five queues, the average estimate of the first-order autocorrelation coefficient ($\rho_1$) is -0.1579 (average t-value = -4.53). This result reflects the self-adjusting mechanism of the order flow. Suppose, in period t-1, more market orders are submitted than limit orders so that there is a scarcity of liquidity. Then, in period t, there will be a natural force for liquidity to get replenished as there will be more influx of limit orders than market orders. The evidence is consistent with Biais, Hillion, and Spatt (1995), who find that in the electronic limit-order book of the Paris Bourse the order flow is affected by the state of the book. In general, there are more trades when the order book is thick, and there are more limit orders submitted when the book is thin.

The impact of transitory volatility on the depth change is not very strong. When we use depth change in all five queues as the dependent variable, the average estimate of coefficient $\beta_1$ is 0.0017 (average t-value =2.55). However, when we use depth changes in the best queue as the dependent variable, the coefficient $\beta_1$ is significantly positive for only 7 stocks. Therefore, the evidence is not totally consistent with the hypothesis that an increase in liquidity-driven price volatility will attract public traders to submit limit orders rather than market orders. There is, however, one problem with regression (6). If the increase in transitory volatility arises from either the ask side or the bid side, its impact on the order flow composition will be on either the buy or sell orders. In that case, we might not be able to find a strong relation between the transitory volatility and the order flow composition for buy and sell orders together.

To address the above problem, we examine explicitly how order flow composition is related to the liquidity-driven price volatility arising from the bid and ask sides. We estimate the following regression models:

$$\mathrm{DIFF}_t^{buy} = \alpha_1 + \beta_1^+ \mathrm{RISK}_{t-1}^+ + \beta_1^- \mathrm{RISK}_{t-1}^- + \sum_{k=1}^{13} \gamma_{1,k} \mathrm{TIME}_{k,t} + \rho_1 \mathrm{DIFF}_{t-1}^{buy} + \varepsilon_t^{buy} \tag{7}$$

$$\mathrm{DIFF}_t^{sell} = \alpha_2 + \beta_2^+ \mathrm{RISK}_{t-1}^+ + \beta_2^- \mathrm{RISK}_{t-1}^- + \sum_{k=1}^{13} \gamma_{2,k} \mathrm{TIME}_{k,t} + \rho_2 \mathrm{DIFF}_{t-1}^{sell} + \varepsilon_t^{sell} \tag{8}$$

where $\mathrm{DIFF}_t^{buy}$ is the difference between the number of newly placed limit buy orders and market buy orders during time interval t, $\mathrm{DIFF}_t^{sell}$ is the difference between the number of newly placed limit sell orders and market sell orders during time interval t, and $\mathrm{RISK}_{t-1}^+$ and $\mathrm{RISK}_{t-1}^-$ are the upside (ask side) volatility and downside (bid side) volatility during time interval t-1. As we do not observe market buy orders and market sell orders directly, we classify our trades into buyer- or seller-initiated by tick test whereby we infer the direction of a trade by comparing its price to the preceding trade's price.[9]

The test results are displayed in Panel A (for regression (7)) and Panel B (for regression (8)) of Table 4. There is pervasive evidence that $\mathrm{DIFF}_t^{buy}$ and $\mathrm{DIFF}_t^{sell}$ are positively autocorrelated, regardless

[9] We also classified the trade by comparing the trade prices with the prevailing bid/ask quotes and obtained similar results to the tick test. See Lee and Ready (1991) for details of trade classification.

of whether we measure the depth based on the best quote or the best five quotes. This is interesting considering that the sum of $\mathrm{DIFF}_t^{buy}$ and $\mathrm{DIFF}_t^{sell}$ equals $\Delta\mathrm{DEPTH}_t$, which we show to be negatively autocorrelated in Table 3. This indicates that there is interaction between market orders and limit orders that will restore the market liquidity. The reason why $\mathrm{DIFF}_t^{buy}$ and $\mathrm{DIFF}_t^{sell}$ are positively autocorrelated is that market orders are batched over consecutive time intervals – market buy (sell) orders at time t-1 will be followed by market buy (sell) orders at time t. On the other hand, the arrival of market buy (sell) orders at time t-1 is likely to attract more limit sell (buy) orders at time t. If the placement of limit orders is more than the market orders submitted at time t, then $\Delta\mathrm{DEPTH}_t$ will be negatively autocorrelated.

Table 4 shows that $\mathrm{DIFF}_t^{buy}$ is positively and significantly related to the downside volatility ($\mathrm{RISK}_{t-1}^{-}$). When we compute market depth based on the best bid, the coefficient $\beta_1^{-}$ is 0.0080 on average and is significantly positive for 17 stocks. Results are even stronger when we compute market depth based on the second through fifth bid prices, as the coefficient $\beta_1^{-}$ is significantly positive for 30 stocks. This indicates that when there is a paucity of limit buy orders so that liquidity-driven price volatility arises from the bid side at time t-1, this will induce potential buyers to submit limit buy orders rather than market buy orders at time t. There is also a strong and positive relation between $\mathrm{DIFF}_t^{sell}$ and the upside volatility ($\mathrm{RISK}_{t-1}^{+}$). The estimate of $\beta_2^{+}$ is significantly positive for 20 (31) stocks when we compute market depth based on the best ask price (second through fifth ask prices). Therefore, when there is a paucity of limit sell orders so that liquidity-driven price volatility arises from the ask side at time t-1, potential sellers will submit limit sell orders rather than market sell orders at time t.

It is interesting to note that $\mathrm{DIFF}_t^{buy}$ is negatively related to the upside volatility ($\mathrm{RISK}_{t-1}^{+}$), and that $\mathrm{DIFF}_t^{sell}$ is negatively related to the downside volatility ($\mathrm{RISK}_{t-1}^{-}$). This indicates that when the price moves up (down), investors submit market buy (sell) orders instead of limit buy (sell) orders. An explanation is that the placement of limit orders depends on the probability of order execution. Some traders who place limit orders might need to execute the transaction within a specified period of time (Handa and Schwartz (1996)). When the price moves up (down), it becomes less likely that the limit buy (sell) orders posted at the original bid (ask) prices will be executed. Therefore, instead of waiting any longer, the impatient buyer (seller) will cancel the limit buy (sell) orders and submit market buy (sell) orders.

