Liquidity, Size and Cycle of Order Flow

in an Order-Driven Stock Exchange

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Abstract

We investigate the order flow composition of an order-driven market, the Hong Kong Stock Exchange. We examine the effect of different market status and time-of-a-day factor on *Cycle of Order Flow* and derive useful hypotheses. We find that increase in number of limit orders attracts trades, then this consumption of liquidity attracts limit orders, which completes the cycle of order flow. The number of block trading increases with more limit order at or within the quote while the number of small size trading decreases with limit orders available within the quote. The spread has a significant negative effect on number of market orders while the order size has significant negative effect on the number of limit orders. Empirical results support the hypothesis that the choice between limit and market order depends on the information asymmetry, market status and the time.

1 Introduction

Liquidity provision is one of the major indicators of the quality of a stock exchange. Limit order, in terms of supplying liquidity, gains increasing spotlight as many emerging markets adopt the order-driven trading mechanism. An exchange can benefit in designing and implementing their regulations and services by deeper understanding of investor's order submission strategy. From the investor's side, order submission strategy based on different market status is an important decision. They have to choose between submitting market or limit orders. While market order guarantees execution against the best opposite quote, the traders have to pay for the price for immediacy as they consume liquidity from the market. On the order hand, limit order provides liquidity to the market and transacts at the traders' desired price, but introduces the execution risk and winner's curse problem. Therefore, the market status and aggressiveness of trades are

among the most crucial element in the determination of traders order submission strategies.

Handa and Schwartz(1996) state that the choice between limit and market orders depends on the beliefs of investors about the probability of their limit orders executing against informed or liquidity traders. Investors who submit limit orders expose to the execution risk and risk of informed trading (or winner curse problem). These investors gain when there is short-term price fluctuation in return. Handa et al.(1996) predict that temporary price fluctuation due to liquidity shocks is one of the main determinants in limit order submission of the investors. Handa et al.(1996) suggest that patient traders have incentive to submit limit orders and other traders (who are less patient) would prefer to submit market orders.

Foucault(1999) analyses theoretically the order flow composition and price formation in dynamic limit order market, where investors choose either posting limit or market orders. He solves the equilibrium of the game and obtains a closed-form solution for order placement strategies. His main finding is that the asset volatility is the main determinant of the choice between limit and market orders. The proportion of limit orders in the order flow is positively related to the asset volatility and the average size of the bid-ask spread. This implies that the proportion of limit orders increase with higher transient volatility or larger spread (or both). However, all orders are of only one unit in his model. The effect of the limit order depth and size of the market on investors choice cannot be analysed. As his model assumes every limit order lasts only one period, the interaction between the order flow composition, the time-of-a-day and the change in states of the order book cannot be analyzed as the book is either full or empty.

Empirically, Biais, Hillion and Spatt(1995) analyze the interaction of order flow and order book status in Paris Bourse. [1] They find that when the *bid-ask spread* is tight, trades are more frequent but when the spread is large, new limit orders inside the quote (i.e. within the spread) are more frequent. [2] Simultaneously, *depth* of the book affects the submission of limit orders and also the amount of market orders. When the depth of the quotes is high, new orders within the spread are more frequent; when the depth is low, new orders at the quotes are more frequent. This reflects undercutting behaviour of investors with respect to their level of acceptance of execution risks. Biais, Hillion and Spatt(1995) also examine the time effect of limit orders or trades. They show that empirically orders and trades both exhibit U-shaped pattern, which is consistent with the

[1] The Paris Bourse has merged with the exchanges of Amsterdam and Brussels in 2000 to form the Euronext. Then group expanded at the beginning of 2002 with the acquisition of LIFFE (London International Financial Futures and Options Exchange) and the Portuguese exchange BVLP.

[2] New orders within the spread when the spread is large may just reflect random order placement; see the detailed explanation of Biais, Hillion and Spatt(1995).

results in Mcinish and Wood (1992). [3] However, Biais et al. (1995) only document the empirical frequency distribution of various kinds of orders but do not perfrom a rigous regression analysis on the effect of one type of order over the others.

Ahn, Bae and Chan(2001) investigate liquidity supply by limit orders in a order-driven market, HKSE. Their analysis is based on the implication from the model developed by Handa and Schwartz(1996) and Foucault(1999) about temporary volatility and placement of limit and/or market orders. They show that increases in short-term price volatility is followed by increase in the market depth and the volatility decreases as market depth increases. While transient price volatility affects the order submission due to liquidity shock, the interaction of market status and time-of-day on the placement of limit and/or market orders are yet to be analyzed extensively.

Ranaldo(2004) investigate the information content of a limit order book in Swiss Stock Exchange. He studies the aggressiveness in the order flow and its relation to the transient price volatility. He find that patient traders are more aggressive when the own side book is thick, opposite side book is thin, larger spread or increase in transient volatility. Limited by the dataset, Ranaldo(2004) cannot analyze the effect of change in market conditions on *limit orders out of the best quotes*. However, Biais et al.(1995) and Ahn, Bae and Chan(2001) show that out of quote limit orders are of *significant* proportion in the order flow and are very important in the price discovery process.

In this paper, we further examine how the investors behave in an order-driven market with resepect to different market status (i.e. spread, depth and size) and time. This is an important question because their choice of orders and aggressiveness reflect their belief in the market. While Ranaldo(2004) concentrates on the change in order aggressiveness with respect to market conditions, we focus on the order flow compositions and the effects of spread and size on market and limit order separately instead of pooling them together. Previous studies focus on either determinants or consequences of investors beliefs, we consolidate the findings into *a cycle of order flow* since the order submission of investors affect the order submission behaviour of the other traders.

We extend the previous empirical analysis of order-driven market by Biais et al.(1995) and Ahn, Bae and Chan(2001) and Ranaldo(2004) by examining the frequency distribution of the order flow cycle. We use one-year data of market depth, size, spread and volatility to explain the change of

[3]Mcinish and Wood (1992), Harris and Hasbrouck (1996) both analyze the NYSE and find that intraday U-shaped pattern of spread and market/limit orders respectively. Cheung and Song(2004) investigate spread, volume and order aggresiveness the Hong Kong Stock Exchange (HKSE), one of the largest pure order-driven market, they find also the U-shaped pattern of spread and transaction volume in their intraday data.

order flow composition in a regression model. [4] Our dataset is highly comprehensive as it is a one-year intraday dataset with over five millions records of transactions and bid-ask quotes. Also from the quote records, we can distinguish and analyze the out-of-quote limit orders, namely the second queue to the fifth queue. Our dataset contain intraday data of thirty-three Hang Seng Index Components, from September 2001 to August 2002 inclusive, compare to Ranaldo(2004) with only fifteen stocks in a two months dataset. The bid and ask quote data are much more informative and transparent in HKSE than other order-driven market as we have order size, depth and broker ID in the best *five* quotes for both bid and ask sides. All of these variables are related to the order flow composition of an order-driven market, but how the traders react to the change of these variable are unknown. The focus of this paper is to explore the *dynamic relationship* between limit and market orders, together with spread, depth, size and time on the order flow cycle in an order-driven market.

We find that after controlling the time factor, spread has a positive effect on trades and market depth and size have negative effects on limit orders. The small trades is more sensitive to the change in the spread than the block trades since the spread is a proxy of liquidity rather than information asymmetry. The limit orders within the quote is positively related to the order size of the opposite queue and the limit orders at and out of the quote is negatively related to it. This is due to the price and time priority and information asymmetry among traders.

This studies about Hong Kong Stock Exchange is valuable because as a prototype of order-driven market, HKSE is among the highest transparency in all order-driven markets, including Paris Bourse, Tokyo Stock Exchange and Swiss Stock Exchange. [5] Hong Kong Stock Exchange is one of the largest stock markets with market capitalization over 704 billions in US dollar. With the rich information of trade records and bid and ask records in the HKSE, investigation of the change in belief of the investors and consequently their choice between limit and market orders using data from HKSE is of high value for both academians and practitioners.

In the next section, we describe the characteristics of the Hong Kong stock market and summarize the data set that will be used in the analysis. In Section 3 we examine the order flow composition in frequency distribution with respect to different market status (depth, size, spread and volatility) and time and then develope testable hypotheses. Section 4 presents the numeri-

[4] Our empirical tests control for the effect of spread and order aggressiveness in the model and use the order book status as an explanatory variable.

[5] Similar to the Paris Bourse, traders can place a hidden order in the Swiss Stock Exchange which is correspond to an order over 200,000 CHF. A hidden order maybe traded outside of the market. Details can be found in Ranaldo(2004).

cal results from GMM estimation of the hypotheses in the previous section and the final section concludes the paper.

