Price Clustering on the Limit-Order Book: Evidence from the Stock Exchange of Hong Kong

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Abstract

We examine the clustering pattern in trade and quote prices on the electronic limit order book of the Stock Exchange of Hong Kong (SEHK). Earlier research into clustering focuses on transaction prices only. We study clustering on quote prices over a maximum of five queues on the limit order book. We observe abnormally high frequency of even and integer prices in trade and quote prices for all tick size groups on the SEHK. The deeper quotes display stronger clustering than the best quotes, indicating that the farther away the quotes are from the best queue, the less information they carry. Our analysis further reveals that an extremely fine tick size itself works as a binding constraint to hinder price resolution process. We also find that short sale prohibition imposed on the majority of stocks listed on the SEHK causes a significant bias in clustering towards the ask side of the limit order book. This implies that a short sale prohibition impairs efficient price discovery in the market.

Key words: electronic limit-order book, price clustering, short sale restrictions, asymmetry in price clustering

JEL classification: C14; G15

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1. Introduction

In standard pricing theories, asset prices could take any value over available units of account. In reality, however, certain prices are preferred to others. This tendency for asset prices to appear more often at certain fractions or integers is called price clustering. Studies on this stylized fact have both a long history and an extensive coverage. Probably the first rigorous investigation on this issue will be the series of work by Niederhoffer (1965, 1966) and Osborne (1962) in the sixties. Since then, a number of papers have documented price clustering for equity, foreign exchange, gold, equity index options and futures, government bond futures contracts, residential real estate, and bank deposit rate markets.[1]

Several hypotheses have been advanced to explain the pattern of price clustering in financial markets. The price resolution hypothesis (Ball, Torous, and Tschoegl, 1985) posits that the degree of price resolution is a function of the amount of information in the market. The attraction hypothesis (Goodhart and Curcio, 1991) asserts that the rounding of asset prices to integers reflects the basic attraction of each round number.[2] The negotiation hypothesis (Harris, 1991) argues that a smaller set of prices lowers the costs of negotiations between traders. Christie and Schultz (1994a, b) propose the collusion hypothesis and present evidence that Nasdaq dealers avoid odd-eighth quotes to maintain wide spreads. Kahn, Pennacchi, and Sopranzetti (1999) observe that retail customers tend to underestimate odd-ending prices when recalling them and suggest a limited-recall hypothesis to explain the more frequent even-ending yields in the bank deposits. Booth, Kallunki, Lin, and Martikainen (2000) examine the relation between internal/preference trading and price clustering, noticing that an internal market is more prone to price manipulation or collusion.

Kandel, Sarig, and Wohl (2001) argue that the price resolution, negotiation, collusion, and limited recall hypotheses all rely on the fact that market makers or sellers either negotiate or unilaterally set prices. The strategic behavior of market makers and sellers leads to the pattern of deliberate price clustering documented in the literature. They study limit orders prices submitted by thousands of

[1] A partial list of recent studies include Ball, Torous, and Tschoegl (1985), Harris (1991), Goodhart and Curcio (1991), Colwell, Rushing, and Young (1994), Grossman, Miller, Cone, and Fischel (1997), Gwilym, Clare, and Thomas (1998), Kahn, Pennacchi, and Sopranzetti (1999), Peltzman (2000), Sopranzetti and Datar (2002), Brown Chua, and Mitchell (2002), Jones and Lamont (2002), Jones (2003).

[2] While Goodhart and Curcio (1991) examine the attraction hypothesis in price clustering in financial markets for the first time, there is a well-established consumer research literature that attributes rounding to human cognitive

individual investors for initial public offerings, in which strategic behavior and deliberate price clustering are unlikely. Their evidence suggests that investors are simply inclined to use round numbers rather than non-round numbers.

In this paper, we provide a comprehensive study on the phenomenon of price clustering in a pure electronic limit order market: the Stock Exchange of Hong Kong (SEHK). Unlike the New York Stock Exchange (NYSE) or NASDAQ, the SEHK has no specialist or dealers. Liquidity is provided solely by the trading public who submit limit orders. Competition among liquidity suppliers is intense, leaving collusion on quoted prices practically impossible. Our research makes an important contribution to the literature for the following reasons. First, electronic markets have emerged as popular venues for trading for a wide variety of financial assets (Bloomfield, O'Hara, and Saar, 2002). Many of these electronic markets are organized as limit order markets and have been very successful in competing with more traditional market structures. However, existing evidence on price clustering focuses primarily on traditional markets such as hybrid or dealer markets.

Second, almost the entire literature on price clustering in equity markets focus on clustering in transaction prices. Most transaction prices are outcomes from a trading process in which an investor who submits a market order accepts the price offered on the limit order book. Inevitably, the transaction prices record closely tracks the limit order prices record. Therefore, trade price clustering can largely be attributed to quote price clustering. While some studies have looked into patterns in quote price clustering, the focus is on the best quotes and on assets other than equities (Spranzetti and Data, 2002; Palmon et al., 2004).[3] There is no evidence from equity markets on the clustering of quote prices, especially quote prices beyond the best quotes. The SEHK provides a valuable dataset that contains the bid and ask quotes for up to five queues. This research offers a first look at the clustering pattern as we walk up and down both sides of the limit order book.

Third, we explore the impact of short sale restrictions on price clustering. Early studies report that short sales convey important information (Aitken, Frino, McCorry, and Swan, 1998). In a market where shorts sales are prohibited, investors with bad news are restricted from trading while investors with

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accessibility. (Tversky and Kahneman, 1973; Higgins et al., 1977; Fazio et al., 1982)

[3] Spranzetti and Data (2002) examine quote clustering in foreign exchange spot markets while Palmon et al. (2004)

good news are allowed to trade without constraints. Therefore short sale restrictions can create an upward bias in stock prices (Miller, 1977; Figlewski, 1981). Diamond and Verrecchia (1987), however, suggest that rationally behaving investors remove any bias in prices caused by short sale constraints. On the SEHK, short sales are prohibited for more than two-thirds of the listed stocks. We empirically test whether any bias exists in price clustering of stocks for which short selling is prohibited. The price resolution hypothesis suggests that the dearth of informed trading caused by short sale prohibition will result in a coarser set of sell-order prices. This implies a stronger clustering pattern on the ask side of the limit order book.

Fourth, equity markets in the U. S. and European countries typically adopt a uniform tick size. A uniform tick size represents a smaller fraction of the price for high-priced stocks than for low-priced stocks. This implies a larger set of possible price levels for high-priced stocks. To lower negotiation costs, market makers will set quotes with more clustering for high-priced stocks. An important feature of the SEHK is that the trading tick varies according to price levels. When the tick size is a step-function of price levels, the tick remains between 0.5 and 2 percent of the price for the majority of the stocks. In fact, the SEHK has the finest tick size schedule among the world's exchanges. By comparing measures of price clustering across different price levels, we can gain additional insight on the relation between tick size, price level, and price clustering.[4]

Fifth, a significant population of stocks listed on the SEHK trade at extremely low prices. On an average trading day during the first half of 2000, about 200 stocks traded below HK$0.50 (almost equivalent to a sixteenth of one U.S. dollar). Naturally, the tick size for these stocks is below the normal recognizable unit of account, at a fraction of one HK cent ($0.01). It will be interesting to examine whether an extremely small tick size itself, not the relative tick size, becomes a binding constraint and leads to a stronger clustering pattern.

Finally, we test Niderhoffer's (1965) claim that an asymmetry between the ask and bid quotes around whole integer prices may exists due to strategic trading by investors who try to capitalize on opportunities created by price clustering. Knowing that orders are clustered on an integer price, sellers

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investigate clustering in listing and transaction prices in real estate markets.

[4] Hameed and Terry (1998) explore relation between price level and clustering for Singapore Stock Exchange on

have incentives to submit sell limit orders just underneath the integer price for the benefit of a quick sale. Likewise, buyers have incentives to submit buy limit orders just above the integer price to gain immediacy. The result will be more limit sell orders than buy orders at the price just underneath an integer price and more buy orders just above an integer price. With detailed order book information, we are able to perform a direct test on Niederhoffer's prediction.

The rest of the paper is organized as follows. Section 2 explains the data source and the selection of sample stocks. Section 3 presents empirical evidence on the clustering of transaction prices, clustering of quote prices on the limit order book, cross-sectional determinants of clustering, and the effect of short sale restrictions on clustering. Finally, Section 4 summarizes empirical findings and concludes the paper.

2. Data Source and Sample Selection

We obtain our data from the SEHK's Trade Record and the Bid and Ask Record on the Main Board. For each listed stock, the trade record includes all transaction price and volume information with the time stamped to the nearest second. The bid and ask record provides 30-second interval snapshots of market information such as the bid and ask quotes, queue length, and bid and ask quantities in number of orders and share volume. The SEHK's bid and ask record is unique since it tracks the number of orders in the same queue and records up to five queues.