Overall, our results indicate that an increase in transitory volatility affects the order flow composition. Furthermore, it is important to distinguish between the volatility arising from the bid side and the ask side, as they have different impacts on the buy and sell order flows. While more limit buy orders are placed than market buy orders if the transitory volatility arises from the bid side, more limit sell orders are placed than market sell orders if the transitory volatility arises from the ask side. These results are consistent with the existence of liquidity providers who enter the market and place limit orders on either the bid or ask side, depending on which side will earn profits for the liquidity provision.

*C. Impacts of Market Depth on Short-Term Volatility*

To examine the effect of market depth on subsequent short-term volatility, we estimate the following regression model for each stock:

$$\mathrm{RISK}_t = \alpha_1 + \beta_1 \mathrm{DEPTH}_{t-1} + \theta_1\, \mathrm{NTRADE}_t + \sum_{k=1}^{14} \gamma_k \mathrm{TIME}_{k,t} + \rho_1\, \mathrm{RISK}_{t-1} + \varepsilon_t \quad . \tag{9}$$

The inclusion of $\mathrm{TIME}_{k,t}$ and $\mathrm{RISK}_{t\text{-}1}$ on the right hand side is to control for intraday patterns and autocorrelation in the short-term volatility. As we discuss in Section III, the RISK variable is likely to be dependent on the number of transactions during the interval. We therefore include $\mathrm{NTRADE}_t$ as an explanatory variable to control for its impact on $\mathrm{RISK}_t$.

Results are presented in Table 5. Consistent with our hypothesis, the transitory volatility at time t is negatively related to the depth at time t-1. For example, when DEPTH is computed based on the best five quotes, the average estimate of $\beta_1$ is -0.5296 (average t-value = -2.21), and the estimate is significantly negative for 21 stocks. We also note that the association between $RISK_{t-1}$ and $DEPTH_t$ is mostly driven by the depth in the first queue. When DEPTH is computed based on the second through fifth queues, the average estimate of $\beta_1$ is -0.1752 (average t-value =-1.24). These results suggest that while the whole limit order book (at least up to five queues) provides us with more information about market depth, what really matters is the amount of depth at the best quote. Our results show that transitory volatility arises mainly from the paucity of limit orders at the best queue. There is no evidence that a reduction in the market depth beyond the first queue will exacerbate the price volatility.

We also separate the depth into the bid and ask sides, and relate them to the downside and upside volatility. We estimate the following regression models:

$$RISK_t^+ = \alpha_1 + \beta_1^- DEPTH_{t-1}^{bid} + \beta_1^+ DEPTH_{t-1}^{ask} + \theta_1 NBUY_t + \sum_{k=1}^{14} \gamma_{1,k} TIME_{k,t} + \rho_1 RISK_{t-1}^+ + \varepsilon_t^+ \qquad (10)$$

$$RISK_t^- = \alpha_2 + \beta_2^- DEPTH_{t-1}^{bid} + \beta_2^+ DEPTH_{t-1}^{ask} + \theta_2 NSELL_t + \sum_{k=1}^{14} \gamma_{2,k} TIME_{k,t} + \rho_2 RISK_{t-1}^- + \varepsilon_t^- \qquad (11)$$

where $DEPTH_{t-1}^{bid}$ is the bid depth at time t, $DEPTH_{t-1}^{ask}$ is the ask depth at time t-1, $NBUY_t$ is the number of market buy orders at time t, and $NSELL_t$ is the number of market sell orders at time t.

Table 6 shows that the upside or downside volatility is significantly related to the market depth in the first queue. The upside volatility is significantly negatively related to the ask depth but not to the bid depth, while the downside volatility is significantly negatively related to the bid depth but not to the ask depth. These results suggest that by distinguishing between depth on the bid side and on the ask side, we have better information in predicting the direction and magnitude of transitory volatility.

*D. Sensitivity Tests*

Since our empirical results could depend on measures of volatility, depth, and the choice of time interval, we evaluate their robustness by conducting a variety of sensitivity tests.

*D.1 Alternative measure of volatility*

A drawback of our volatility measure ($\sum_{i=1}^{N} R_{i,t}^{2}$) is that it may proxy the number of orders executed rather than price movement. The fact that there are many trades means that a lot of limit orders are being executed, so that investors will replenish limit orders. Therefore, we may observe that more limit orders are submitted subsequent to an increase in our volatility measure regardless of whether there is an increase in price movement.

We therefore consider an alternative measure of volatility that is less dependent on the number of transactions. The alternative measure is the absolute return for the 15-minute interval, 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 interval t-1 and t. The absolute return is not directly related to the number of transactions, but its drawback is that it might not be able to detect transitory price volatility.[10] We replicate our tests using the absolute return as volatility measure, and results are insensitive to the alternative measure of volatility. This suggests that our empirical results are not purely driven by the number of transactions, but are related to the magnitude of price fluctuation within the interval.

*D.2 Alternative measures of depth and order flow*

In previous empirical tests, all depth and order flow measures are based on the number of trades. We also calculate the depth and order flow based on the share volume, and repeat the empirical

[10] Suppose 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 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.

analysis. Results based on the share volume are qualitatively similar, although we find that the impact of depth measured in share volume on the price volatility is weaker than the depth measured in number of trades (Table 5 and 6). This may be consistent with Jones, Kaul and Lipson (1994) who show that the number of transactions affects the price volatility more than the share volume.

*D.3 Alternative measure of time interval*

All our empirical results are based on the 15-minute interval (except the last interval) to measure the return volatility and order flows. We replicate the empirical analysis, using 30-minute interval. The results are qualitatively similar. However, the significance levels weaken as we increase the time interval.

*E. Discussion*

Overall, our findings are consistent with Handa and Schwartz (1996) who hypothesize that there exist equilibrium levels of limit-order trading and transitory volatility. When there is a lack of limit orders, temporary order imbalance triggers transitory volatility, which will attract public investors to place limit orders instead of market orders. The influx of limit orders will continue until transitory price volatility decreases, which in turn results in a paucity of limit orders that causes temporary order imbalance again.