2 Data and Descriptive Statistics

The data set used in this study are from the *Trade Record* and *Bid and Ask Record* of the HKSE. Trade record provides trade details, such as date, time, price and quantity, of each transaction recorded, whereas Bid and Ask Record provides intraday bid and ask information including the quote price, order size, queue length and quantity from the first to fifth queue, recorded at 30 second intervals. [6] A trade or bid-ask record has to satisfy the following conditions before it is included in the data set.

Stocks inclusion: only the 33 index component stocks of the Hang Seng Index (HSI) are included, ranging from September 2001 to August 2002. These 33 stocks contribute over 70% of the total market capitalization of the exchange, which are quite representative of the market.

Trade inclusion: all trades are included except those that have been arranged before opening or after closing time, or with special condition such as non-automatched. [7]

Quote condition: all quotes are included except those submitted before opening or after closing time.

Spread condition: negative spread are excluded.

Table 1 summarizes the descriptive statistics of component stocks of the Hang Seng Index from September 2001 to August 2002. [8] Only automatched trade data for the HSI conponents are considered here since other trade methods, like manaul trade, special trade are of different trading mechanisms, which are of small proportion. Order size is defined by the total number of outstanding shares available at both best bid and best ask queues of the book. Depth at primary queue is defined by the total number of outstanding orders available at both best bid and best ask queues of the book.

[6] We have assumed therefore, through out the analysis that, the corresponding variable are constant within a 30 seconds interval.

[7] All of these tradings are of different architecture from standard automatched trade and should be of special considerations. For the analysis of preopening period in Paris Bourse, see Biais, Hillion and Spatt (1999).

[8] By comparing with the market figures, trading frequency of the HSI stocks is over five times more than the stocks in rest of the market, confirming the representativeness of the HSI component stocks for the whole market.

Table 1: Cross-Sectional Descriptive Statistics Summary for Aggregated Daily Limit Orders, Market Orders, Transaction Volume, Average Spread, Per-10-min Primary Queue Depth and Order Size for the 33 component stocks of Hang Seng Index from September 2001 to August 2002. For each of the 33 stocks, cross-sectional average of daily time-series average of Limit Orders, Market Orders, Transaction Volume, Average Spread are calculated. While the figures for Primary Queue Depth and Order Size, cross-sectional average of time-series average are calculated in each of the 29 ten-minute intervals.

	Mean	Minimum	Lower 1st Quantile	Median	Upper 3rd Quantile	Maximum
		Daily	Description			
Limit Order	722.574	55	378	613	960	5219
Market Order	746.081	13	260	486	898	20339
Price	26.852	1.430	7.400	13.950	36.000	98.250
Volume	7,897,529.09	33,800.00	1,926,536.50	3,795,385.00	7,367,954.00	358,647,299
Spread	0.0944	0.010	0.050	0.050	0.100	0.800
		Per 10-min	Intervals	Description		
Primary Queue Depth	38.5945709	2.0	10.0	19.0	40.0	1252.0
Order Size	1,106,028.2	800.0	124,500.0	285,000.0	670,000.0	143,152,000

Table 2: Quote data HSBC Holdings on March 2, 2004. the actual data of HSBC Holdings, one of the thirty three component stocks of Hang Seng Index on 11:33am of 2nd March, 2004.

Bid			Ask		
No. of Buyers	Volume	Price	Price	Volume	No. of Sellers
130	2,162,400	HKD 126.500	HKD 127.000	2,137,200	131
251	1,868,400	HKD 126.000	HKD 127.500	3,101,200	83
290	2,482,000	HKD 125.500	HKD 128.000	2,623,600	109
443	1,922,400	HKD 125.000	HKD 128.500	2,299,200	57
66	851,200	HKD 124.500	HKD 129.000	1,153,600	105

The mean and median number of daily market orders per component stock are about 746 and 486 while the mean and median number of daily limit orders per component stock are about 723 and 613, suggesting a moderate level for both types of orders. The mean and median spread are 0.094 and 0.050 respectively, which are about one tick size of stock with price HK$30.00 − 50.00 and HK$5.00 − 30.00, matching the average price of 26.85.

To illustrate the high transparency of the HKSE, we display in Table2 an example of publicly available information on each side of the limit order book. The figures are from the actual data of HSBC Holdings, one of the thirty three component stocks of Hang Seng Index on 11:33am of 2nd March, 2004. The contemporanous spread is now $301 − $300 = $1. The best bid (ask) quote now is 126.5 (127.0). The depth at the primary bid (ask) queue is 130 (131) with order size $2,162,400$

Table 3: Correlation of Market Status Variables and Orders, in 10 minutes intervals, for the 33 component stocks of Hang Seng Index from September 2001 to August 2002. For each of the 33 stocks, cross-sectional averages of correlation coefficients are calculated. Values in boldface indicate a p-value less than 0.0001 for test of zero correlation.

Market Status Variables	Depth	log(Size)	Spread	log(Volume)	Limit Orders
Depth	1.000				
log(Size)	**0.661**	1.000			
Spread	-0.020	0.002	1.000		
log(Volume)	**0.197**	**0.280**	-0.048	1.000	
Order Variables					
Limit Orders	-0.058	-0.093	0.118	0.151	1.000
Market Orders	-0.035	-0.037	0.055	**0.216**	**0.340**

Table 4: Autocorrelation of Number of Limit and Market Orders, up to $4th$ order in 10 minutes intervals, for the 33 component stocks of Hang Seng Index from September 2001 to August 2002. For each of the 33 stocks, cross-sectional averages of autocorrelation coefficients are calculated. All values have p-value less than 0.0001 for test of zero autocorrelation.

Order of Lag Variables	1	2	3	4
Number of Limit Order	0.4684363	0.3519296	0.3067373	0.2650683
Number of Market Order	0.3671531	0.2865935	0.2638522	0.2432122

$(2, 137, 200)$.

In Table 3, log(volume) is correlated with depth and log(size), suggesting a choice of instrumental variable in the regression analysis in later session. Depth is positively correlated with log(size) due to the mechanical effect of order, the number of market order submitted is also positively correlated with the number of limit order submitted, which is less intuitive. Given the total number of orders, the higher proportion of market (limit) orders submitted during a time interval should simultaneously lower the proportion of limit (market) order received by the order book, which suggests a negative correlation in number of limit and market order, at least in that specific interval. However, a positive correlation can also exist if there is *continuous* supply of liquidity through limit order when the market demand order increases and vice versa.

Table 4 provides the data of autocorrelations up to 4th order, which is equal to 40 minutes lag of newly submitted limit order and market order. The autocorrelation coefficients of Limit Order, LO, are decreasing monotonically from 0.468 to 0.265. While the autocorrelation coefficients of Market Order, MO, up to 4th order lag are also decreasing monotonically from 0.367 to 0.243, this shows that although the 1st order autocorrelation is much lower for market orders than imit

orders, it is a longer memory process.

3 Order Flow Composition

In this section, we analyze empirically the order flow composition. Because of the availability of high frequency data from the intraday trade and bid-ask record, we can divide the market trading activities into different categories in Table, The classifications are similar to Biais, Hillion and Spatt(1995) and Harris and Hasbrouck(1996).

3.1 Unconditional Frequency of Trades and Orders

In Table 6, the most frequent market activity is *small sell* and *small buy*, next is *bid at the quote*, followed by *ask above the quote*, *ask at the quote* and *bid below the quote*, suggesting that most of the market activities are at or out of the best quotes and confirm the empirical result from Biais, Hillion and Spatt(1995). The only exception is the low intensity of activities within the quote compared with to the Paris Bourse. Our finding is different from the result of Harris and Hasbrouck(1996) who found that limit orders away from the best quotes are infrequent in NYSE. We have two explanations for each of the above observations. First, for out of quote activities, it may indicate that there exists noise (or irrational) traders who neither supply immediate liquidity (by placing orders at or within the quote) to gain time and price priority and higher probability of execution, nor consume liquidity through trade to gain immediate execution. Thus, noise trading results in a lot of out of quote orders which need to be revised and adjusted, consequently producing a larg r proportion of orders at 2nd to 5th queue and cancellation of orders in the total market activities. Second, patient traders who are not hurry to take part in trading activities make a lot of attempts in the price discovery process by making use of 2nd to 5th queues and cancellations. This may be due to the fact that small and individual investors lack information compared with institutional investors. They produce a lot of out of quote activities in order to protect themselves from trading against informed traders. On the other hand, the informed traders are more patient when observing the above behaviour of those small investors, they use the 2nd to 5th queues and cancellations of orders in the price discovery process. The high intensity of at the quote activities including small sell, small buy, bid at the quote and ask at the quote, shows that the existence of small/individual traders who make a lot of small size trades and also institutional traders who