Our sample period runs from January to June 2000. We only consider ordinary shares listed on the SEHK, leaving out debt securities, rights, warrants, unit trusts, preferred shares, and ordinary shares in investment companies. We also exclude stocks that have conducted splits during the sample period and stocks with parallel trading or that trade in foreign currencies.[5] Finally, we exclude stocks whose prices exceed HK$200, albeit only a few stocks trade above that price. These criteria allow us to gather enough observations for the analysis of quotes and transaction prices. Our final sample contains 698 stocks.[6]

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which mandatory tick size also varies with price level.

[5] There were 20 stock splits during our sample period.

[6] There were 19 option class stocks during our sample period. For these stocks, we exclude the last business day of the option contract maturing month and one day prior to it from our investigation. The last business days of

The tick size on the SEHK follows a gradual schedule across several price ranges. Table 1 reports the complete list of the schedule. For the lowest price range, between $0.01 and $0.25, the trading tick is set to be $0.001. For the highest price range, between $100 and $200, the trading tick is $0.5. We sort all 698 stocks into different tick size categories based on their average price over the sample period. Among eight groups of tick size, the third group contains the largest number (333) of stocks in our sample. Almost half (48 percent) of 698 stocks have average prices ranging between $0.5 and $2, with a tick size of $0.01. An additional 118 stocks (17 percent) trade between $0.25 and $0.5, with a tick size of $0.005. The two groups combined account for 65 percent of the entire sample of stocks. It is interesting to note that about two-third of the stocks trade in the price range $0.25 to $2, which is equivalent to 3 cents to 26 cents in U.S. currency.

Table 1 also provides summary statistics on a number of firm and trade characteristics. Using 333 stocks in Group 3 as an example, the average price is $1.02. The average market capitalization is $723 million. The average daily return standard deviation is 7.67 percent. The average daily number of trades is 183. The average daily trading volume is 8,143,000 shares. The average bid-ask spread is $0.029 or 3.22 percent. The average ask and bid sizes are 172,000 and 199,000 shares respectively. Table 1 also shows that the spread measured in dollars increases with price, while the spread measured as a percentage of price decreases with it.

3. Empirical Evidence

Since our sample covers a six-month period, many of the 698 stocks traded at more than on price range. Instead of examining 698 stocks, we examine the clustering pattern for trading cases. In each of these trading cases, the particular stock trades within one of the eight price ranges. We require that a stock must have at least 300 transactions within a particular price range during the sample period.[7] Altogether, our sample contains 1,052 such trading cases. We analyze the clustering phenomenon for these trading cases at two levels. First, we classify 1,052 trading cases into three classes based on the

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the option contract maturing months in our sample period are January 28, February 28, March 30, April 27, May 30, and June 29, 2000.

[7] We have also applied an alternative screening method that requires at least 20 days of trading within a particular

final digit of tick sizes. Class 1 stocks have a tick size of \$0.005, \$0.05, or \$0.5. Class 2 stocks have a tick size of \$0.025 or \$0.25. Class 3 stocks have a tick size of \$0.001, \$0.01, or \$0.1. There are 328, 164, and 557 stocks in Class 1, Class 2, and Class 3, respectively.[8] We carry out the clustering analysis for each of the three classes. Second, since these trading cases are distributed over all tick size groups, we examine the clustering pattern for each of the eight tick size groups.

3.1. Clustering Measures

To examine the clustering phenomenon on the SEHK, we consider two clustering measures. The first is the frequency of even prices. This measure examines the percentage frequency of prices that end at even multiples of the tick. Note that even prices do not mean that they are actually divisible by 2 without rounding errors. In fact, even prices mean that prices are multiples of 2 times the tick size, or 2(\$0.001), 2(\$0.005), 2(\$0.01), 2(\$0.025), 2(\$0.05), 2(\$0.1), 2(\$0.25), 2(\$0.5), corresponding to the eight tick size categories. Under the null hypothesis of no clustering, the expected probability for an even price to occur is 1/2 for each of the eight tick size categories. The 'abnormal even price frequency' is calculated as the sum of even-price frequencies minus 1/2. For example, suppose a stock has a tick size of \$0.025 and always trades between \$3.00 and \$3.075 during the sample period. There are four possible price levels, i.e., \$3.00, \$3.025, \$3.05, and \$3.075. Further suppose that the realized frequencies at these four prices are 0.35, 0.20, 0.25, and 0.20, respectively. The abnormal even-price frequency is then 10 percent (0.35 + 0.25 – 0.5 = 0.10).

The second clustering measure is the frequency of integer prices. This measure examines the percentage frequency of prices that end with (i) a multiple of \$0.01 for the ticks of \$0.001 and \$0.005, (ii) a multiple of \$0.1 for the ticks of \$0.01, \$0.025, and \$0.05, and (iii) a multiple of \$1 for the ticks of \$0.1, \$0.25, and \$0.5. In other words, it measures the frequency of prices that end with 10, 4, or 2 times the tick size. Under the null hypothesis of no clustering, the expected probabilities for an integer price to occur is 1/2 for Class 1, 1/4 for Class 2, and 1/10 for Class 3 stocks. We subtract this expected probability from the realized frequency. The difference between the realized and expected frequency,

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price range. The results are essentially the same.

called 'the abnormal integer frequency', is used to measure price clustering. For example, suppose a stock has a tick size of \$0.025 and always trades between \$3 and \$4 during the sample period. With a tick of \$0.025, the stock belongs to Class 2. Further suppose that the frequency of price observed with a multiple of \$0.10 (i.e., \$3.00, \$3.10, \$3.20, …, or \$4.00) is 32 percent for this stock. Then, since the expected frequency at the multiple of \$0.10 is 25%, the abnormal integer frequency is 7 percent (0.32 − 0.25 = 0.07). For Class 1 stocks, the abnormal integer price frequency equals the abnormal even price frequency since the tick size is \$0.005, \$0.05, or \$0.5.

3.2 Clustering of Transaction Prices

3.2.1 Clustering Patterns

Table 2 presents the results for the clustering of transaction prices. All three stock classes display substantial and highly significant clustering patterns. Class 1 (tick sizes of \$0.005, \$0.05, or \$0.5) has the highest mean abnormal even frequency and integer price frequency both at 12.21 percent. Class 2 (tick sizes of \$0.025 or \$0.25) has the abnormal even price and integer price frequencies of 10.33 percent and 9.58 percent respectively. Class 3 (tick sizes of \$0.001, \$0.01, or \$0.1) has the lowest abnormal even price and integer price frequencies at 4.85 percent and 6.78 percent respectively. The abnormal frequencies are significant at the 1 percent level for all three classes. When we further split the three classes into different tick size groups, the clustering patterns remain strong, except for a few cases where the sample size is small.

Table 2 reveals a couple of interesting patterns related to the SEHK's tick size schedule. First, the magnitude of clustering is similar across different price groups. Focusing on groups with a relatively large sample size (greater than or equal to 93, groups 2, 5, 4, 1, 3), four out of the five groups have an abnormal even price frequency of around 10 percent. This appears to be related to the adoption of step function tick schedule on the SEHK. In a market with a uniform tick size, price clustering is an inverse function of price levels. This is because the tick represents a smaller fraction of price for higher-priced stocks. Therefore, prices for these stocks will cluster more as traders try to reduce negotiation costs. However, given the variable tick schedule on the SEHK, the tick size depends on price levels. For the

[8] We exclude three trading cases with a tick size of \$1 from our analysis.

majority of stocks, the proportional tick size remains relatively stable across different price levels. Thus, the variation in clustering over different price levels is much weaker on the SEHK.

Another pattern that emerges is that for each stock class the group in the lowest price range displays the strongest clustering. Specifically, Groups 2, 4, and 1 exhibit the strongest clustering pattern within their respective stock classes. For these three groups, the tick size represents a relatively large fraction of price. In fact, the proportional tick size these three groups represent is the largest within each respective class.[9] Hence, the idea that price clustering is an inverse function of proportional tick size cannot explain the clustering pattern for these groups of stocks. Rather, the pattern seems to be attributable to the dollar unit of the tick size itself. For all three groups, the tick involves a fraction of a cent. For example, the tick for Group 1 is $0.001, hardly used in daily life as a unit of price. It appears that an extremely small unit of account itself works as a binding constraint to hinder the price resolution process. As investors find it costly to deal with these tiny price increments, they choose to round transaction prices. This is consistent with the negotiation hypothesis, which suggests that traders choose a smaller set of prices in order to reduce negotiation costs.

3.2.2 Cross-Sectional Determinants of Trade Price Clustering

To relate the clustering patterns observed in transaction prices to firm and trading characteristics, we regress the two clustering measures on a number of variables. Since the results from abnormal even frequency and integer frequency are virtually identical, for simplicity we only report the results from abnormal even frequency. The set of independent variables is similar to those in Ball, Torous, and Tschoegl (1985) and Harris (1991): the natural log of average stock price (ln(p)), the natural log of average daily share volume (ln(vom)), the inverse of return standard deviation (1/vol), and the natural log of market capitalization (ln(mv)). As an alternative set of trading activity variables, we also use the log of average daily number of trades (ln(nt)) and the log of average trade size (ln(ts)) in a different regression. We run separate regressions for each class and each price group. We exclude Group 8 since this only contains a handful of stocks.