Critics of the pure order-driven trading system without market makers often argue that limit order traders can be reluctant to submit orders into the system in a volatile market environment, since trading via limit orders is costly in an environment in which the adverse selection problem is severe. Although limit-order traders resemble market makers in providing liquidity and immediacy to the market, they have the freedom to choose whether to post a bid or an ask quote. This is different from market makers who have obligations to provide an orderly and smooth market by continuously posting both bid and ask quotes.

Contrary to the above view, the evidence shown in our study indicates that limit-order traders play a pivotal role in providing liquidity to the market. When there is an increase in liquidity-driven price volatility, investors will be encouraged to place limit orders as the gains from supplying liquidity can more than offset the potential loss from trading with informed traders. Our evidence is consistent with the view that an order-driven trading mechanism without the presence of market makers can be viable and self-sustaining.

## V. Conclusions

This paper examines the role of limit orders in liquidity provision in the Hong Kong stock market, which uses a computerized limit-order trading system. Consistent with Handa and Schwartz (1996), our results show that a rise in transitory volatility will be followed by an increase in market depth, and a rise in market depth will be followed by a decrease in transitory volatility. We also find that a change in transitory volatility affects the order flow composition. 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. These results are consistent with the existence of liquidity providers who enter and place limit orders to earn profits for their liquidity provision.

Our results are closely related to some recent empirical studies. Biais, Hillion, and Spatt (1995) find that in the Paris Bourse, a thin order book attracts orders and a thick book results in trades. Chung, Van Ness, and Van Ness (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. A distinct contribution of our paper is that while previous work examines the interaction between order flow and the state of the order book, we focus on the dynamic relation between transitory volatility and order flow. Furthermore, we illustrate that it is important to distinguish between volatility arising from the bid side or the ask side, as it provides information on which side needs liquidity. Nevertheless, our paper shares with previous studies the conclusion that investors provide liquidity when it is valuable to the marketplace and consume liquidity when it is plentiful. Although these investors do this for their own benefit, this selfmotivated trading behavior seems to result in an ecological balance between the suppliers and demanders of immediacy.

## References

Angel, J., 1997, Tick size, share prices, and stock splits, *Journal of Finance* 52, 655-681.

Admati, A., and P. Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, *Review of Financial Studies* 1, 3-40.

Biais, B., P. Hillion, and C. Spatt, 1995, An empirical analysis of the limit order book and the order flow in the Paris Bourse, *Journal of Finance* 50, 1655-1689.

Chung, K., B. Van Ness, and R. Van Ness, 1999, Limit orders and the bid-ask spread, *Journal of Financial Economics*, forthcoming.

Chakravarty, S., and C. Holden, 1996, An integrated model of market and limit orders, *Journal of Financial Intermediation* 4, 213-241.

Foucault, T., 1997, Order flow composition and trading costs in a dynamic limit order market, Working Paper, Carnegie-Mellon University, Pittsburgh, PA.

Glosten, L., 1994, Is the electronic open limit order book inevitable? *Journal of Finance* 49, 1127-1161.

Greene, J., 1996, The impact of limit order executions on trading costs in New York Stock Exchange stocks, Working paper, Georgia State Unviersity.

Hamao, Y., and J. Hasbrouck, 1995, Securities trading in the absence of dealers: Trades and quotes in the Tokyo Stock Exchange, *Review of Financial Studies* 8, 849-878.

Handa, P., and R. Schwartz, 1996, Limit order trading, *Journal of Finance* 51, 1835-1861.

Handa, P., R. Schwartz, and A. Tiwari, 1998, Determinants of the bid-ask spread in an order driven market, Working paper, University of Iowa.

Harris, L., and J. Hasbrouck, 1996, Market vs. limit Orders: The SuperDOT evidence on order submission strategy, *Journal of Financial and Quantitative Analysis* 31, 213-232.

Jones, C., G. Kaul, and M. Lipson, 1994, Transactions, volume, and volatility, *Review of Financial Studies* 7, 631-651.

Kavajecz, K., 1999, A specialist's quoted depth and the limit order book, *Journal of Finance* 54, 747-771.

Kumar, P., and D. Seppi, 1994, Limit and market orders with optimizing traders, Working paper, Carnegie Mellon University.

Lee, C., and M. Ready, 1991, Inferring trade direction from intradaily data, *Journal of Finance* 46, 733-746.

Lee, C., B. Mucklow, and M. Ready, 1993, Spreads, depths, and the impact of earnings information: An intraday analysis, *Review of Financial Studies* 6, 345-374.

Lehmann, B., and D..Modest, 1994, Trading and liquidity on the Tokyo Stock Exchange: A bird's eye view, *Journal of Finance* 48, 1595-1628.

Newey, W., and K. West, 1987, A simple positive semi-definite heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Parlour, C., and D. Seppi, 1996, Liquidity based competition for the order flow, Working Paper, Carnegie-Mellon University.

O'Hara, M., 1995, *Market Microstructure Theory*, Blackwell Publishers, Cambridge, Mass.

Ross, K., J. Shapiro, and K. Smith, 1996, Price improvement of SuperDot market orders on the NYSE, Working Paper #96-02, New York Stock Exchange, New York, NY.

Seppi, D., 1997, Liquidity provision with limit orders and a strategic specialist, *Review of Financial Studies* 10, 103-150.

Viswanathan, S. and J. Wang, 1998, Market Architecture: Limit-order books versus dealership markets, Working Paper, Duke University, Raleigh, NC.