Table 5: Classification Table for market trading activitives and orders.

order nature	limit order trade order
initiative direction	buyer-initiated seller-initiated
level of aggressiveness in decreasing level of aggressiveness, we define, with sell-side in parentheses, an order to be:	
large buy(sell) LB(LS)	order to buy(sell) a quantity larger than the best quote can offer with a price higher(lower) than the best ask(bid) quote
market buy(sell) MB(MS)	order to buy(sell) a quantity larger than or equal to the best quote can offer (since the exchange doesn't allow walking up and down the book, and remaining portion will be converted to limit order)
small buy(sell) SB(SS)	order to buy(sell) a quantity smaller than the best quote can offer
limit bid(ask) order within the quote, BOW(AOW)	limit order to buy(sell) at a price higher (lower) than the current best bid(ask)
limit bid(ask) order at the quote, BOA(AOA)	limit order to buy(sell) at the current best bid(ask) quote
limit bid(ask) order outside of the quote BOO(AOO)	limit order to buy(sell) at a price lower(higher) than the current best bid(ask) quote, which will be submitted to 2nd, 3rd, 4th or 5th bid(ask) queues according to their bid(ask) price
cancellation of limit orders BOC(AOC)	since investors can cancel their orders or decrease the trade size of the orders before the transaction take place, but they can't increase that once the order is submitted, which can be identified as cancellation of bid(ask) order at the 1st, 2nd, 3rd, 4th or 5th queues

Table 6: Unconditional Frequency of Trades and Orders.

Limit Order		Frequency	%
Buy	bid order within the quote	133925	1.129
	bid order at the quote	1333387	11.236
	bid order below the quote	965561	8.137
	cancellation of bid order	510501	4.302
Sell	ask order within the quote	130480	1.100
	ask order at the quote	1028214	8.665
	ask order above the quote	1240213	10.451
	cancellation of ask order	496117	4.181
Trades			
Buy	small buy	2537699	21.385
	market buy	372737	3.141
	large buy	59502	0.501
Sell	small sell	2606943	21.968
	market sell	429174	3.617
	large sell	22280	0.188
Total		11866733	100

split their large market order into relatively smaller trades to avoid significant price impact.

After a primary classification of distribution of orders, we further investigate the order flow composition not only with respect to type but also time of orders as follows.

3.2 Frequency of Trades and Orders with respect to Trading Hours

Time-of-day effect on stocks have been investigated by many researchers. However there are still not much concrete conclusion, at least empirically, in order flow composition with respect to time. Following Mcinish and Wood(1992), Biais et al. (1995) and Harris and Hasbrouck(1996), we investigate the order flow composition not only with respect type but also time of orders. We start by dividing the intraday order flow into different categories with respect to trading hours. In this section, we develop hypothesis about time of trade, market orders, limit orders, and perform regression analysis in later sections.

In Table 7, we find that trades only account for less than 50% of the market activities, consistent with our results of high intensity of market activities at the best quote in previous section. It is consistent with 47% in Paris Bourse as documented by Biais, Hillion and Spatt(1995) and 50% of the SuperDOT submitted to NYSE by Harris and Hasbrouck (1996). Among these orders and trades, 59% of limit orders are submitted in the 1st and last trading hours, while 61% of trades are conducted between these two hours. Also orders are most intense at the start of a trading day

Table 7: Frequency of Market and Limit Orders with respect to Trading Hours

Trading Hours	Trades / Market Orders (%)	Limit Orders (%)
1000-1100	1424051 (13.43)	1911814(18.03)
1100-1200	892868 (8.42)	1078582(10.17)
1200-1300	413277 (3.90)	471899(4.45)
1300-1400	0	$< 10^{-3}$
1400-1500	679335(6.41)	732217(6.90)
1500-1600	1620211(15.28)	1381162(13.02)
total	5029742 (47.43)	5575674 (52.57)

Table 8: Frequency of Trades and Orders, Condition on Trading Hours, with breakdown in %. The largest value in each row is in bold faced.

Trading Hours	BOC	BOO	BOA	BOW	AOW	AOA	AOO	AOC
1000-1100	2.57	6.50	6.71	1.37	1.34	5.11	**8.2**	2.49
1100-1200	1.66	2.97	**4.40**	0.65	0.67	3.56	3.79	1.65
1200-1300	0.80	1.24	**1.90**	0.29	0.28	1.57	1.59	0.78
1400-1500	1.19	2.07	**2.91**	0.40	0.39	2.29	2.70	1.17
1500-1600	2.73	3.11	**5.89**	0.78	0.73	4.56	4.30	2.67
Trading Hours	SB	MB	LB	LS	MS	SS		
1000-1100	**10.82**	2.94	0.49	0.22	3.16	10.69		
1100-1200	7.08	1.16	0.10	0.05	1.29	**8.06**		
1200-1300	**3.58**	0.51	0.04	0.01	0.51	3.57		
1400-1500	5.53	0.95	0.12	0.04	1.08	**5.78**		
1500-1600	**14.16**	2.01	0.29	0.076	2.22	13.45		

while trades are most intense before the end of a trading day. These findings are consistent with price discovery process in the morning and bargaining agreement before the end of trading period.

As reported in Table 8, the largest percentage of limit order is bid at the quote except the first hour, led by ask above the quote. Also, by comparing Figure 1 and Figure 2, we observe that in the first hour, the number of out of quote orders is very significant for both bid and ask, due to the price discovery process and the lack of information anticipated by investors. The informed traders quickly take advantage of this surplus supply of liquidity and make aggressive trades in the morning as shown by the highest proportion of large trades conducted. However, as time goes by, the execution risk for orders of bid below and ask above the best quotes increases, patient traders have less room for posting passive quotes and also their price discovery process may have finished compared with the 1st hour. Then, they have to submit more aggressive limit orders in order to gain price-and-time priority and lower the execution risk. Consequently, this pattern of liquidity supply match the demand of the market, reflected by the market orders. Also, with the end-of-day effect binding the investors, dramatic increase in market orders, especially small trades have been

observed. These behaviour suggest our first hypothesis, H_0: *order flow composition have a strong relationship with time-of-a-day factor.*

3.3 Frequency of Trades, Orders and Book Status

As documented by Biais, Hillion and Spatt(1995), Foucault(1999), Ahn, Bae and Chan(2001), limit order book status have significant effect on traders decision as different book status reflect different market situations, execution risk and levels of information asymmetry. Therefore, in this section, we investigate the effect of book status on order flow composition. Following Ahn, Bae and Chan(2001), we focus on two different attributes of market status variables, namely the depth at primary queue and contemporaneous bid-ask spread. Order size that the primary queue can offered is also used as a measure of liquidity. As we find that both depth and size have similar effect on frequency distribution of orders, only figures correspond to depth variable has reported here for simplicity.

Order size is defined by the total number of outstanding shares available at both best bid and best ask sides of the book. Depth at primary queue is defined by the total number of outstanding orders available at both best bid and best ask queues of the book. [9] The bid-ask spread is defined by the best ask quote minus the best bid quote contemporaneously. [10] We classify the market status into four categories, in decreasing (increasing) liquidity supply (demand): [11]

I. small spread and large depth,

II. large spread and large depth,

III. small spread and small depth,

IV. large spread and small depth.

We decompose all of the trades and limit orders according to these four categories and their aggressiveness. [12]

[9] The limit order book of Hong Kong Stock Exchange consists of five queues for each bid and ask sides, corresponding to different posted quotes of limit orders and the underlying discrete price grid, more details can be found in Cheung and Song(2004).

[10] We aggregate the depth of bid and ask, also size of bid and ask orders at the corresponding best quotes because our focus is on the overall effect of depth and size to order submission but not on the orientation of buy and sell, bid and ask.

[11] The liquidity supply is decreasing non-strictly because the levels of liquidity supply in categories II and III cannot be distinguished as they reflect different attributes of liquidity.

[12] Order aggressiveness definitions can be found in Cheung and Song(2004).

Table 9: Frequency of Trades, Orders and Book Status, in terms of Spread and Depth. All figures are in % terms. The largest four values in each row are in bold faced. Spread of each stock is defined to be large when it is greater than its time-series median. Depth of each stock is defined to be large when it is greater than its time-series median. Cross-sectional averages of each of the proportion over the 33 HSI stocks are reported.