[9] For Class 1 stocks, the proportional tick is 1-2% for Group 2, 0.17-1% for Group 5, and 0.25-0.5% for Group 8. For Class 2 stcoks, the proportional tick is 0.5-1.25% for Group 4 and 0.25-0.5% for Group 7. For Class 3

The OLS regression results appear in Table 3. The table shows that the coefficients on ln(p) are positive and highly significant, suggesting that in general higher-priced stocks are associated with more clustering. But within each stock class, lower-priced stocks display more clustering as indicated by greater intercepts. For all three classes, the intercepts for the lowest price groups (Group 1, Group 2, and Group 4) are highest. This is consistent with the pattern observed earlier in Table 2, where extremely small ticks lead to more clustering. The negative coefficients on both ln(mv) and ln(vom) support the price resolution hypothesis. Larger and more liquid firms are better known than small and illiquid firms. Stock prices of better-known firms have less clustering because there is less dispersion in the traders' reservation prices. The negative coefficient on 1/volat is also consistent with the price resolution hypothesis. With more uncertainty in asset values (less information in the market) traders will use a coarse set of prices, resulting in more clustering. The average daily number of trades – one of the two measures of trading activity used in the regression – bears significant negative signs. More transactions mean greater liquidity and greater information arrival (Kaul and Lipson, 1992). As a result, transaction prices will display less clustering. The other measure of trading activity, the average trade size has negative coefficients for all seven models even if only one is statistically significant. The result hints that investors with large trades find it worthwhile negotiating or searching for more refined prices.

3.3 Clustering of Quote Prices

3.3.1 Clustering Patterns

The SEHK is a pure order-driven market.[10] Investors submit limit orders in the absence of designated market makers. The limit orders 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). The AMS displays the best five bid and ask prices, and the number of shares demanded or offered at each of the five best bid and ask queues. The SEHK tracks these five best queues at every 30-second interval. This unique feature of the dataset offers a valuable opportunity for us to examine the clustering of quote prices on the limit order book for the first time.

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stocks, the proportional tick is 0.4-10% for Group 1, 0.5-2% for Group 3, and 0.2-0.33% for Group 6.

[10] Ahn, Bae, and Chan (2001) provide a more detailed description of the trading mechanism on the SEHK.

In the previous section, we witnessed a strong pattern of clustering in transaction prices. However, in an electronic limit order market such as the SEHK, transaction prices are the result of market orders hitting waiting limit orders. In this environment, the transaction prices' record closely tracks the limit order prices' record. This suggests that clustering in transaction prices could largely be attributed to the clustering in limit order prices. Therefore, it is important to understand the clustering of limit order prices. While there are studies that examine quote clustering patterns, they typically focus on the best quotes and on markets other than equity markets. There is little evidence on the clustering of quotes from limit order equity markets, especially quotes beyond the best ones.

Table 4 provides the overall look of price clustering on the limit order book of the SEHK. The table reports the frequency distributions of the last digits of limit order prices. The frequencies are reported separately for each different queue up to five queues as well as for all five queues combined. We apply t-tests to check if actual frequencies are different from their expected values given no clustering. The expected values are 0.5 for class 1 stocks, 0.25 for class 2 stocks, and 0.1 for class 3 stocks. The table shows a clear pattern of clustering across all three classes and all five queues. For Class 1 stocks, whole integers are strongly preferred to halves. For Class 2 stocks, preferences are in the order of whole integers, halves, and quarters. Class 3 stocks which have decimal ticks show a more complex pattern. Whole integers are most favored. Halves come next, followed by even multiples of the minimum ticks. The odd multiples are used least. There is also an interesting pattern that not all odd or even ticks are equally likely. For the stocks with decimal ticks (Class 3) as an example, among all odd ticks, halves are most frequent with a percentage frequency of 11% when all the orders on all five queues are combined. On the other hand, the prices just underneath a whole integer ($0.009, $0.09, or $0.9) are least frequent at 7.2%. The latter result appears to be attributed to attraction to whole integers. However, it is puzzling why attraction does not affect equally the tick just above a whole integer. The percentage frequency for the tick just above a whole integer ($0.001, $0.01, or $0.1) is highest among odd ticks except for halves at 9%. Meanwhile, among all even ticks excluding whole integers, the even ticks surrounding halves ($0.04 and $0.06 or $0.004 or $0.006) are used less than the other even ticks. It appears that, as halves are actively used as an odd tick, the prices on the surrounding even ticks cluster less. Besides, attraction to halves seems to be at work, since halves are a more representative number.

Table 5 presents the results for the clustering of quote prices based on the two formal clustering measures, the abnormal even price frequencies and the abnormal integer price frequencies. We report the two clustering measures for the best queue, for the 2nd and 3rd queues combined, for the 4th and 5th queues combined, and for all queues.[11] A salient feature of the table is that as we move away from the best queue, clustering in quote prices becomes stronger. Take Class 1 stocks as an example. For the best queue, the abnormal even frequency is 12.59 percent, similar to the abnormal frequency reported for the transaction prices in Table 2. For the 2nd and 3rd queues, the abnormal frequency is 14.65 percent. For the 4th and 5th queues, the abnormal frequency is 18.01 percent. The same pattern is observed for Class 2 and Class 3 stocks. When we subgroup the stocks in each class based on tick size, almost all tick size groups display the same pattern. Clustering intensifies as we move away from the best queue.

Table 6 formally examines the difference in the two clustering measures between the deeper queues and the best queue. For both measures of price clustering, we calculate the difference in abnormal frequencies between the 2nd and 3rd queues combined and the best queue as well as the difference between the 4th and 5th queues combined and the best queue. The results from Class 1 and Class 2 stocks produce strong evidence that prices in deeper queues cluster more. Taking Class 1 stocks as an example, the difference in abnormal even price frequency between the 2nd and 3rd queues combined and the best queue is 2.06 percent. The difference between the 4th and 5th queues combined and the best queue is 5.42 percent. Similarly, when we look at the abnormal integer frequencies, the corresponding differences between the deeper queues and best queue are 2.06 percent and 5.42 percent. All of these differences are statistically highly significant. The results from Class 3 stocks are weaker but remain consistent. As we move down the table when stocks are divided into eight tick size groups, the overall conclusion remains unchanged, i.e., the 4th and 5th queues display more clustering than the 2nd and 3rd queues, and the 2nd and 3rd queues display more clustering than the best queue.[12]

The theoretical literature on trader behavior in a limit order market typically assumes that informed traders consume liquidity by submitting market orders instead of limit orders (Glosten, 1994;

[11] To obtain the abnormal frequency measures for the 2nd and 3rd queues combined and the 4th and 5th queues combined, we first measure the abnormal even or integer frequencies for individual queues separately and then add the measured frequencies between the neighboring queues (i.e., 2nd + 3rd and 4th + 5th).

[12] One exception is Class 3 Group 1 stocks where the pattern is reversed; the deeper queues show less clustering.

Seppi, 1997). Bloomfield, O'Hara, and Saar (2002) recently find that informed traders strategically choose their order type and use limit orders actively. One possible implication is that the order book has information content. Here our evidence shows that there is more clustering in limit orders away from the best queue. This suggests that the book's information content varies between different queues. Order flows in the best queue might contain more information than order flows on the further side of the book.[13]

In Section 3.2.1 we showed that clustering is stronger when the tick size is too small. To further augment for the claim that too small a tick size works as an important determinant of clustering, we examine the clustering pattern of limit order prices for the cases where a stock crosses tick breakpoints and trades in different price ranges. Since our clustering measures are sensitive to the size of the minimum tick, we focus only on the cases that lead to a move within the same Class.[14] Specifically, we analyze the stocks that move from price group 1 (tick size of $0.001) to price group 3 (tick size of $0.01) or from group 3 to group 1. During the six-month sample period, 13 stocks moved up from price group 1, via group 2, to group 3. For the same period 15 moved down from group 3, via group 2, to price group 1. We compare the abnormal even price frequencies before and after the moves. Since we compare the clustering patterns of the same stock before and after the move, if there is any significant difference in clustering patterns, it is not likely due to differences in stock characteristics but due to the differences in price ranges and tick sizes. Table 7 summarizes the results. Panel A reports the clustering measures when the price range moves from price groups 1 to 3. Regardless of the queue positions in the order book, the abnormal even price frequencies all decrease significantly. For example, the mean abnormal even-price frequency for the orders at all queues combined is 13.80% when the tick size is $0.001. With the tick size of $0.01, the clustering measure goes down to 1.26%. The drop is highly significant. The clustering measures for the case that moves from price groups 3 to 1 exhibit the opposite pattern (Panel B). Price clustering increases significantly when a stock moves from the group with tick size of $0.001 to a group with tick size of $0.01. The evidence presented in Table 3 reassures

[13] Of course, some portion of investors submitting orders away from the best queue is those who believe that the current market price is too high or too low.