**Table 1. Summary Statistics**

This table reports the cross-sectional distributions of the average price, spread in HK dollars, spread in the percentage of the stock price, daily number of trades, daily share volume, and daily dollar volume for the 33 component stocks of the Hang Seng Index. For a given stock, we compute the averages for the one-year period between July 1996 and June 1997.

| | Price (HK$) | Spread (HK$) | Spread (%) | No. of trades | Share volume (1,000) | Dollar volume (HK$1,000) |
|---|---|---|---|---|---|---|
| Mean | 32.6 | 0.120 | 0.47 | 387 | 4,367 | 118,103 |
| Std. dev. | 34.2 | 0.113 | 0.30 | 258 | 4,143 | 129,276 |
| Minimum | 3.5 | 0.030 | 0.23 | 35 | 335 | 6,710 |
| 1st quartile | 10.4 | 0.054 | 0.31 | 198 | 2,137 | 27,203 |
| Median | 19.8 | 0.066 | 0.39 | 346 | 3,140 | 61,125 |
| 3rd quartile | 38.5 | 0.130 | 0.58 | 581 | 4,729 | 181,336 |
| Maximum | 169.2 | 0.585 | 1.03 | 924 | 18,927 | 625,599 |

**Table 2. Regression of Depth on Lagged Transitory Volatility**

This table presents the GMM estimates from the regressions estimated for each of the 33 Hang Seng Index component stocks based on 15-minute intervals. The regression model is:

$$\mathrm{DEPTH}_t = \alpha_1 + \beta_1 \mathrm{RISK}_{t-1} + \theta_1 \mathrm{NTRADE}_t + \sum_{k=1}^{14} \gamma_k \mathrm{TIME}_{k,t} + \rho_1 \mathrm{DEPTH}_{t-1} + \varepsilon_t$$

where $\mathrm{DEPTH}_t$ is the depth measured as the total number of limit orders outstanding at the bid and ask quotes at the end of time interval t; $\mathrm{RISK}_{t-1}$ denotes the transitory volatility measured as sum of returns squared during time interval t-1; $\mathrm{NTRADE}_t$ is the number of transactions made during time interval t; $\mathrm{TIME}_{kt}$ represents a dummy variable that takes the value of one if time t belongs to the 15-minute intraday interval k, and zero otherwise; and $\varepsilon_t$ is a random error term. Regression coefficients are cross-sectional averages from the 33 stocks. Average t-statistics are in parentheses. Numbers in brackets are those of coefficients that are significantly positive at the 0.10 level and those of coefficients that are significantly negative at the 0.10 level, respectively.

| Definition of depth | $\beta_1$ | $\theta_1$ | $\rho_1$ |
|---|---|---|---|
| (1) | 0.0053 | -0.2345 | 0.9472 |
| Best 5 asks + best 5 bids | (5.47) | (-9.16) | (69.62) |
| | [32,0] | [0,33] | [33,0] |
| (2) | 0.0022 | -0.1553 | 0.7674 |
| Best ask + best bid | (4.24) | (-9.11) | (31.06) |
| | [33,0] | [0,33] | [33,0] |
| (1) – (2) | 0.0025 | -0.0364 | 0.9092 |
| | (3.76) | (-2.09) | (60.32) |
| | [30,0] | [1,21] | [33,0] |

**Table 3. Regression of Depth Change on Lagged Transitory Volatility**

This table presents the GMM estimates from the regressions estimated for each of the 33 Hang Seng Index component stocks based on 15-minute intervals. The regression model is:

$$\Delta \text{DEPTH}_t = \alpha_1 + \beta_1 \text{RISK}_{t-1} + \sum_{k=1}^{13} \gamma_k \text{TIME}_{kt} + \rho_1 \Delta \text{DEPTH}_{t-1} + \varepsilon_t$$

where $\Delta \text{DEPTH}_t$ is the change of depth (total number of outstanding limit orders at the bid and ask quotes) from time interval t-1 to t; $\text{RISK}_{t-1}$ denotes the volatility measured as sum of returns squared during time interval t-1; $\text{TIME}_{kt}$ represents a dummy variable that takes the value of one if time t belongs to the 15-minute intraday interval k, and zero otherwise; and $\varepsilon_t$ is a random error term. Regression coefficients are cross-sectional averages from the 33 stocks. Average t-statistics are in parentheses. Numbers in brackets are those of coefficients that are significantly positive at the 0.10 level and those of coefficients that are significantly negative at the 0.10 level, respectively.

| Definition of depth | $\beta_1$ | $\rho_1$ |
|---|---|---|
| (1) | 0.0017 | -0.1579 |
| Best 5 asks + best 5 bids | (2.55) | (-4.53) |
| | [25,0] | [0,30] |
| (2) | 0.0001 | -0.2965 |
| Best ask + best bid | (0.57) | (-11.83) |
| | [7,0] | [0,33] |
| (1) – (2) | 0.0014 | -0.1937 |
| | (2.40) | (-5.27) |
| | [27,1] | [0.30] |

**Table 4. Regression of the Difference between Limit Buy (Sell) Order and Market Buy (Sell) Order on Lagged Upside and Downside Volatility**

This table presents the GMM estimates from the regressions estimated for each of the 33 Hang Seng Index component stocks based on 15-minute intervals. The regression models are:

$$\mathrm{DIFF}_t^{buy} = \alpha_1 + \beta_1^+ \mathrm{RISK}_{t-1}^+ + \beta_1^- \mathrm{RISK}_{t-1}^- + \sum_{k=1}^{13} \gamma_{1,k} \mathrm{TIME}_{k,t} + \rho_1 \mathrm{DIFF}_{t-1}^{buy} + \varepsilon_t^{buy}$$

$$\mathrm{DIFF}_t^{sell} = \alpha_2 + \beta_2^+ \mathrm{RISK}_{t-1}^+ + \beta_2^- \mathrm{RISK}_{t-1}^- + \sum_{k=1}^{13} \gamma_{2,k} \mathrm{TIME}_{k,t} + \rho_2 \mathrm{DIFF}_{t-1}^{sell} + \varepsilon_t^{sell}$$

where $\mathrm{DIFF}_t^{buy}$ ($\mathrm{DIFF}_t^{sell}$) measures the difference between the number of newly placed limit buy (sell) orders and market buy (sell) orders during time interval t; $\mathrm{RISK}_{t-1}^{+}$ ($\mathrm{RISK}_{t-1}^{-}$) denotes the upside (downside) volatility during time interval t-1, being measured as the sum of returns squared based on positive (negative) return observations within the interval t-1; $\mathrm{TIME}_{kt}$ represents a dummy variable that takes the value of one if time t belongs to the 15-minute intraday interval k, and zero otherwise; $\varepsilon_t^{buy}$ and $\varepsilon_t^{buy}$ are usual random error terms. Regression coefficients are cross-sectional averages from the 33 stocks. Average t-statistics are in parentheses. Numbers in brackets are those of coefficients that are significantly positive at the 0.10 level and those of coefficients that are significantly negative at the 0.10 level, respectively.