Large Spread in % term	BOC	BOO	BOA	BOW	SB	MB	LB	LS	MS	SS	AOW	AOA	AOO	AOC
Large Depth	4.91	7.95	**11.28**	2.64	**20.40**	1.63	0.12	0.04	1.86	**20.08**	2.62	9.90	**11.64**	4.93
Small Depth	5.20	10.08	**10.90**	3.27	**16.00**	3.75	0.59	0.21	3.81	**16.10**	3.19	8.63	**13.19**	5.08
Small Spread in % term	BOC	BOO	BOA	BOW	SB	MB	LB	LS	MS	SS	AOW	AOA	AOO	AOC
Large Depth	4.50	7.00	**11.79**	0.84	**22.90**	2.77	0.22	0.09	2.99	**23.09**	0.79	**9.64**	8.97	4.42
Small Depth	4.55	8.42	**11.75**	1.23	**19.01**	4.66	0.74	0.27	5.33	**19.54**	1.20	8.48	**10.42**	4.40

In Table 9, we observe that both frequencies of small buys and sells decrease with respect to decreasing liquidity supply. Aggressive trades like large buys and large sells do not follow the same trend as they depend on the level of information asymmetry among traders. This observation is consistent with the findings in Cheung and Song(2004), who find that more aggressive trades have higher probability being information-driven and less dependent on market liquidity supply. However, small buys and sells are less information-driven and more liquidity-driven, so the change in supply of liquidity by the market participants affect directly the proportion of small trades. In addition, six out of eight types of limit orders have increasing frequencies for decreasing liquidity supply. This may due to the undercutting behaviour of traders who are willing to provide liquidity and transact at their specific quoted price. Moreover, when there is large depth or small spread, there are more trades but less limit orders than in small depth or large spread. large orders. All of these observations confirm with Biais, Hillion and Spatt(1995) and Foucault(1999) that when the market lack of liquidity, the participants supply it and consume when it is in excess.

Although we still cannot distinguish the effect of depth and spread on trades and orders, Table 9 helps us to develope two testable hypotheses, H_0: *spread has larger effect on Trade submission than depth* and H_0: *depth have larger effect on limit order submission than spread.* Together with the one developed in last section, we have the following hypotheses for testing:

Hypothesis 1: **Spread** *have larger effect on* **Trade** *submission than depth.*

Hypothesis 2: **Size and Depth** *have larger effect on* **Limit Order** *submission than spread.*

Hypothesis 3: **Order flow** *composition has a strong relationship with* **Time** *factor.*

4 Emipirical Result

In order to extend the analysis of Ahn, Bae and Chan(2001) and test the hypotheses in the last section, we develope the follow regression models for newly submitted market orders, MO and limit orders, LO:

$$\begin{aligned} MO_t &= \alpha_0 + \alpha_1 Depth_t + \alpha_2 log(size)_t + \alpha_3 spread_t + \alpha_4 LO_t + \alpha_5 Vola_t \\ &\quad + \alpha_6 MO_{t-1} + \sum_{i=7}^{10} \alpha_i Time_{i,t} + \epsilon_t, \end{aligned} \tag{1}$$

$$LO_t = \alpha_0 + \alpha_1 Depth_t + \alpha_2 log(size)_t + \alpha_3 spread_t + \alpha_4 MO_t + \alpha_5 Vola_t + \alpha_6 LO_{t-1} + \sum_{i=7}^{10} \alpha_i Time_{i,t} + \epsilon_t. \quad (2)$$

We use both *Depth* and *Size* in the regressions though their effect on orders and trades are similar in terms of empirical frequency distribution. The reason is that with time and spread working simultaneously, depth and size may have different effects since depth represent the **total number of traders** who are willing to trade at the best quotes while size is the **total number of shares** available at the best quotes.

Spread is used to explain orders and trades as its significance has shown in previous tables and analyses of Biais et al.(1995) and Foucault(1999). LO_t and MO_{t-1} are used in Equation (2) to control for the mechanical effect introduced by the trading mechanism and autocorrelation for market orders respectively. MO_t and LO_{t-1} are used in Equation (2) to control for the mechanical effect introduced by the trading mechanism and autocorrelation for limit orders respectively. $Time_{i,t}$ is intraday dummy variable which equals to 1 if the transaction or order submission at time t is in trading hour i and 0 otherwise. It is to capture the effect of intraday variation. To avoid multicollinearity, we use only four intraday dummy variable of 5 trading hours. Because of the significant autocorrelations detected in MO and LO, we follow Ahn, Bae and Chan(2001) to adopt the Generalized Method of Moments (GMM) to estimate the Equations (2) and (2) and to obtain estimates of coefficient robust to non-spherical error. [13]

In the column of market order in Table 10, we see that the spread is statistically significant while both variables Depth and log(Size) are insignificant, supporting the first part of our hypothesis that the spread has larger effect on the submission of market order by investors. The negative coefficient estimate of the spread indicates that the smaller spread, the more frequently the market orders submitted, which leads to more transactions. All four trading hour dummy variables are highly significant, reflecting a strong time-of-a-day effect on market order. We will investigate further this effect by repeating the regressions at each trading hour. Both estimates of LO_t and MO_{t-1} are positive and significant. When the number of market orders increases, these orders execute against the quotes at the primary queue. These executions attract limit order traders to place new orders so as to gain priority in price and time. Thus, the informed or impatient traders consume this excess supply of liquidity and therefore, the number of market order in the next

[13] For detailed analysis of using GMM to tackle heteroskedasticity and autocorrelation, see Ahn, Bae and Chan(2001) and Newey and West(1987).

Table 10: Cross-Sectional Average of GMM Estimates of the regression analysis of Limit Orders(LO) and Market Orders(MO) against Depth, log(Size), Spread and time, for each component stock of Hang Seng Index(HSI) in 10 minute intervals. The models for market and limit orders are: $MO_t = \alpha_0 + \alpha_1 Depth_t + \alpha_2 log(size)_t + \alpha_3 spread_t + \alpha_4 LO_t + \alpha_5 MO_{t-1} + \sum_{i=6}^{9} \alpha_i Time_{i,t} + \epsilon_t$, and $LO_t = \alpha_0 + \alpha_1 Depth_t + \alpha_2 log(size)_t + \alpha_3 spread_t + \alpha_4 MO_t + \alpha_5 LO_{t-1} + \sum_{i=6}^{9} \alpha_i Time_{i,t} + \epsilon_t$. The values in bold face are significant at 5% significant level.

	MO_t	LO_t
$Depth_t$	0.019	-0.002
$log(Size)_t$	0.394	**-0.471**
$Spread_t$	**-22.492**	12.780
LO_t	**0.621**	
MO_{t-1}	**0.215**	
MO_t		**0.164**
LO_{t-1}		**0.212**
$1stHour$	**-2.899**	-0.409
$2ndHour$	**-2.848**	**-0.579**
$3rdHour$	**-2.835**	**-1.214**
$4thHour$	**-3.756**	**-0.630**
$Adj.R^2$	0.157	0.192

period increases.

In the third column, we report the estimates of the model for LO. The coefficient of spread is positive while the size and the depth are negative. Surprisingly the variable depth is insignificant in explaining LO statistically. Its effect may have been captured by log(size) and LO_{t-1}. Only the order size variable is significant negatively. This implies that the larger number of shares available in the primary queue, the less the number of newly submitted limit orders. Since the large size available in the primary queue implies a high level of liquidity provision, additional liquidity by submitting limit orders at or out of quote is not as desirable because of increasing execution risk. Therefore, the effect of size on limit order is larger compared with that of spread.

The estimates of LO_{t-1} and MO_t positive and sigificant. This is because the increasing supply of limit order at the last period attract market orders to consume this excess market liquidity. Consequently, the demand of liquidity by these market orders attract more limit orders, thus increasing the number of limit order submitted at this period.

By combining the explanations MO_{t-1} for MO_t and LO_{t-1} for LO_t, we observe, not only a sequence of trades and quote updates, but a cycle of order flow. The supply of liquidity by the limit order traders and demand of liquidity by market order traders construct the major parts of the cycle while spread, depth and size of the order book serve as indicators of the market liquidity level. Participants use these publicly available information and their own belief to adjust their

Table 11: Cross-Sectional Average of GMM Estimates of the regression analysis, in each of 5 trading hours, of Market Orders(MO) against Depth, log(Size), Spread and Limit Orders (LO), for each component stock of Hang Seng Index(HSI) in per minute. The models for market order is as follows $MO_t = \alpha_0 + \alpha_1 Depth_t + \alpha_2 log(size)_t + \alpha_3 spread_t + \alpha_4 LO_t + \alpha_5 MO_{t-1} + \epsilon_t$, number in bracket is the p-value of the t-statistics of zero coefficient test of α_i, only those significant at 5%, are reported.