[14] We also require that there be at least 500 valid transactions before and after the move and that there be at least ten stocks among the group of stocks that move within the same Class to maintain at least the minimum level of

that too small a tick size binds price resolution.

3.3.2 Cross-Sectional Determinants of Quote Price Clustering

Now we further investigate the cross-sectional determinants of quote price clustering in the SEHK's limit order book. For the sake of brevity, our analysis focuses again on the abnormal even price frequency. We use the same set of independent variables as in the regression for transaction prices except that the trading activity variables are replaced by the natural logs of average daily order volume (ln(ov)), average number of orders (ln(no)), and average order size (ln(os)). In the regressions, we treat clustering measures from the best queue, the 2nd and 3rd queues combined, and the 4th and 5th queues combined as different observations for the dependent variable. The values of the order flow variables, i.e., ln(ov), ln(no), and ln(os), are also calculated separately for the best queue and deeper queues. We add two additional dummy variables Q2+Q3 and Q4+Q5 in the regressions. Q2+Q3 takes the value of one if the clustering measure is from the 2nd or 3rd queue. Q4+Q5 takes the value of one if the clustering measure is from the 4th or 5th queue.

Table 9 presents the results. The coefficients on average stock price, return volatility, and stock class dummies all have the same signs as those from the regression for trade price clustering. Order volume, number of orders, and order size display significant negative coefficients, supporting the price resolution and negotiation hypotheses. The coefficients of two dummy variables representing deeper queues are negative and highly significant for almost all price groups. Further, the coefficients of Q4+Q5 are smaller than the coefficients of Q2+Q3 most of the cases. The results of the F-test to check equality between the coefficients of two dummy variables are rejected at the one percent level for groups 2, 4, 5, and 7. These results suggest that quotes further away on the limit order book display a stronger clustering pattern after controlling for variations in order volume, order numbers, and order size over different queues.

3.3.3 Clustering and Propensity of Queue Emptiness and Order Cancellation

One interesting question related to clustering in order prices is whether investors show

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validity in statistical tests.

systematically different tendencies to fill in empty queues or to cancel submitted orders depending on whether the tier has an odd or even price. If even prices are used more frequently than odd prices, an empty queue would be filled in more quickly if it is with an even price. Likewise, order cancellation will be more prevalent for even prices. To check if these are indeed the cases, we measure the duration of tier emptiness and the daily frequencies of order cancellation.

For duration of queue emptiness, we measure the length of time during which a specific queue remains empty (i.e., until the empty queue is filled in).[15] The duration is measured in seconds and estimated separately depending on whether the queue has an even price or an odd price. To accurately measure the duration of order emptiness, one needs to have complete information on the order flow. However, our data are just snap shots of the order book that are refreshed by every 30 seconds. Thus, our duration of queue emptiness is a rough estimate because it is measured by 30-second intervals.

Daily frequencies of order cancellation are measured in the following fashion. Since we cannot have complete matching between transactions and the orders that have been waiting on the limit order book, when we measure order cancellation frequencies, we deliberately exclude the orders from the best queue and use only the orders from the 2nd thru 5th queues. Then, we consider any reduction in number of orders as order cancellation. Excluding the best queue also makes sure that the reduction in number of orders is not due to large transactions that consume limit orders beyond the best queue.[16] While we believe that we have come up with the best measure of order cancellation frequency available with our dataset, our measure of order cancellation could understate the actual frequencies of order cancellations since it does not consider the cancellations of orders on the best queue.

Table 8 reports the results. Panel A reports the results on tier emptiness. The cross-sectional medians of the individual firms' durations are reported. It is obvious that the durations of tier emptiness are substantially shorter with even prices. For Class 2 stocks, durations are twice shorter when the tier has an even price than an odd price (804 seconds vs. 420 seconds). The differences are highly

[15] Technically, the best queue cannot be empty unless there is no single order during the day.

[16] Suppose there are 500 shares at $20.05 on the best queue and another 500 shares at $20.10 on the ask side of the limit order book. Further suppose that a buy market order with the quantity of 800 shares comes in. The buy market order will be matched with the 500 shares at $20.05 and 300 shares at $20.10, leaving 200 shares at $20.10. Now the refreshed order book will record 200 shares at the new best ask of $10.10. However, this case will be automatically filter out from our measurement since we do not include the orders on the best queue in our measure.

significant for most cases.

Panel B reports the results on order cancellation. Mean frequencies are reported since there are not much difference between means and medians. The upper half of the panel reports the results by stock classes and price groups. For all classes and all price groups, cancellation frequencies are greater with even prices than with odd prices. The differences in daily frequencies are statistically significant for all cases except two where the sample sizes are small. The lower half of the panel shows the results by individual queues. Again, through out all queues order cancellations are more prevalent with even prices. There is also a clear pattern that order cancellation frequencies decrease monotonically as the orders are submitted away from the best queue.

3.4 Short Sale Prohibition and Price Clustering on the SEHK

In this section, we explore the implications of short sale constraints on price clustering. The issue is important because during the first half of 2000, shorts sales were allowed for about 22 percent of the stocks listed on the SEHK. For the remaining (majority) of listed stocks, short sales were prohibited. Aitken, Frino, McCorry, and Swan (1998) find that short sales initiated using both limit orders and market orders convey significant negative information. Diamond and Verrecchia (1987) consider the effect of short sale constraints on trading and explore its empirical implications. Without any short sale constraints, investors with good news will buy. Investors with bad news will sell, whether they own the stock or not. With shorting prohibited, investors with bad news will not be able to trade if they do not own the stock. Miller (1977), Duffie (1996), and Duffie et al. (2002) show that restricting short sales shuts part of pessimists out of the market. Naturally, there will be an imbalance in the proportion of informed order flow between when there is good news and when there is bad news. How does this imbalance affect quote price clustering and trade price clustering? The price resolution hypothesis asserts that clustering is less likely when there is more information in the order flow. The implication is that a short sale constraint could cause an asymmetry in price resolution between buy and sell orders.

Short selling could also be associated with non-information motivated trading such as speculation, hedging, or arbitraging in underlying markets or in derivative markets. Many of the investors who trade for these reasons are likely to rely on program trading, which tends to choose more

refined prices. Restricting these investors from short selling will also lead to an asymmetry in price resolution in the same direction as short sale prohibition does for informed traders.

3.4.1 Imbalance in Quote and Trade Price Clustering

The above considerations lead us to investigate whether a bias is manifest in price clustering between buy and sell orders. Our empirically testable hypothesis is that sell order prices are more clustered than buy order prices. Short sale orders can take the form of either limit orders or market orders.[17] The lack of short sale in the form of limit orders will cause a clustering on the ask side quotes. It is less clear how a prohibition on short sales will affect clustering in trade prices. The bias in quote price clustering towards the ask side will imply a price clustering in buy transactions. This is because market buy orders will hit limit sell orders (i.e., the clustered ask prices). At the same time, the lack of short sale orders in the form of market orders will induce a bias in price clustering towards sell transactions. Overall, short sale constraints could affect price clustering on both buy and sell transactions. Whether buy or sell transaction prices display stronger clustering depends on which of the two forces dominates.

Table 10 reports the difference in quote price clustering between the ask and bid sides of the order book. The results suggest that ask quotes are more clustered than bid quotes, regardless of different clustering measures, stock classes, tick size groups, or sequence of queues. Use Class 1 stocks as an example. The difference in the abnormal even price frequency between the best ask and best bid queues is 3.76 percent. The difference between the 2nd and 3rd queues combined is 2.63 percent. The difference between the 4th and 5th queues combined is 1.99 percent. All these imbalances are statistically significant at 1 percent. The imbalances in abnormal integer frequencies are similar in magnitude and highly significant.[18]

[17] Aitken, Frino, McCorry, and Swan (1998) report that limit orders account for two-thirds of all short sale orders on the Australian Stock Exchange. The proportion of limit orders among all short sale orders could be much greater than two-thirds. This is because short sale orders using limit orders, especially those submitted at deeper queues, are less likely to be executed than short sale order using market orders.

[18] Our sample period, the first half of 2000, is characterized as a neutral market with the Hang Seng Index (HSI) starting at 15,423 and ending at 14,941. To check whether the asymmetry in clustering is sample specific, we examine two alternative periods: the first six months of 1999 and the first six months of 2001. These two sample

Table 10 also provides differences in trade price clustering between the buy and sell transactions. Since the SEHK's trade record does not contain flags for the direction of the transactions, we use the tick-test rule to classify buyer- and seller-initiated transactions.[19] The overall results from individual stock classes and tick size groups suggest that, in general, buy transaction prices display more clustering than sell transaction prices. However, the evidence is marginally significant and much weaker when compared with quote prices.