Panel A: Dependent variable is the difference between limit buy order and market buy order.

| Definition of depth | $\beta_1^+$ | $\beta_1^-$ | $\rho_1$ |
|---|---|---|---|
| (1) | -0.0118 | 0.0125 | 0.2120 |
| Best 5 bids | (-2.79) | (3.32) | (6.86) |
| | [0,28] | [31,0] | [33,0] |
| (2) | -0.0083 | 0.0080 | 0.1702 |
| Best bid | (-1.68) | (1.81) | (6.03) |
| | [0,16] | [17,0] | [33,0] |
| (1) – (2) | -0.0177 | 0.0173 | 0.1614 |
| | (-4.02) | (4.18) | (5.66) |
| | [0,31] | [30,0] | [33,0] |

Panel B: Dependent variable is the difference between limit sell order and market sell order.

| Definition of depth | $\beta_2^+$ | $\beta_2^-$ | $\rho_2$ |
|---|---|---|---|
| (1) | 0.0172 | -0.0130 | 0.1614 |
| Best 5 asks | (3.78) | (-2.78) | (4.58) |
| | [30,0] | [0,26] | [31,0] |
| (2) | 0.0103 | -0.0084 | 0.1601 |
| Best ask | (2.14) | (-1.56) | (5.73) |
| | [20,0] | [0,20] | [31,0] |
| (1) – (2) | 0.0225 | -0.0189 | 0.1177 |
| | (4.65) | (-3.95) | (3.38) |
| | [31,0] | [0,29] | [28,0] |

**Table 5. Regression of Transitory Volatility on Lagged Depth**

This table presents the GMM estimates from the regressions estimated for each of the 33 Hang Seng Index component stocks based on 15-minute intervals. The regression model is:

$$RISK_t = \alpha_1 + \beta_1 DEPTH_{t-1} + \theta_1 NTRADE_t + \sum_{k=1}^{14} \gamma_k TIME_{kt} + \rho_1 RISK_{t-1} + \varepsilon_t$$

where $RISK_t$ denotes the volatility measured as sum of returns squared during time interval t; $DEPTH_{t-1}$, is the depth (total number of outstanding limit orders at the bid and ask quotes) at the end of time interval t-1; $TIME_{kt}$ represents a dummy variable that takes the value of one if time t belongs to the 15-minute intraday interval k, and zero otherwise; and $\varepsilon_t$ is a random error term. Regression coefficients are cross-sectional averages from the 33 stocks. Average t-statistics are in parentheses. Numbers in brackets are those of coefficients that are significantly positive at the 0.10 level and those of coefficients that are significantly negative at the 0.10 level, respectively.

| Definition of depth | $\beta_1$ | $\theta_1$ | $\rho_1$ |
|---|---|---|---|
| (1) | -0.5296 | 20.8405 | 0.2594 |
| Best 5 asks + best 5 bids | (-2.21) | (12.98) | (6.62) |
| | [3,21] | [33,0] | [33,0] |
| (2) | -3.6442 | 21.2486 | 0.2552 |
| Best ask + best bid | (-3.37) | (13.28) | (6.50) |
| | [2,25] | [33,0] | [33,0] |
| (1) – (2) | -0.1752 | 20.6468 | 0.2613 |
| | (-1.24) | (12.92) | (6.65) |
| | [5,15] | [33,0] | [33,0] |

**Table 6. Regression of Upside (Downside)Volatility on Lagged Buy and Sell Depth**

This table presents the GMM estimates from the regressions estimated for each of the 33 Hang Seng Index component stocks based on 15-minute intervals. The regression model is:

$$RISK_t^+ = \alpha_1 + \beta_1^- DEPTH_{t-1}^{bid} + \beta_1^+ DEPTH_{t-1}^{ask} + \theta_1 NBUY_t + \sum_{k=1}^{14} \gamma_{1,k} TIME_{k,t} + \rho_1 RISK_{t-1}^+ + \varepsilon_t^+$$

$$RISK_t^- = \alpha_2 + \beta_2^- DEPTH_{t-1}^{bid} + \beta_2^+ DEPTH_{t-1}^{ask} + \theta_2 NSELL_t + \sum_{k=1}^{14} \gamma_{2,k} TIME_{k,t} + \rho_2 RISK_{t-1}^- + \varepsilon_t^-$$

where $RISK_t^+$ ($RISK_t^-$) denotes the upside (downside) volatility during time interval t, being measured as the sum of returns squared based on positive (negative) return observations within the interval t; $DEPTH_{t-1}^{bid}$ ($DEPTH_{t-1}^{ask}$) measures the number of limit orders at the bid (ask) side at the end of time interval t-1; $NBUY_t$ ($NSELL_t$) is the number of transactions initiated by market buy (sell) orders during time interval t; $TIME_{kt}$ represents a dummy variable that takes the value of one if time t belongs to the 15-minute intraday interval k, and zero otherwise; $\varepsilon_t^+$ and $\varepsilon_t^-$ are random error terms. Regression coefficients are cross-sectional averages from the 33 stocks. Average t-statistics are in parentheses. Numbers in brackets are those of coefficients that are significantly positive at the 0.10 level and those of coefficients that are significantly negative at the 0.10 level, respectively.