	1000-1100	1100-1200	1200-1300	1400-1500	1500-1600
$Depth_t$	**0.046**	0.018	0.014	0.017	0.023
	(0.014)				
$log(Size)_t$	-0.010	0.229	0.267	0.323	**0.684**
					(0.044)
$Spread_t$	**-73.530**	**-48.760**	**-32.310**	-45.500	**-145.726**
	(0.010)	(0.006)	(0.01)		(0.034)
LO_t	**0.492**	**0.518**	**0.524**	**0.791**	**0.855**
	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)
MO_{t-1}	**0.165**	**0.111**	0.079	0.088	**0.159**
	(< 0.0001)	(< 0.0001)			(< 0.0001)
$Adj.R^2$	0.113	0.064	0.050	0.118	0.045

order submission strategies.

Table 11 supports strongly both of our hypotheses as spread is significant in four out of five trading hours while depth and log(size) only significant in the first and last hour, suggesting that there exist a larger effect by spread on market orders while the effects of depth or size are not significant. This support the hypothesis that the spread has larger effect on trades than that of the depth or the size.

In addition, in the third row of Table 11, we observe that the values of GMM estimates of the spread in explaining MO is significant for four out of five trading hours. In terms of its magnitude, the coefficient estimate is less negative when after the 1st hour, then bounces back after lunch and reaches the highest negative point at the last trading hour. Throughout a trading day, the spread has negative effect on newly submitted market orders, i.e., the smaller (larger) the spread, the larger number of (less) newly submitted market orders. This observation is consistent with Biais et al.(1995) as traders consume the liquidity with small spread and supply it when it is scarce, reflected by a widen spread. This negative effect diminishs throughout the morning as the coefficient estimate is less negative from -73.53 to -32.31, a drop of 56%. It even becomes insignificant statistically after lunch and then reverts and has its highest effect in terms of value by the end of a trading day when the estimate is highly negative at -147.726 which is a 351% increment. This shows the significance of time in market order submission, especially the end-of-

Table 12: Cross-Sectional Average of GMM Estimates of the regression analysis, in each of 5 trading hours, of Limit Orders(LO) against Depth, log(Size), Spread and Market Orders (MO), for each component stock of Hang Seng Index(HSI) in per minute. The models for limit orders is as follows, $LO_t = \alpha_0 + \alpha_1 Depth_t + \alpha_2 log(size)_t + \alpha_3 spread_t + \alpha_4 MO_t + \alpha_5 LO_{t-1} + \epsilon_t$, number in bracket is the p-value of the t-statistics of zero coefficient test of α_i, only those significant at 5%, are reported.

	1000-1100	1100-1200	1200-1300	1400-1500	1500-1600
$Depth_t$	-0.008	-0.002	0.0004	-0.002	-0.004
$log(Size)_t$	**-0.532**	**-0.296**	**-0.352**	**-0.509**	**-0.415**
	(0.01)	(0.035)	(0.030)	(0.030)	(0.050)
$Spread_t$	7.367	20.897	20.567	-5.170	24.771
MO_t	**0.228**	**0.218**	**0.176**	**0.244**	**0.179**
	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)
LO_{t-1}	**0.235**	**0.172**	**0.160**	**0.165**	**0.227**
	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)
$Adj.R^{2}$‘	0.203	0.094	0.090	0.140	0.111

day effect on traders when they reach the end of a bargaining period. Consequently, there is a strong relationship of time and order flow composition.

The effect of the spread on market order is negative, exceptionally high for the last trading hour, which implies that a small decrease in the spread in the last trading hour triggers a large number of trades. This is consistent with the fact that by the end of a trading period, a small increase in liquidity induces a large number of trades, see similar findings in Mcinish and Woods(1992).

In the second row of Table 12, the coefficient estimates of $log(size)_t$ are significant in all five trading hours while those of spread are not, consistent with the larger effect by size of orders on limit order submission than spread. The variable depth is insignificant for all trading hours and it is consistent with Table 10. To uncover the time effect on limit order, we have to compare Figure 5 to Figure 6 and also the value of estimates in the row of log(size). First we compare Figure 5 and Figure 6 as both size and depth reflect the liquidity supply in the market. In the morning section of a trading day, the liquidity level increases until about 10 minutes before lunchtime, which resembles an end of a trading period. Then the liquidity level decreases to local minimum as the risk of being picked by informed traders is higher. Similar process happens in the afternoon except execution risk is monotonically increasing and becomes even more dominant when approaching the end of a trading day. Considering the coefficients of log(size) in 1st and 2nd trading hours, -0.532 and -0.296 respectively, it implies that the same magnitute of decrease in size induces less increase in the number of newly submitted limit orders from 1st to 2nd hour. This is consistent with the increasing supply of liquidity in the morning. By the start of afternoon trading session,

liquidity supply has a huge jump in both Figure 5 and Figure 6, from the very low point at lunchtime. Increasing liquidity supply implies that submitting limit orders may not produce the reward traders expect to, so there is less increase in number of newly submitted limit orders in 4th to 5th hour, from -5.09 to -0.415. Overall, these observations confirm all of our hypotheses stated previously.

After confirming these hypotheses, we move deeper into the order flow composition by elaborating all of the market and limit orders in different aggresiveness. Biais et al.(1995) have worked on the order flow composition by constructing empirical frequency distribution of different orders but have not investigated the relationship in terms of more robust statistical estimation. We use the models in equations 2 and 2 for each kind of market and limit

4.1 Results on Market Orders

In this section, we breakdown all market orders into different categories as in section 3. Similar to the aggregate market orders, we develope the following regression model for newly submitted Small Buys (SB), Market Buys (MB), Large Buys (LB), Small Sells (SS), Market Sells (MS) and Large Sells (LS):

$$\begin{aligned} Dept_t &= \alpha_0 + \alpha_1 Depth_t^{ask} + \alpha_2 Depth_t^{bid} + \alpha_3 Size_t^{ask} + \alpha_4 Size_t^{bid} \\ &\quad + \alpha_5 Spread_t + \alpha_6 Vola_t + \alpha_7 BOW_t + \alpha_8 BOA_t + \alpha_9 BOO_t \\ &\quad + \alpha_{10} AOW_t + \alpha_{11} AOA_t + \alpha_{12} AOO_t + \alpha_{13} Dept_{t-1} + \epsilon_t, \end{aligned} \tag{3}$$

where $Dept_t$ is the dependent variable in each model, i.e.. the newly submitted market orders and $Dept_{t-1}$ is the lag one period dependent variable.

Table13 summarizes the results of the above regression analysis as follows.

1. The negative significance of spread implies that the tighter (larger) spread, the more (less) small and market trades. This is consistent with the findings in Biais, Hillion and Spatt(1995), Chung, Van Ness and Van Ness (1999) and Ahn, Bae and Chan(2001) that traders demand liquidity when it is in excess. Also, the significance and values of the coefficient estimates of the spread decreases when aggressiveness increases, which implies that the same decrease in the spread will induce less market or large trades than small trades (for both buys and

Table 13: Cross-Sectional Average of GMM Estimates of the regression analysis of all six market orders, namely, newly submitted Small Buys (SB), Market Buys (MB), Large Buys (LB), Small Sells (SS), Market Sells (MS) and Large Sells (LS) against Bid and Ask Depths, Bid and Ask Sizes, Volatility, Spread and Limit Orders in different aggressiveness(BOW, BOA, BOO, AOW, AOA, AOO), for each component stock of Hang Seng Index(HSI) in per minute. Number in bracket is the p-value of the t-statistics of zero coefficient test of α_i, for $i = 1, \ldots, 13$ with only those significant at 5%, are reported. Those with an asterisk indicating p-value smaller than 10^{-10}.

Dependent Variable	LS_t	MS_t	SS_t	SB_t	MB_t	LB_t
$Depth_t^{ask}$	-0.0001	-0.0002	0.004	**0.02**	-0.003	0.0001
$Depth_t^{bid}$	-0.0001	**-0.003**	0.021	0.005	-0.001	-0.0003
$Size_t^{ask}$	-3.651×10^{-8}	-2.570×10^{-7}	$\mathbf{2.631}\times10^{-6}$	-1.255×10^{-6}	-4.121×10^{-7}	2.891×10^{-9}
$Size_t^{bid}$	3.200×10^{-8}	5.030×10^{-8}	-1.213×10^{-6}	3.022×10^{-6}	1.350×10^{-7}	-4.471×10^{-8}
$Spread_t$	-0.030	**-6.973**	**-25.564**	**-28.086**	**-7.69**	-1.972
$Vola_t$	6.340	7.971	214.808	206.529	54.623	18.919
BOW_t	0.006	**0.332**	**-0.907**	**2.64**	**0.899***	0.207
BOA_t	0.027	**0.621***	**0.590**	-0.081	-0.008	-0.007
BOO_t	-0.004	**0.014**	0.194	0.061	-0.004	-0.002
AOW_t	0.028	**0.76***	**2.071**	**-1.500**	0.147	-0.006
AOA_t	-0.003	0.017	-0.117	**0.579**	**0.173**	0.030
AOO_t	-0.001	-0.008	0.025	**0.115**	**0.031**	0.005
$Dept_{t-1}$	0.003	0.001	0.008	0.007	0.002	0.014

sells). This is because the small trades are more liquidity driven than information driven as they are less aggressive than market and large trades and the spread is a proxy of liquidity rather than information asymmetry.