3.4.2 Short Sale Prohibition and Asymmetry in Quote and Trade Prices

We have so far documented strong evidence of buy-sell asymmetry in quote price clustering. The evidence from transaction price clustering is weaker. Now we examine whether the asymmetry is attributable to short sale prohibitions. The SEHK introduced regulated short selling for a pilot group of 17 stocks in 1994. The list of short sale eligible stocks expanded in 1996. By May 2000, the number of stocks that could be short sold reached 201. In an attempt to prevent short sellers from feeding sell orders into a declining market and sending prices further downwards, the exchange imposed the 'tick rule'. The 'tick rule' mandates that a short sale cannot be made below the best ask price.[20] The SEHK revises the list of securities designated for short selling on a quarterly basis. Three revisions were effective during our sample period of the first half of 2000: November 12, 1999, February 28, 2000 and May 31, 2000[21].

Naturally we partition the entire stocks into two groups. The first group includes stocks for which short selling was never allowed during the entire six-month sample period. The second group

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periods represent a bull market and a bear market, respectively. The HSI went up from 9,976 to 12,364 points during the first alternative period and dropped from 15,096 to 13,141 points during the second alternative period. We observe the same asymmetry regardless of the sample periods.

[19] A trade is classified as an uptick (downtick) if the transaction price is higher (lower) than the previous one. A zero-tick occurs when the price is the same as the previous one. A zero-uptick occurs when the current trade is a zero-tick while the previous one is an uptick. A trade is classified as a buy if it occurs on an uptick or zero-uptick. If a trade occurs on a downtick or zero downtick, it is classified as a sell (Lee and Ready, 1991).

[20] The tick rule was abolished in March 1996 and reinstated in September 1998 in a modified form. Exemptions were allowed for stock options or futures hedging short selling and index arbitrage short selling

[21] There were 182 stocks on the list released on November 12, 1999, 194 stocks on the list released on February 28, 2000, and 201 stocks on the list released on May 31, 2000.

includes stocks that remained eligible for short-sale during the same period. The stocks that made the list only once or twice are excluded from the analysis. This process leaves 231 trading cases from 180 stocks for which short sales were permitted and 525 trading cases from 497 stocks for which short sales were prohibited. For convenience, we call the former sample of stocks the 'short sale' group and the latter the 'no short sale' group. We test if there is any significant difference in the asymmetric pattern of clustering between the two samples. We do not expect the 'short sale' group to show no signs of asymmetry at all. This is because the 'tick rule' will impose costs on investors who want to short and therefore eliminate a portion of informed and uninformed traders who would otherwise short sell stocks. We predict that as long as the costs imposed by the tick rule will not bind as strongly as short sale prohibition, bid-ask asymmetry in price clustering will manifest itself.[22]

Table 11 summarizes the test outcomes. Since the two clustering measures produce virtually the same results, we focus on the results from abnormal even price frequencies. Panel A reports the difference in abnormal even price frequencies between the ask and bid quotes for 'short sale' and 'no short sale' groups in each stock class. We refer to this difference as the asymmetric clustering measure. All ask or bid quotes from the entire five queues combined are used in the calculation. Panel A displays a stark difference in the asymmetry pattern between 'short sale' and 'no short sale' groups. With the mean values at 3.939 and 0.439 percent for Class 1 stocks, the asymmetric clustering measure is much larger for stocks with the short sale prohibition than that for stocks without the short sale prohibition It is clear that the strong asymmetry between ask and bid quotes (in Table 10) is driven mainly by the 'no short sale' group. The 'short sale' stocks show much weaker evidence of asymmetry. The magnitude of asymmetry clustering measure is small for all three classes of stocks and the significance is mixed. Overall, the most important evidence comes from the Wilcoxon two-sample tests. For all three classes of stocks, the median tests reject firmly the null hypothesis that there is no difference in the bid-ask asymmetry between stocks with and without short sale restriction.

Panel B of Table 11 presents the results from transaction prices. There is no significant difference in the degree of asymmetry between stocks with and without the short sale prohibition, except

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[22] Option listing can mitigate the impact of short sale restrictions on price clustering. However, there were only 19

for Class 1 stocks where the 8 percent significance level is marginal. Even in this case, the mean values of asymmetric clustering measure for both stock groups are not significantly different from zero. We can therefore conclude that the short sale prohibition does not cause much difference in buy-sell asymmetry in trade price clustering. This result appears to be consistent with the generally weak pattern of asymmetric clustering observed in transaction prices (in Table 10). It also confirms our conjecture that the ask-side bias is partially offset by the bid-side bias induced by the dearth of short sell market orders. Alternatively, the pattern may also imply investors' rational response to the existence of short sale constraints. Diamond and Verrecchia (1987) point out that in a rational expectations world investors understand the informational effects of short sale constraints and thus change their trading rules. Short sale prohibition on the SEHK results in blocking part of informed investors with negative news and buy-sell asymmetry in clustering on the limit order book. However, rational investors take these effects into consideration when they submit market buy orders, hence canceling off part of severe clustering in limit order prices. The asymmetry in clustering manifests itself in limit order prices but disappears in the trading process.

3.4.3 Cross-Sectional Determinants of Clustering with Short Sale Prohibition

Stocks designated for short sales tend to be larger, more liquid, and actively traded. It is important to check whether the short sale prohibition still explains the asymmetry in quote price clustering after we control for firm and trading characteristics. Here, we use firm size, order volume, and number of orders to account for the characteristics of individual stocks. We regress clustering measures on these control variables, the price group dummies, and a short sale dummy. The dummy variable 'shortsale' takes the value of one if the stock is short-sale eligible and zero otherwise. The regression is run separately for each of the six price groups.[23] Because of multicollinearity among the control variables, we run regressions separately for each of the three control variables.[24]

Table 12 reports the OLS regression results. The significant negative signs on the coefficients

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stocks with traded options during our sample period. All of them were short-sale eligible.

[23] We exclude Price Group 6 form the regression analysis since all of the stocks in the group are short-sale eligible.

[24] When the three control variables are put together in a regression, the variance inflation factors are 11.3 ~ 21.6 for order volume, 13.8~21.1 for number of orders, and 4.9 ~ 7.4 for market values

of the control variables indicate that the larger the firm size and the greater the order flow, the less asymmetry in price clustering. The coefficient of the key variable – the short sale dummy – is negative and significant for the most of the cases regardless of the choice of control variables and stocks classes. This result provides strong evidence that short sale prohibition is an important factor explaining the bias in price clustering towards the ask side of the order book. Overall, the evidence suggests that price resolution on the ask side of the limit order book is not as efficient as in the case when investors can sell short. The absence of short sales potentially hinders the market's ability to process information efficiently. Our findings add important evidence suggesting adverse consequences of limitations on transparency in financial markets.

3.4.4. Bid-Ask Asymmetry just underneath and above Integer Price

In this section we examine a slightly different type of asymmetry between the ask and bid quotes driven by price clustering. Niederhoffer (1965) claims that an asymmetry between bid and ask quotes may exist because of strategic price setting by buyers and sellers who try to capitalize on opportunities created by price clustering. An investor who wants to submit a limit sell order, knowing that there will be concentration of sell orders at an integer price, has incentives to submit the order just underneath the integer price to gain the benefit of a quick sale. Likewise, an investor who wants to submit a limit buy order can gain immediacy by submitting the buy order just above an integer price. A prediction is that there are more limit sell orders just underneath an integer price and more buy limit orders just above an integer price. Since a sell (buy) limit order is matched with a buy (sell) market order, the same prediction implies more buy transactions than sells just underneath an integer price and more sells than buys just above an integer price. We test this prediction by comparing the percentages of limit buy and sell order volume placed at prices just underneath and over integer prices. We focus on group 1 and 3 stocks (tick size of $0.001 and $0.01 respectively) because these stocks are expected to show the above mentioned asymmetry most notably.

Table 13 reports the percentages of ask and bid order volume, both in number of orders and in number of shares, at one tick above and one tick below integer prices. It is apparent in the table that at one tick above integer prices (at $0.001 or $0.01) the bid volume exceeds the ask volume. The

differences are highly significant at the 1 percent level for both mean and median tests. It is also obvious in the table that at one tick below integer prices (at $0.009 or $0.09) the ask volume tops the bid volume significantly. The results on Table 13 provide direct evidence to the strategic trading behavior by investors predicted by Niederhoffer (1965).

4. Summary and Conclusions

In this paper, we examine price clustering on the SEHK's limit order book. Existing studies on the issue typically look at clustering in transaction prices only. For the first time, we present evidence on the clustering pattern of the best and deeper quotes on the limit order book. We also examine the impact of short sale restrictions on price clustering.