Panel A: Dependent variable is upside volatility.

| Definition of depth | $\beta_1^-$ | $\beta_1^+$ | $\theta_1$ | $\rho_1$ |
|---|---|---|---|---|
| (1) | -0.2911 | 0.3234 | 14.1922 | 0.2639 |
| Best 5 depths | (-0.64) | (0.01) | (11.62) | (6.98) |
| | [7,13] | [7,8] | [33,0] | [32,0] |
| (2) | -0.9737 | -1.1545 | 14.4106 | 0.2641 |
| Best depth | (-0.79) | (-1.93) | (11.92) | (7.05) |
| | [4,12] | [3,20] | [33,0] | [32,0] |
| (1) – (2) | -0.0111 | 0.5206 | 14.1411 | 0.2643 |
| | (-0.22) | (0.54) | (11.60) | (6.94) |
| | [7,7] | [11,7] | [33,0] | [32,0] |

Panel B: Dependent variable is downside volatility.

| Definition of depth | $\beta_2^-$ | $\beta_2^+$ | $\theta_2$ | $\rho_2$ |
|---|---|---|---|---|
| (1) | -0.1705 | 0.4912 | 14.5403 | 0.2329 |
| Best 5 depths | (-0.50) | (0.84) | (12.45) | (6.41) |
| | [7,13] | [12,2] | [33,0] | [32,0] |
| (2) | -2.1217 | 0.0343 | 14.9127 | 0.2350 |
| Best depth | (-2.04) | (-0.24) | (12.74) | (6.48) |
| | [3,19] | [9,8] | [33,0] | [31,0] |
| (1) – (2) | 0.4388 | 0.5614 | 14.4976 | 0.2332 |
| | (0.51) | (0.91) | (12.41) | (6.39) |
| | [12,7] | [12,2] | [33,0] | [32,0] |

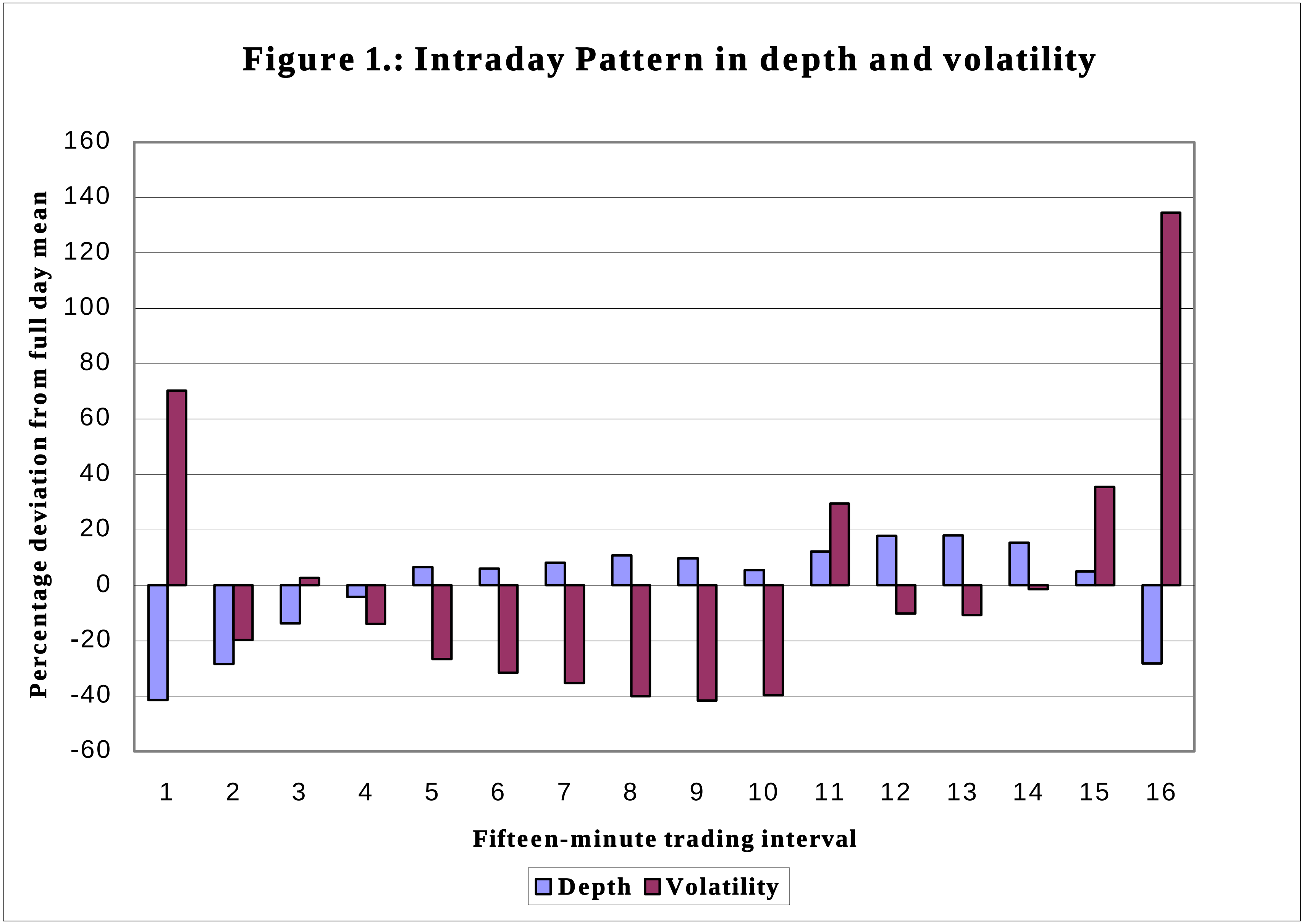

Figure 1.: Intraday Pattern in depth and volatility
Percentage deviation from full day mean
160
140
120
100
80
60
40
20
0
-20
-40
-60
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
Fifteen-minute trading interval
Depth
Volatility