2. While bid (ask) at the quote induces *larger* number of small sells (buys) due to increasing liquidity supply directly at the primary quote, an interesting finding is that more bid (ask) within the quote induces *less* number of small sells (buys). That is, at least partially, because of the information asymmetry again. More within the quote bid (ask) orders provide a better chance for more aggressive trader to sell (buy) with relatively less price impact. Thus traders who would like to perform small sells (buys) have less chance to execute at that specific bid (ask) quote as all of the bid (ask) orders at the primary queue have already been cleared by the market sells (buys). This explanation is consistent with the highly significant, positive coefficient estimates of bid (ask) order within the quote in market sells (buys) columns.

3. Depth and size of orders at the quote are insignificant in explaining these market orders, confirming with our findings in the last section. Moreover, the insignificance of our model in explaining large sells and buys are expected as those trades are of more information driven

than liquidity or market status driven. As shown in Cheung and Song (2004), the large sells and buys are the most aggressive trades and they are more information-based. [14]

4.2 Results on Limit Orders

In this section, we breakdown all limit orders into different categories as in section 3. Similar to the aggregate limit orders, we develope the following regression models for newly submitted Bid Order Within (BOW), Bid Order At the quote (BOA), Bid Order Out of quote (BOO), Ask Order Within (AOW), Ask Order At the quote (AOA), Ask Order Out of quote (AOO), in each of five trading hours.

$$\begin{aligned} Dept_t &= \alpha_0 + \alpha_1 Depth_t^{bid} + \alpha_2 Depth_t^{ask} + \alpha_3 Size_t^{bid} + \alpha_4 Size_t^{ask} \\ &\quad + \alpha_5 Spread_t + \alpha_6 Vola_t + \alpha_7 SB_t + \alpha_8 SS_t + \alpha_9 MB_t \\ &\quad + \alpha_{10} MS_t + \alpha_{11} LB_t + \alpha_{12} LS_t + \alpha_{13} Dept_{t-1} + \epsilon_t, \end{aligned} \tag{4}$$

where $Dept_t$ is the dependent variable in each model, i.e., the newly submitted limit orders and $Dept_{t-1}$ is the lag one period dependent variable.

1. In Table14, all six kinds of limit orders increase when volatility increases. This is consistent with Ahn, Bae and Chan(2001) as transitory volatility increases, depth increases consequently. The effect of volatility decreases dramatically as limit order aggressiveness increases. However it is not significant in explaining the number of newly submitted limit orders.

2. As predicted by Table10 in the last section, queue depth and order size are, at least partially, significant in explaining the submission of limit orders. In the first row of Table14, depth of primary ask queue has negative effect on bid orders, especially significant for out of quote bid. The higher depth at the ask queue, the larger number of traders(or broker ID) selling at the contemporaneous ask quote induce less limit bid orders. This implies that the traders who submit limit bid orders at the moment have less chance to be executed unless using

[14] In our regression results in trading hours, depth and size at the primary quotes (bid and ask) are both not significant, confirming with the results of Table10. Spread has a negative effect on Small Sells in every trading hours, highest (most negative) at the 1st and 5th hours, i.e. opening and closing hours of a trading day. Volatility is only siginificant in the last hour, with highest positive effect on SS, indicating that approaching the end-of-day, the same increase in volatility, the more small sells as the information risk is higher for limit orders in the last trading hour. These intraday results in trading hours are available upon request.

Table 14: Cross-Sectional Average of GMM Estimates of the regression analysis of all six market orders, namely, newly submitted Bid Order Within (BOW), Bid Order At the quote (BOA), Bid Order Out of quote (BOO), Ask Order Within (AOW), Ask Order At the quote (AOA), Ask Order Out of quote (AOO), against Bid and Ask Depths, Bid and Ask Sizes, Volatility, Spread and Market Orders in different aggressiveness(SB, MB, LB, SS, MS, LS), for each component stock of Hang Seng Index(HSI) in per minute. Number in bracket is the p-value of the t-statistics of zero coefficient test of α_i, for $i = 1, \ldots, 13$ with only those significant at 5%, are reported. Those with an asterisk indicating p-value smaller than 10^{-10}.

	BOO_t	BOA_t	BOW_t	AOW_t	AOA_t	AOO_t
$Depth_t^{ask}$	**-0.005**	-0.001	-0.001	0.0003	**0.003**	0.003
$Depth_t^{bid}$	**0.003**	**0.005**	0.0001	**-0.001**	-0.002	**-0.006**
$Size_t^{ask}$	7.159×10^{-8}	$\mathbf{6.593}\times10^{-7}$	$\mathbf{-1.658}\times10^{-7}$	$\mathbf{1.485}\times10^{-7}$	$\mathbf{-6.394}\times10^{-7}$	$\mathbf{-9.77}\times10^{-7}$
$Size_t^{bid}$	$\mathbf{-8.371}\times10^{-7}$	$\mathbf{-5.541}\times10^{-7}$	1.724×10^{-7}	$\mathbf{-2.600}\times10^{-7}$	$\mathbf{6.957}\times10^{-7}$	5.119×10^{-7}
$Spread_t$	4.521	-3.289	**6.878**	**6.616**	**-3.263**	1.492
$Vola_t$	**75.643**	36.818	0.224	1.553	40.584	94.422
SB_t	-0.008	-0.006	**0.004**	**-0.005**	0.013	0.013
MB_t	0.053	**-0.060**	**0.090***	0.018	**0.088**	**0.234**
LB_t	-0.065	-0.046	0.021	-0.015	-0.012	-0.047
SS_t	-0.004	-0.005	**-0.005**	0.003	**-0.01**	-0.010
MS_t	**0.139**	**0.752***	0.014	**0.080**	**-0.045**	0.081
LS_t	-0.179	0.029	-0.106	-0.135	-0.120	-0.155
$Dept_{t-1}$	-0.009	0.0004	-0.006	-0.005	-0.0001	-0.007

more aggressive buy orders, like small, market or large buy.

3. Order size of primary ask queue has negative effect on at and out of quote ask orders, bid within the quote but has positive effect on bid order at or out of quote and ask within the quote. We have the following explanation. The larger size at the current ask quote lowers the chance of execution for limit orders at the 2nd to 5th queue and even the primary queue because of the price and time priorities implemented by the exchange. [15] The larger size accumulated at the primary queue, the less incentives for submitting limit ask order at or out of quote. Thus, more limit order traders submit ask order within the quote to increase their chance of execution by gaining advantage over those large, accumulated orders at the (previously) primary queue. The reason for increasing in ask order size induce less bid order within is similar to the negative effect of ask depth. However, at the same time, increases in order size reflect the information level for those at the quote seller. As large ask order size may attract larger trade volume, limit order buyers only submit less aggressive orders,

[15] The price and time priority employed by HKSE is that a limit order is of the highest priority among other limit orders if it has the most aggressive price quote, i.e. lowest ask and highest bid with respect to the current quote. If two orders are of the same quote, then the time submitted to the order book is used to determine their priority, i.e. the earlier submission time, the higher priority. Details can be found in the website of HKEx, www.hkex.com.hk.

like at or out of quote orders to minimize their chance of trading against more informed traders. This also explains the decrease in the number of bid order within submitted when ask order size increase. Another possible explanation is that when more volume available at the primary ask queue, one can use at or out of quote orders to test out the urgency of those limit order sellers and also push them to sell at maybe even lower price. Symmetric explanations can be drawn for the effect of bid order size on dependent variables of ask and bid limit orders.