Our major findings can be summarized as follows. We find highly significant clustering patterns for both transaction prices and quote prices. While both transaction prices and quote prices display significant clustering, the latter exhibit a much stronger pattern. For the best queues on the limit order book, the abnormal even price and integer price frequencies are similar to those found for transaction prices. As we move away from the best queue, clustering around quote prices becomes stronger. Formal statistical tests suggest that there is a highly significant difference in clustering between the deeper queues and the best queue. One possible implication is that part of investors submitting limit orders away from the best queue are less certain about the underlying value of the stock, or that they face greater uncertainty in executing their orders in a timely way.

Unlike the finding from markets with a uniform tick size, where higher-priced stocks display a stronger pattern of clustering, the clustering on the SEHK is relatively stable over various price ranges. This result conforms with adoption of the step-function tick rule by the Exchange. Nevertheless, regression results indicate that within each price group there is a significant negative relationship between clustering and price levels. Our analysis also reveals that an extremely small unit of account itself works as a binding constraint to hinder price resolution process.

Finally, short sale restrictions induce a significant bias in price clustering towards the ask side of the limit order book. Ask quotes are more clustered than bid quotes for most of the tick size groups on the SEHK. While a buy-side bias in clustering is also found in transaction prices, the degree of

asymmetry is much weaker. Subgroup analysis that compares short-sale-eligible stocks and short-sale-ineligible stocks reveals that the short sale prohibition is a significant factor explaining the bias in clustering. Our results imply that short sale restrictions can potentially hamper the market's ability to process information efficiently.

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Table 1 Descriptive Statistics of Sample Firms

The sample covers 698 common stocks listed on the SEHK for the six-month period from January to June 2000, excluding the days immediately preceeding and including the last business day of the option contract maturing month. For each tick size group, the means and medians (in parentheses) of average stock price, market capitalization, daily return standard deviation, average daily number of trades, average daily share volume, bid ask spread in Hong Kong dollars and in percentage, average ask size, and average bid size are reported. The data are obtained from the PACAP dataset, and the SEHK's Main Board's trade record, and bid and ask record.

Price Groups	Price Range (HK$)	Number of Stocks	Tick Size (HK$)	Price (HK$)	Market Cap. (HK$M)	Daily Return Std. Dev. (%)	Avg. Daily No. of Trades	Avg. Daily Volume (1,000 Shares.)	Bid-Ask Spread (HK$)	Percent Spread	Ask Size (1,000 Shares)	Bid Size (1,000 Shares)
1	0.01 ~ 0.25	83	0.001	0.16	230	11.781	402	74,854	0.005	2.980	7,594	9,532
				(0.17)	(161)	(8.678)	(163)	(18,937)	(0.004)	(2.820)	(359)	(387)
2	0.25 ~ 0.50	118	0.005	0.38	307	8.776	158	12,113	0.014	3.800	338	476
				(0.38)	(172)	(7.579)	(53)	(3,268)	(0.012)	(3.760)	(155)	(162)
3	0.50 ~ 2	333	0.010	1.02	723	7.670	183	8,143	0.029	3.220	172	199
				(0.95)	(360)	(5.755)	(41)	(1,338)	(0.026)	(2.870)	(78)	(88)
4	2 ~ 5	76	0.025	3.09	1,583	11.996	234	4,497	0.067	2.260	76	82
				(2.96)	(992)	(5.226)	(50)	(754)	(0.053)	(1.800)	(47)	(52)
5	5 ~ 30	72	0.050	11.58	13,607	9.467	565	6,522	0.126	1.270	79	89
				(9.33)	(6,484)	(3.823)	(141)	(1,548)	(0.096)	(0.890)	(34)	(38)
6	30 ~ 50	7	0.100	37.60	50,714	3.638	485	2,531	0.235	0.570	36	34
				(35.61)	(56,800)	(3.534)	(435)	(1,985)	(0.138)	(0.380)	(38)	(26)
7	50 ~ 100	7	0.250	70.72	363,365	3.441	1,304	5,195	0.303	0.440	105	93
				(65.17)	(200,743)	(3.217)	(1,027)	(3,048)	(0.269)	(0.390)	(67)	(64)
8	100 ~ 200	2	0.500	112.01	264,194	2.857	802	3,040	0.493	0.430	56	77
				(112.01)	(264,194)	(2.857)	(802)	(3,040)	(0.493)	(0.430)	(56)	(77)

Table 2 Clustering of Trade Prices

This table examines the clustering pattern for 1,052 trading cases in our sample of 698 stocks from January to June 2000. The analysis is carried out for three stock classes and for eight tick size groups. In each of the 1,052 trading cases, the particular stock is traded within one of the eight price ranges (tick size groups). Based on the final digit in tick size, all trading cases are divided into three classes. Class 1 stocks have a tick size of $0.005, $0.05, or $0.5. Class 2 stocks have a tick size of $0.025 or $0.25. Class 3 stocks have a tick size of $0.001, $0.01, or $0.1. Mean abnormal even price and abnormal integer price frequencies are reported. The p-values from the t-test for the null hypothesis – that the abnormal frequency is not different from zero – are in parentheses.

Stock Class		Sample Size (No. of Stocks)	Abnormal Even Price Frequencies (%)	Abnormal Integer Price Frequencies (%)
Class 1		328	12.21 (0.00)	12.21 (0.00)
Class 2		164	10.33 (0.00)	9.58 (0.00)
Class 3		557	4.85 (0.00)	6.78 (0.00)
Stock Class	Price Group (Tick Size)			
1	2 ($0.005)	231	12.84 (0.00)	12.84 (0.00)
	5 ($0.05)	93	11.02 (0.00)	11.02 (0.00)
	8 ($0.5)	4	3.84 (0.27)	3.84 (0.27)
2	4 ($0.025)	153	10.59 (0.00)	9.88 (0.00)
	7 ($0.25)	11	6.79 (0.00)	5.41 (0.00)
3	1 ($0.001)	128	9.58 (0.00)	13.37 (0.00)
	3 ($0.01)	413	3.42 (0.00)	4.68 (0.00)
	6 ($0.1)	16	4.12 (0.00)	7.44 (0.00)

Table 3 OLS Regression of Trade Price Clustering

This table reports the coefficients from the cross-sectional regressions of abnormal even price frequencies in transaction prices on firm and trading characteristic. Based on the final digit in tick size, all 1,052 trading cases are divided into three classes. Class 1 stocks have a tick size of \$0.005 or \$0.05. Class 2 stocks have a tick size of \$0.025 or \$0.25. Class 3 stocks have a tick size of \$0.001, \$0.01, or \$0.1. Independent variables include the natural log of stock price (ln(p)), the inverse of the daily return standard deviation (1/volat), the natural log of market capitalization (ln(mv)), the natural log of average daily share volume (ln(vom)), the natural log of average daily number of trades (ln(nt)), and the natural log of average trade size (ln(ts)). The regression is run for each tick-size group in each stock class *, **, and *** indicate that the coefficients are different from zero at the 10, 5, and 1 percent levels, respectively.

Panel A: Class 1 Stocks

	Group 2 (Tick Size = \$0.005)		Group 5 (Tick Size =\$0.05)	
	(1)	(2)	(3)	(4)
Intercept	0.668 ***	0.530 ***	0.328 ***	0.314 ***
ln(p)	0.110 ***	0.133 ***	0.107 ***	0.090 ***
1/volat	-0.003 ***	-0.004 ***	-0.003 ***	-0.003 ***
ln(mv)	-0.006		-0.014 ***	
ln(vom)	-0.040 ***		-0.037 ***	
ln(nt)		-0.047 ***		-0.041 ***
ln(ts)		-0.000		-0.053 ***
Adj. R^2(%)	71.88	72.25	84.54	81.37
Sample Size	174	174	76	77

Panel B: Class 2 Stocks

	Group 4 (Tick Size = \$0.025)		Group 7 (Tick Size =\$0.25)	
	(5)	(6)	(7)	(8)
Intercept	0.375 ***	0.298 ***	-0.243	-0.200
ln(p)	0.130 ***	0.130 ***	0.127 **	0.121 **
1/volat	-0.002 ***	-0.003 ***	-0.004 **	-0.002
ln(mv)	-0.012 **		0.009	
ln(vom)	-0.036 ***		-0.030 **	
ln(nt)		-0.041 ***		-0.028 **
ln(ts)		-0.024		-0.005
Adj. R^2(%)	68.90	66.84	89.64	85.12
Sample Size	110	110	7	7

Table 3 (Continued)

Panel C: Class 3 Stocks	Group 1 (Tick Size = $0.001)		Group 3 (Tick Size = $0.01)		Group 6 (Tick Size = $0.1)	
	(9)	(10)	(11)	(12)	(13)	(14)
Intercept	0.371 ***	0.368 ***	0.167 ***	0.155 ***	0.262	-0.053
ln(p)	0.028 **	0.047 ***	0.048 ***	0.051 ***	-0.048	0.051
1/volat	-0.001 ***	-0.001 ***	-0.001 ***	-0.001 ***	-0.002 **	-0.001
ln(mv)	0.009 **		-0.000		0.018	
ln(vom)	-0.027 ***		-0.013 ***		-0.023	
ln(nt)		-0.026 ***		-0.014 ***		-0.015
ln(ts)		-0.010		-0.009		0.017
Adj. R^2(%)	64.04	61.92	41.64	41.53	14.80	4.75
Sample Size	121	121	356	356	12	13

Table 4 Frequency Distribution of Limit Order Prices Over Different Queues

This table reports the frequency distributions of limit order prices over different queues of the limit order book. The sample covers 1,052 trading cases from 698 stocks during the period from January to June 2000. The table reports mean frequencies for each unit of the last digit of the order prices for the best, 2nd, 3rd, 4th, 5th queues and all queues combined. Based on the final digit of tick size, all trading cases are divided into three classes. Class 1 stocks have a tick size of \$0.005, \$0.05, or \$0.5. Class 2 stocks have a tick size of \$0.025 or \$0.25. Class 3 stocks have a tick size of \$0.001, \$0.01, or \$0.1. *, **, and *** indicate that measured frequencies are different from their expected frequencies under no clustering (0.5 for Class 1, 0.25 for Class 2, and 0.1 for Class 3) at the 10%, 5%, and 1% levels, respectively.