## Appendix

**Table 2'. Regression of Depth on Lagged Transitory Volatility**

This table presents the GMM estimates from the regressions estimated for each of the 33 Hang Seng Index component stocks based on 15-minute intervals. The regression model is:

$$\mathrm{DEPTH}_t = \alpha_1 + \beta_1 \mathrm{RISK}_{t-1} + \theta_1 \mathrm{NTRADE}_t + \sum_{k=1}^{14} \gamma_k \mathrm{TIME}_{k,t} + \rho_1 \mathrm{DEPTH}_{t-1} + \varepsilon_t$$

where $\mathrm{DEPTH}_t$ is the depth measured as the total number of limit orders outstanding at the bid and ask quotes at the end of time interval t; $\mathrm{RISK}_{t-1}$ denotes the transitory volatility measured as the absolute return during time interval t-1; $\mathrm{NTRADE}_t$ is the number of transactions made during time interval t; $\mathrm{TIME}_{kt}$ represents a dummy variable that takes the value of one if time t belongs to the 15-minute intraday interval k, and zero otherwise; and $\varepsilon_t$ is a random error term. Regression coefficients are cross-sectional averages from the 33 stocks. Average t-statistics are in parentheses. Numbers in brackets are those of coefficients that are significantly positive at the 0.10 level and those of coefficients that are significantly negative at the 0.10 level, respectively.

| Definition of depth | $\beta_1$ | $\theta_1$ | $\rho_1$ |
|---|---|---|---|
| (1) | 0.0071 | -0.2035 | 0.9534 |
| Best 5 asks + best 5 bids | (5.35) | (-8.02) | (70.46) |
| | [32,0] | [0,33] | [33,0] |
| (2) | 0.0018 | -0.1367 | 0.7659 |
| Best ask + best bid | (2.35) | (-8.34) | (30.30) |
| | [22,0] | [0,33] | [33,0] |
| (1) – (2) | 0.0027 | -0.0202 | 0.9132 |
| | (2.64) | (-1.28) | (61.34) |
| | [28,0] | [3,14] | [33,0] |

## Appendix

**Table 3'. Regression of Depth Change on Lagged Transitory Volatility**

This table presents the GMM estimates from the regressions estimated for each of the 33 Hang Seng Index component stocks based on 15-minute intervals. The regression model is:

$$\Delta DEPTH_t = \alpha_1 + \beta_1 RISK_{t-1} + \sum_{k=1}^{13} \gamma_k TIME_{kt} + \rho_1 \Delta DEPTH_{t-1} + \varepsilon_t$$

where $\Delta DEPTH_t$ is the change of depth (total number of outstanding limit orders at the bid and ask quotes) from time interval t-1 to t; $RISK_{t-1}$ denotes the volatility measured as the absolute return during time interval t-1; $TIME_{kt}$ represents a dummy variable that takes the value of one if time t belongs to the 15-minute intraday interval k, and zero otherwise; and $\varepsilon_t$ is a random error term. Regression coefficients are cross-sectional averages from the 33 stocks. Average t-statistics are in parentheses. Numbers in brackets are those of coefficients that are significantly positive at the 0.10 level and those of coefficients that are significantly negative at the 0.10 level, respectively.

| Definition of depth | $\beta_1$ | $\rho_1$ |
|---|---|---|
| (1) | 0.0030 | -0.1521 |
| Best 5 asks + best 5 bids | (2.42) | (-4.25) |
| | [25,0] | [0,29] |
| (2) | 0.0002 | -0.2963 |
| Best ask + best bid | (0.33) | (-11.63) |
| | [3,0] | [0,33] |
| (1) – (2) | 0.0018 | -0.1905 |
| | (1.77) | (-5.17) |
| | [20,0] | [0,30] |

## Appendix

### Table 4'. Regression of the Difference between Limit Buy (Sell) Order and Market Buy (Sell) Order on Lagged Upside and Downside Volatility

This table presents the GMM estimates from the regressions estimated for each of the 33 Hang Seng Index component stocks based on 15-minute intervals. The regression models are:

$$DIFF_t^{buy} = \alpha_1 + \beta_1^{+} RISK_{t-1}^{+} + \beta_1^{-} RISK_{t-1}^{-} + \sum_{k=1}^{13} \gamma_{1,k} TIME_{k,t} + \rho_1 DIFF_{t-1}^{buy} + \varepsilon_t^{buy}$$

$$DIFF_t^{sell} = \alpha_2 + \beta_2^{+} RISK_{t-1}^{+} + \beta_2^{-} RISK_{t-1}^{-} + \sum_{k=1}^{13} \gamma_{2,k} TIME_{k,t} + \rho_2 DIFF_{t-1}^{sell} + \varepsilon_t^{sell}$$

where $DIFF_t^{buy}$ ( $DIFF_t^{sell}$ ) measures the difference between the number of newly placed limit buy (sell) orders and market buy (sell) orders during time interval t; $RISK_{t-1}^{+}$ ( $RISK_{t-1}^{-}$ ) denotes the upside (downside) volatility during time interval t-1, being measured as the absolute return (upside (downside) volatility for positive (negative) return observation) during the interval t-1; $TIME_{kt}$ represents a dummy variable that takes the value of one if time t belongs to the 15-minute intraday interval k, and zero otherwise; $\varepsilon_t^{buy}$ and $\varepsilon_t^{buy}$ are usual random error terms. Regression coefficients are cross-sectional averages from the 33 stocks. Average t-statistics are in parentheses. Numbers in brackets are those of coefficients that are significantly positive at the 0.10 level and those of coefficients that are significantly negative at the 0.10 level, respectively.

Panel A: Dependent variable is the difference between limit buy order and market buy order.

| Definition of depth | $\beta_1^{+}$ | $\beta_1^{-}$ | $\rho_1$ |
|---|---|---|---|
| (1) | -0.0033 | 0.0079 | 0.1973 |
| Best 5 bids | (-1.59) | (4.25) | (6.09) |
| | [0,15] | [33,0] | [33,0] |
| (2) | -0.0029 | 0.0049 | 0.1607 |
| Best bid | (-1.09) | (2.31) | (5.23) |
| | [0,8] | [25,0] | [33,0] |
| (1) – (2) | -0.0074 | 0.0084 | 0.1417 |
| | (-3.37) | (4.34) | (4.77) |
| | [0,32] | [33,0] | [32,0] |

Panel B: Dependent variable is the difference between limit sell order and market sell order.