4. Depth is significant for at and out of quote limit orders while size is significant for almost all limit orders. The ask (bid) depth has negative effect on all bid (ask) orders, and the ask (bid) size has negative effect only on bid (ask) order within. More market buys (sells) induce more bid (ask) order within, while increase small buys (sells) induce less ask (bid) within. [16]

5 Conclusion

In this paper, we investigate the effect of different market status and time-of-a-day factor on order submission in Hong Kong stock market, a prototype order-driven market. We develop new models for order flow composition with respect to order aggressiveness based on analysis of Biais et al.(1995) and Ahn, Bae and Chan(2001). We use the depth and size in both side of the quotes, spread, volatility, lagged market and limit orders in explaining contemporaneous limit (market) orders in aggressiveness with Generalized Method of Moment estimation. For each model, we use four market status variables including Depth, Size, Spread and a hourly dummy variable. After controlling for mechanical effect and autocorrelation in dependent variable, we obtain robust coefficient estimates with GMM. We have some conclusions as follows:

1. A highly significant, negative effect of Spread on market order was found while the effect of depth and size was relatively weaker. This means the smaller the spread, the larger number of market orders. We also find that The informed traders are less aggressive then the liquidity traders when the spread gets smaller.

[16] In our regression results in trading hours, depth and size at the primary quotes (bid and ask) are both not significant, confirming with the results of Table10. Spread has a negative effect on Small Sells in every trading hours, highest (most negative) at the 1st and 5th hours, i.e. opening and closing hours of a trading day. Volatility is only siginificant in the last hour, with highest positive effect on SS, indicating that approaching the end-of-day, the same increase in volatility, the more small sells as the information risk is higher for limit orders in the last trading hour. These intraday results in trading hours are available upon request.

2. Order size has significant negative effect on the submission of limit orders. The larger size at the primary bid (ask) queue, the larger number of bid (ask) within the quote and smaller number of bid (ask) at or out of quote. We find that the bid and ask sides of the order book affect the order flow symmetrically.

3. Time effect, especially End-of-day effect is very strong, characterized by large jump of market order at last ten minutes of a trading day.

4. The number of block trading increases with more limit order at or within the quote.

5. The number of small size trading decreases with limit orders available within the quote.

Our paper has consistent results with Biais, Hillion and Spatt(1995), Ahn, Bae and Chan(2001) and Ranaldo(2004). All papers have come to the conclusion that investors demand liquidity when it is in excess and supply it when it is scarce. Our paper contributes to the literature in investigating the reaction of traders when exposed to different market status, while Biais, Hillion and Spatt(1995) concentrate in empirical frequency distribution of book status and orders; Ahn, Bae and Chan(2001) focus in dynamic relation between transitory volatility and depth and Ranaldo(2004) focus in order aggressiveness. While most of the literature consider either the consequence or determinants of traders belief, we consider the order flow composition as a cycle of adjustment in the traders belief. The supply of liquidity by the limit order traders and demand of liquidity by market order traders construct the major parts of the cycle. Spread, volatility, depth and size of the order book serve as indicators of the market liquidity level and information asymmetry within this cycle. All participants use these publicly available information and their own belief to adjust their order submission strategies and as a result, stimulating a series of adjustments among traders.

We conduct empirical analysis of order flow composition in order-driven market and arrive at some useful results and implication about the market. Comparison of the intensity and nature of information aymmetry between limit order and market order is an interesting topic. Also, theoretical model of the order flow composition, with transaction volume and order size as endogenous variables, is one of the important research direction.

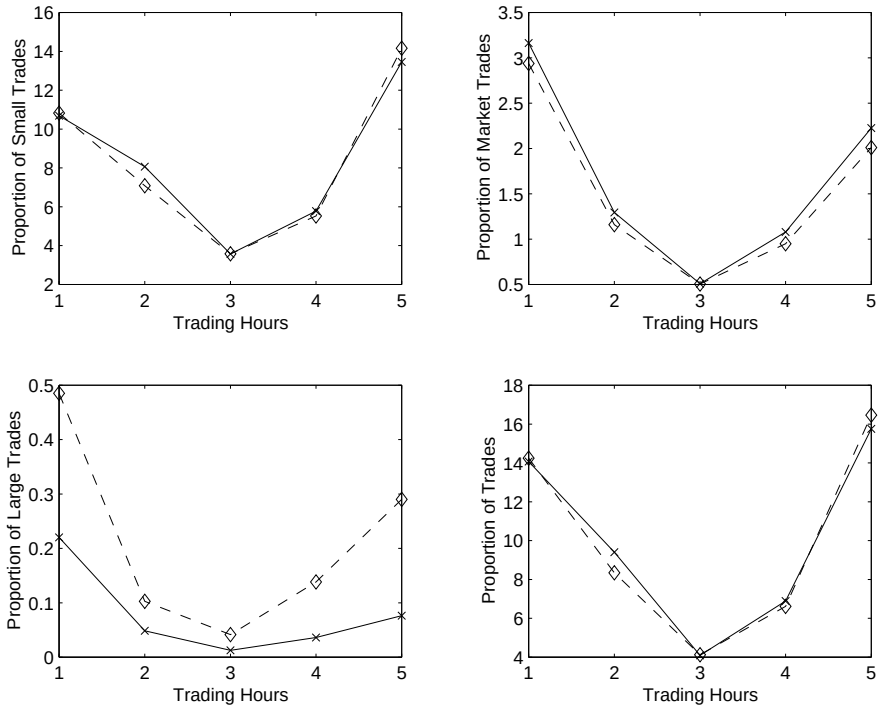

Figure 1: Cross-Sectional intraday proportion of Newly Submitted Buy orders in dash line with diamond and Sell orders in solid line with cross. Top left: small trades against trading hours; Top right: market trades against trading hours; Bottom left: large trades against trading hours; Bottom right: overall buy and sell against trading hours; A trading day is divided into 5 trading hours and the cross-sectional averages of time-series averages of 33 HSI component stocks are calculated for 245 trading days.

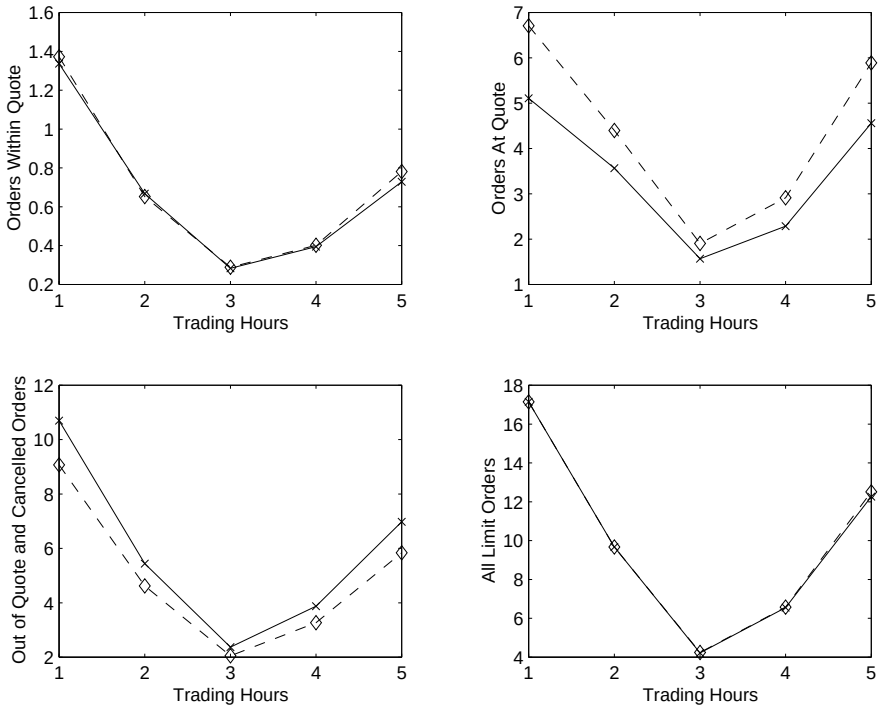

Figure 2: Cross-Sectional intraday proportion of Newly Submitted Bid orders in dash line with diamond and Ask orders in solid line with cross. Top left: orders within the quote against trading hours; Top right: orders at the quote against trading hours; Bottom left: orders out of quote and cancellation of orders against trading hours; Bottom right: overall bids and asks against trading hours; A trading day is divided into 5 trading hours and the cross-sectional averages of time-series averages of 33 HSI component stocks are calculated for 245 trading days.