Stock Class (tick size)	Last Digit Value	Queues					
		Best	2nd	3rd	4th	5th	All
Class 1	Whole	0.661***	0.600***	0.736***	0.626***	0.763***	0.674***
(\$0.005, \$0.05, \$0.5)	0.5	0.339***	0.400***	0.264***	0.375***	0.237***	0.326***
	Whole	0.368***	0.348***	0.438***	0.390***	0.488***	0.405***
Class 2	0.25	0.186***	0.194***	0.137***	0.217**	0.166***	0.179***
(\$0.025, \$0.25)	0.5	0.267**	0.242	0.294***	0.214***	0.233**	0.251
	0.75	0.179***	0.216***	0.132***	0.180***	0.114***	0.165***
	Whole	0.182***	0.187***	0.198***	0.193***	0.185***	0.189***
	0.1	0.092***	0.086***	0.088***	0.091**	0.091***	0.090***
	0.2	0.104*	0.097	0.096*	0.088***	0.109***	0.098
	0.3	0.091***	0.088***	0.085***	0.088***	0.069***	0.085***
Class 3	0.4	0.092***	0.092***	0.088***	0.076***	0.100	0.090***
(\$0.001, \$0.01, \$0.1)	0.5	0.107***	0.109***	0.106**	0.127***	0.099	0.110***
	0.6	0.087***	0.093***	0.090***	0.078***	0.111***	0.092***
	0.7	0.073***	0.076***	0.075***	0.095*	0.069***	0.078***
	0.8	0.098	0.089***	0.113***	0.100	0.092***	0.097**
	0.9	0.074***	0.084***	0.061***	0.066***	0.075***	0.072***

Table 5 Clustering of Quote Prices

This table examines the clustering pattern in quote prices on the SEHK's limit order book. The sample covers 1,052 trading cases from 698 stocks during the period from January to June 2000. The table reports mean abnormal even price and abnormal integer price frequencies for the best queue, the 2nd and 3rd queues, the 4th and 5th queues, and all queues combined. The analysis is carried out for three stock cases and for eight tick size groups. In each of the 1,052 trading cases, the particular stock is traded within one of the eight price ranges (tick size groups). Based on the final digit in tick size, all trading cases are divided into three classes. Class 1 stocks have a tick size of \$0.005, \$0.05, or \$0.5. Class 2 stocks have a tick size of \$0.025 or \$0.25. Class 3 stocks have a tick size of \$0.001, \$0.01, or \$0.1. In parentheses are the p-values from t-tests for the null hypothesis that the abnormal frequency is not different from zero. *, **, and *** indicate that the coefficients are different from zero at the 10, 5, and 1 percent levels respectively.

		Abnormal Even Price Frequencies (%)				Abnormal Integer Price Frequencies (%)			
Stock Class		Best Queue	2nd & 3rd Queues	4th & 5th Queues	All Queues	Best Queue	2nd & 3rd Queues	4th & 5th Queues	All Queues
Class 1		12.59***	14.65***	18.01***	15.49***	12.59***	14.65***	18.01***	15.49***
Class 2		11.37***	15.06***	16.80***	14.84***	9.86***	13.24***	19.02***	14.64***
Class 3		4.51***	5.09***	5.20***	5.07***	6.14***	6.99***	6.63***	6.89***
Stock Class	Price Group (Tick Size)								
1	2 (\$0.005)	13.01***	14.72***	18.66***	15.88***	13.01***	14.72***	18.66***	15.88***
	5 (\$0.05)	11.82***	14.49***	16.32***	14.60***	11.82***	14.49***	16.32***	14.60***
	8 (\$0.5)	6.01	14.53***	19.73***	13.74***	6.01	14.53***	19.73***	13.74***
2	4 (\$0.025)	11.60***	15.06***	16.53***	14.81***	9.87***	13.24***	18.82***	14.59***
	7 (\$0.25)	7.78***	15.11***	20.84***	15.25***	9.61***	13.35***	22.15***	15.35***
3	1 (\$0.001)	9.64***	9.04***	8.83***	9.19***	13.35***	12.46***	11.09***	12.49***
	3 (\$0.01)	2.82***	3.82***	3.85***	3.68***	3.83***	5.15***	5.19***	5.05***
	6 (\$0.1)	3.11***	5.83***	5.21***	5.07***	8.25***	9.66***	10.07***	9.61***

Table 6 Differences in Quote Clustering over Different Queues

This table examines the difference in clustering between quotes in the deeper queues and quotes in the best queue on the SEHK's limit order book. The sample covers 1,052 trading cases from 698 stocks during the period from January to June 2000. The table reports the difference in mean abnormal even price and integer price frequencies between the 2nd and 3rd queues combined and the best queue and between the 4th and 5th queues combined and the best queue. The analysis is carried out for three stock cases and for eight tick size groups. In each of the 1,052 trading cases, the particular stock is traded within one of the eight price ranges (tick size groups). Based on the final digit in tick size, all trading cases are divided into three classes. Class 1 stocks have a tick size of \$0.005, \$0.05, or \$0.5. Class 2 stocks have a tick size of \$0.025 or \$0.25. Class 3 stocks have a tick size of \$0.001, \$0.01, or \$0.1. The p-values from t-test for the null hypothesis – that the difference in abnormal frequency not different from zero – are in parentheses. $^{+}$, *, and ** indicate that the coefficients are different from zero at the 10, 5, and 1 percent levels respectively.

		Difference in Abnormal Even Price Frequencies (%)		Difference in Abnormal Integer Price Frequencies (%)	
Stock Class		2nd & 3rd – Best	4th & 5th – Best	2nd & 3rd – Best	4th & 5th – Best
Class 1		2.06 (0.00)	5.42 (0.00)	2.06 (0.00)	5.42 (0.00)
Class 2		3.70 (0.00)	5.43 (0.00)	3.39 (0.00)	9.16 (0.00)
Class 3		0.59 (0.01)	0.69 (0.00)	0.85 (0.00)	0.49 (0.11)
Stock Class	Price Group (Tick Size)				
1	2 (\$0.005)	1.71 (0.00)	5.65 (0.00)	1.71 (0.00)	5.65 (0.00)
	5 (\$0.05)	2.67 (0.00)	4.51 (0.00)	2.67 (0.00)	4.51 (0.00)
	8 (\$0.5)	8.53 (0.08)	13.73 (0.02)	8.53 (0.08)	13.73 (0.02)
2	4 (\$0.025)	3.46 (0.00)	4.93 (0.00)	3.37 (0.00)	8.94 (0.00)
	7 (\$0.25)	7.32 (0.06)	13.05 (0.01)	3.73 (0.33)	12.53 (0.00)
3	1 (\$0.001)	-0.59 (0.07)	-0.81 (0.01)	-0.89 (0.09)	-2.26 (0.00)
	3 (\$0.01)	0.99 (0.00)	1.02 (0.00)	1.33 (0.00)	1.36 (0.00)
	6 (\$0.1)	2.72 (0.02)	2.10 (0.03)	1.41 (0.25)	1.82 (0.18)

Table 7 Quote Clustering for Cases Where Tick Size Moves Up or Down

This table presents the cross-sectional mean and median percentage abnormal even-price frequencies and their changes before and after the tick size moves up from \$0.001 to \$0.01 (Panel A) and before and after the tick size moves down from \$0.01 to \$0.001 (Panel B). *** indicates that the changes is different from zero at the 1 percent level from the test (for mean) or the sign test (for median).