| Definition of depth | $\beta_2^{+}$ | $\beta_2^{-}$ | $\rho_2$ |
|---|---|---|---|
| (1) | 0.0109 | -0.0030 | 0.1469 |
| Best 5 asks | (4.75) | (-1.52) | (4.09) |
| | [33,0] | [0,16] | [30,0] |
| (2) | 0.0064 | -0.0022 | 0.1498 |
| Best ask | (2.54) | (-0.98) | (4.92) |
| | [28,0] | [0,11] | [31,0] |
| (1) – (2) | 0.0119 | -0.0070 | 0.0991 |
| | (5.00) | (-3.12) | (2.80) |
| | [33,0] | [0,31] | [26,0] |

# Appendix

**Table 5'. Regression of Transitory Volatility on Lagged Depth**

This table presents the GMM estimates from the regressions estimated for each of the 33 Hang Seng Index component stocks based on 15-minute intervals. The regression model is:

$$RISK_t = \alpha_1 + \beta_1 DEPTH_{t-1} + \theta_1 NTRADE_t + \sum_{k=1}^{14} \gamma_k TIME_{kt} + \rho_1 RISK_{t-1} + \varepsilon_t$$

where $RISK_t$ denotes the volatility measured as the absolute return during time interval t; $DEPTH_{t-1}$, is the depth (total number of outstanding limit orders at the bid and ask quotes) at the end of time interval t-1; $TIME_{kt}$ represents a dummy variable that takes the value of one if time t belongs to the 15-minute intraday interval k, and zero otherwise; and $\varepsilon_t$ is a random error term. Regression coefficients are cross-sectional averages from the 33 stocks. Average t-statistics are in parentheses. Numbers in brackets are those of coefficients that are significantly positive at the 0.10 level and those of coefficients that are significantly negative at the 0.10 level, respectively.

| Definition of depth | $\beta_1$ | $\theta_1$ | $\rho_1$ |
|---|---|---|---|
| (1) | -0.9466 | 9.0672 | 0.0921 |
| Best 5 asks + best 5 bids | (-5.70) | (12.64) | (3.96) |
| | [0,30] | [33,0] | [32,0] |
| (2) | -3.4537 | 9.1532 | 0.0848 |
| Best ask + best bid | (-6.45) | (12.65) | (3.61) |
| | [0,33] | [33,0] | [31,0] |
| (1) – (2) | -0.8338 | 8.8654 | 0.1007 |
| | (-4.22) | (12.36) | (4.36) |
| | [0,25] | [33,0] | [32,0] |

## Appendix

**Table 6'. Regression of Upside (Downside)Volatility on Lagged Buy and Sell Depth**

This table presents the GMM estimates from the regressions estimated for each of the 33 Hang Seng Index component stocks based on 15-minute intervals. The regression model is:

$$RISK_t^+ = \alpha_1 + \beta_1^- DEPTH_{t-1}^{bid} + \beta_1^+ DEPTH_{t-1}^{ask} + \theta_1 NBUY_t + \sum_{k=1}^{14} \gamma_{1,k} TIME_{k,t} + \rho_1 RISK_{t-1}^+ + \varepsilon_t^+$$

$$RISK_t^- = \alpha_2 + \beta_2^- DEPTH_{t-1}^{bid} + \beta_2^+ DEPTH_{t-1}^{ask} + \theta_2 NSELL_t + \sum_{k=1}^{14} \gamma_{2,k} TIME_{k,t} + \rho_2 RISK_{t-1}^- + \varepsilon_t^-$$

where $RISK_t^+$ ($RISK_t^-$) denotes the upside (downside) volatility during time interval t, being measured as the absolute return (upside (downside) volatility for positive (negative) return observation) within the interval t; $DEPTH_{t-1}^{bid}$ ($DEPTH_{t-1}^{ask}$) measures the number of limit orders at the bid (ask) side at the end of time interval t-1; $NBUY_t$ ($NSELL_t$) is the number of transactions initiated by market buy (sell) orders during time interval t; $TIME_{kt}$ represents a dummy variable that takes the value of one if time t belongs to the 15-minute intraday interval k, and zero otherwise; $\varepsilon_t^+$ and $\varepsilon_t^-$ are random error terms. Regression coefficients are cross-sectional averages from the 33 stocks. Average t-statistics are in parentheses. Numbers in brackets are those of coefficients that are significantly positive at the 0.10 level and those of coefficients that are significantly negative at the 0.10 level, respectively.

Panel A: Dependent variable is upside volatility.

| Definition of depth | $\beta_1^-$ | $\beta_1^+$ | $\theta_1$ | $\rho_1$ |
|---|---|---|---|---|
| (1) | -0.0046 | -0.0100 | 0.1347 | -0.0638 |
| Best 5 depths | (-2.59) | (-5.77) | (14.65) | (-3.74) |
| | [0,21] | [0,31] | [33,0] | [0,27] |
| (2) | -0.0258 | -0.0242 | 0.1345 | -0.0652 |
| Best depth | (-4.80) | (-4.39) | (14.56) | (-3.81) |
| | [0,30] | [0,31] | [33,0] | [0,27] |
| (1) – (2) | -0.0017 | -0.0110 | 0.1329 | -0.0624 |
| | (-1.26) | (-5.40) | (14.34) | (-3.62) |
| | [1,15] | [0,31] | [33,0] | [0,25] |

Panel B: Dependent variable is downside volatility.

| Definition of depth | $\beta_2^-$ | $\beta_2^+$ | $\theta_2$ | $\rho_2$ |
|---|---|---|---|---|
| (1) | -0.0181 | -0.0013 | 0.1355 | -0.0698 |
| Best 5 depths | (-6.42) | (-2.03) | (15.47) | (-4.44) |
| | [0,33] | [2,20] | [33,0] | [0,28] |
| (2) | -0.0323 | -0.0230 | 0.1358 | -0.0671 |
| Best depth | (-4.23) | (-5.32) | (15.35) | (-4.27) |
| | [0,31] | [0,30] | [33,0] | [0,26] |
| (1) – (2) | -0.0170 | -0.0006 | 0.1336 | -0.0666 |
| | (-5.82) | (-1.02) | (15.17) | (-4.25) |
| | [0,33] | [2,13] | [33,0] | [0,27] |