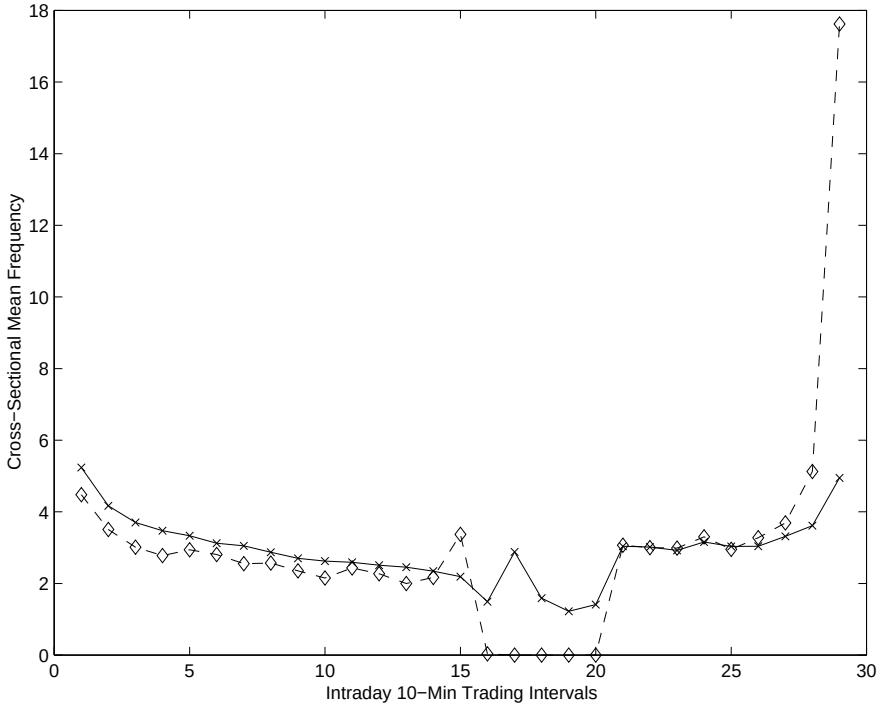

Figure 3: Cross-Sectional, intraday empirical frequency distribution of Newly Submitted Market Order(MO or Trade) in dash line and Limit Order(LO) in solid line. A trading day is divided into 29 sub-intervals in every 10-mins and the cross-sectional averages of time-series averages of 33 HSI component stocks are calculated for 245 trading days.

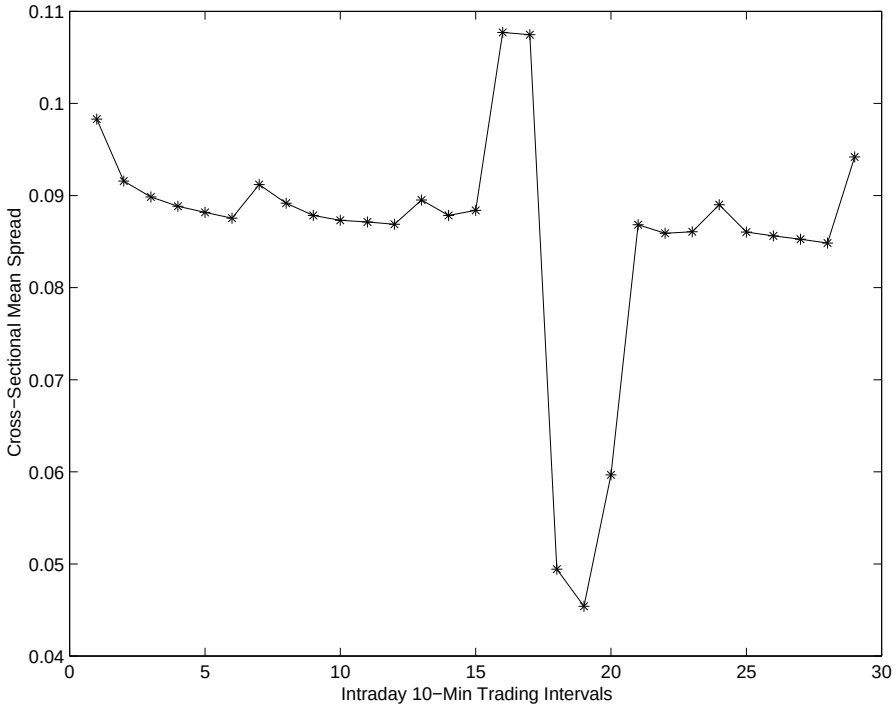

Figure 4: Cross-Sectional empirical distribution of intraday Bid-Ask Spread. A trading day is divided into 27 sub-intervals in every 10-mins and the cross-sectional averages of time-series averages of 33 HSI component stocks are calculated for 245 trading days.

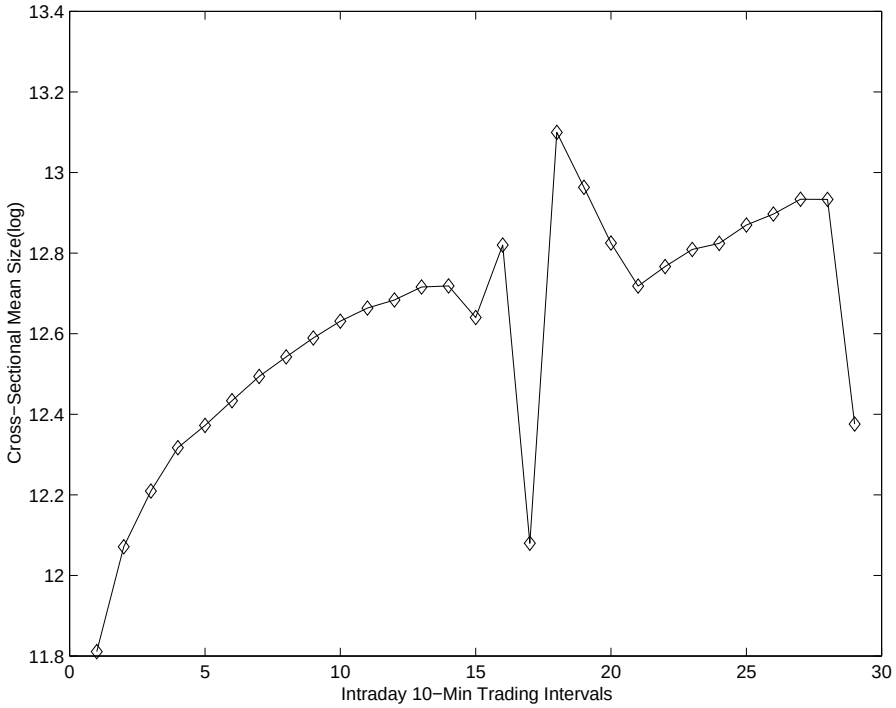

Figure 5: Cross-Sectional empirical distribution of intraday Limit order size, in logarithmic values. A trading day is divided into 27 sub-intervals in every 10-mins and the cross-sectional averages of time-series averages of 33 HSI component stocks are calculated for 245 trading days.

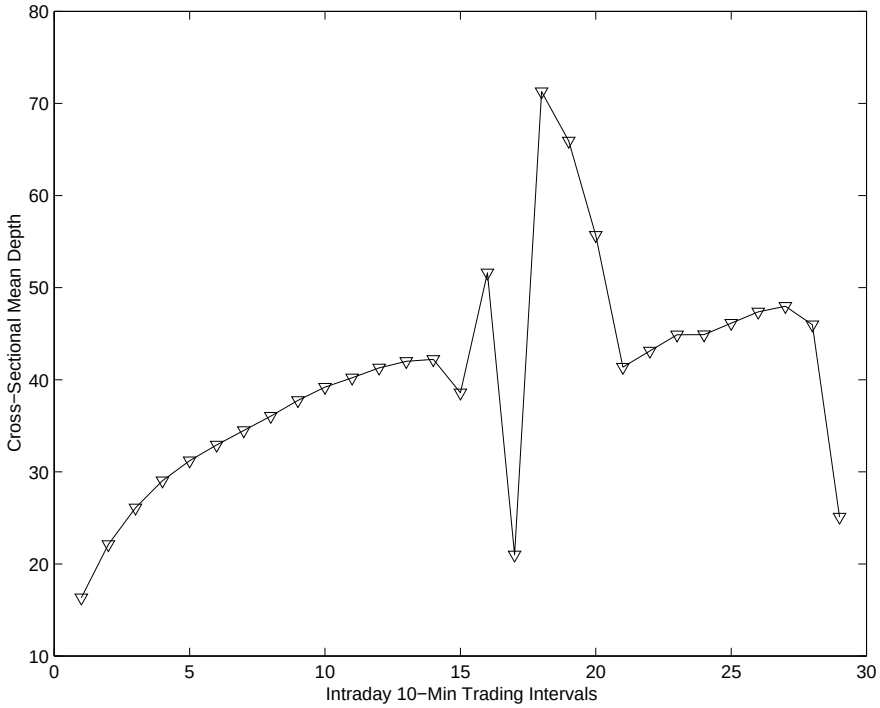

Figure 6: Cross-Sectional empirical distribution of intraday Depth in Primary Queue. A trading day is divided into 27 sub-intervals in every 10-mins and the cross-sectional averages of time-series averages of 33 HSI component stocks are calculated for 245 trading days.

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