Panel A. Tick Size Changes from \$0.001 to \$0.01 (from Group 1 to Group 3, N = 13)				
		Before	After	After – Before
Best Queue	Mean	14.63	-1.95	-16.58***
	Median	13.72	-0.09	-15.27***
2nd and 3rd Queue	Mean	13.41	2.36	-11.05***
	Median	12.48	2.09	-10.56***
4th and 5th Queue	Mean	13.54	1.89	-11.65***
	Median	10.87	2.79	-9.78***
All Queues	Mean	13.80	1.26	-12.54***
	Median	13.14	2.12	-11.25***

Panel B. Tick Size Change from \$0.01 to \$0.001 (from Group 3 to Group 1, N = 15)				
		Before	After	After – Before
Best Queue	Mean	-2.27	11.34	13.61***
	Median	-1.22	11.02	13.98***
2nd and 3rd Queue	Mean	1.72	12.00	9.28***
	Median	1.23	11.54	9.33***
4th and 5th Queue	Mean	0.84	11.10	10.26***
	Median	2.47	10.57	7.86***
All Queues	Mean	0.56	11.25	10.69***
	Median	0.31	11.40	9.95***

Table 8 Propensity of Tier Emptiness and Order Cancellation

Panel A reports the cross-sectional medians of the length of time taken until an empty tier in the limit order book gets refilled. Panel B reports the cross-sectional means of daily frequencies of limit order cancellation. The durations and daily frequencies are measured for odd prices and even prices separately. The p-values are from the signed-rank test (t-test) for the null hypothesis that the difference in the durations (daily frequencies) between odd prices and even prices is zero.

Panel A. Duration of Tier Emptiness

Stock Class		Median Duration (in seconds)		
		Odd Price	Even Price	Sign test (p-value)
Class 1		1,168	776	(0.000)
Class 2		804	420	(0.000)
Class 3		1,032	951	(0.000)
Stock Class	Price Group (Tick Size)			
1	2 ($0.005)	1,252	852	(0.000)
	5 ($0.05)	892	599	(0.000)
	8 ($0.5)	178	129	(0.250)
2	4 ($0.025)	816	428	(0.000)
	7 ($0.25)	219	161	(0.004)
3	1 ($0.001)	902	804	(0.001)
	3 ($0.01)	1097	959	(0.000)
	6 ($0.1)	440	552	(0.669)

Panel B. Order Cancellation Frequency*

Stock Class		Mean Daily Frequency		
		Odd Price	Even Price	t-test (p-value)
Class 1		8.96	10.16	(0.000)
Class 2		11.53	13.77	(0.000)
Class 3		6.75	7.03	(0.000)
Stock Class	Price Group (Tick Size)			
1	2 ($0.005)	7.46	8.41	(0.000)
	5 ($0.05)	12.94	14.73	(0.000)
	8 ($0.5)	20.89	25.71	(0.275)
2	4 ($0.025)	10.70	12.84	(0.000)
	7 ($0.25)	23.26	26.11	(0.002)
3	1 ($0.001)	4.78	5.05	(0.001)
	3 ($0.01)	7.90	8.16	(0.072)
	6 ($0.1)	12.18	12.87	(0.173)

Mean Daily Frequency by Queue Position

Stock Class	Odd/Even	2nd Queue	3rd Queue	4th Queue	5th Queue
1	Odd	3.74	3.46	2.83	2.10
	Even	3.69	3.76	3.09	2.59
	t-test (p-value)	(0.780)	(0.000)	(0.000)	(0.000)
2	Odd	4.51	4.06	3.39	2.50
	Even	4.54	4.75	3.95	3.33
	t-test (p-value)	(0.811)	(0.000)	(0.000)	(0.000)
3	Odd	2.87	2.78	2.37	1.94
	Even	2.89	2.84	2.38	2.06
	t-test (p-value)	(0.525)	(0.000)	(0.002)	(0.000)

* Orders on the best queue are not counted.

Table 9 OLS Regression of Quote Price Clustering

This table reports the cross-sectional regressions of abnormal even price frequencies in quote prices on firm and trading characteristics. Based on the final digit in tick size, all trading cases are divided into three classes. Class 1 stocks have a tick size of \$0.005 or \$0.05. Class 2 stocks have a tick size of \$0.025 or \$0.25. Class 3 stocks have a tick size of \$0.001, \$0.01, or \$0.1. In the regressions, abnormal frequencies from different queues are treated as different observations. Independent variables include the natural log of stock price (ln(p)), the inverse of the daily return standard deviation (1/volat), the natural log of average order volume (ln(ov)), the natural log of average daily number of orders (ln(on)), and the natural log of average order size (ln(os)). Finally, Q2+Q3 and Q4+Q5 are dummy variables indicating the combined orders on the 2nd and 3rd queues and the 4th and 5th queues respectively. The regression is run for each tick-size group in each stock class. *, **, and *** indicate that the coefficients are different from zero at the 10, 5, and 1 percent levels respectively. The p-values from the multivariate test for the equality between coefficients Q2+Q3 and Q4+Q5 are reported in parentheses.

Panel A: Class 1 Stocks

	Group 2 (Tick Size = \$0.005)		Group 5 (Tick Size =\$0.05)	
	(1)	(2)	(3)	(4)
Intercept	53.64 ***	54.18 ***	17.10 ***	33.03 ***
ln(p)	13.96 ***	14.46 ***	8.71 ***	4.50 ***
1/volat	-0.15 ***	-0.02	-0.17 ***	-0.09
ln(ov)	-2.71 ***		-2.68 ***	
ln(on)		-3.40 ***		-2.11 ***
ln(os)		-1.52 **		-6.43 ***
Q2+Q3	0.81 **	2.55 ***	1.51 **	2.46 ***
Q4+Q5	4.33 ***	4.67 ***	4.51 ***	4.14 ***
p-value (Q2+Q3 = Q4+Q5)	(0.00)	(0.00)	(0.00)	(0.02)
Adj. R^2	56.96	54.76	69.66	68.72
Sample Size	530	530	233	233

Panel B: Class 2 Stocks

	Group 4 (Tick Size = \$0.025)		Group 7 (Tick Size =\$0.25)	
	(5)	(6)	(7)	(8)
Intercept	21.41 ***	36.66 ***	-40.81 **	40.89 **
ln(p)	10.26 ***	5.65 ***	11.98 **	12.59 **
1/volat	-0.12 ***	-0.02	-0.15 *	-0.18 *
ln(ov)	-2.34 ***		-0.63	
ln(on)		-2.21 ***		-0.99
ln(os)		-5.51 **		-0.78
Q2+Q3	2.60 ***	4.15 ***	4.63 ***	5.27 ***
Q4+Q5	5.50 ***	6.17 ***	9.04 ***	9.17 ***
p-value (Q2+Q3 = Q4+Q5)	(0.00)	(0.00)	(0.00)	(0.01)
Adj. R^2	53.99	52.99	82.05	81.73
Sample Size	335	335	23	23

Table 9 (Continued)

Panel C: Class 3 Stocks	Group 1 (Tick Size = $0.001)		Group 3 (Tick Size = $0.01)		Group 6 (Tick Size = $0.1)	
	(9)	(10)	(11)	(12)	(13)	(14)
Intercept	34.16 ***	28.19 ***	10.32 ***	9.27 ***	-15.16	-8.03
ln(p)	5.28 ***	6.44 ***	4.19 ***	4.12 ***	7.49 **	5.62
1/volat	-0.02	0.03	-0.03 **	0.00	-0.14 ***	-0.17 **
ln(ov)	-1.56 ***		-0.77 ***		-0.66 *	
ln(on)		-1.87 ***		-1.01 ***		0.15
ln(os)		0.44		-0.07		-2.59
Q2+Q3	-0.60	0.33	0.44 *	0.82 ***	2.44 **	2.20 *
Q4+Q5	-0.71	-0.88	0.85 ***	0.83 ***	1.83 *	1.29
p-value (Q2+Q3 = Q4+Q5)	(0.84)	(0.33)	(0.12)	(0.99)	(0.53)	(0.36)
Adj. R^2	48.35	44.63	28.15	27.55	34.40	33.64
Sample Size	365	365	1073	1073	41	41

Table 10 Imbalance in Quote and Trade Price Clustering between Buy and Sell Sides

This table presents the difference in clustering between the ask side and bid side of the SEHK's limit order book as well as buy and sell side transactions. For quote price clustering, the table reports the difference in mean abnormal even price and integer price frequencies between the ask and bid sides for the best queue, the 2nd and 3rd queue, the 4th and 5th queue, and all queues combined. The analysis is carried out for three stock cases and eight tick size groups. In each of the 1,052 trading cases, the particular stock is traded within one of the eight price ranges (tick size groups). Based on the final digit in tick size, all trading cases are divided into three classes. Class 1 stocks have a tick size of \$0.005, \$0.05, or \$0.5. Class 2 stocks have a tick size of \$0.025 or \$0.25. Class 3 stocks have a tick size of \$0.001, \$0.01, or \$0.1. The p-values from t-test for the null hypothesis – that the difference in abnormal frequency is not different from zero – are in parentheses. *, **, and *** indicate that the coefficients are different from zero at the 10, 5, and 1 percent levels respectively.

		Quote Price								Trade Price	
		Difference in Abnormal Even Price Frequency (%, Ask – Bid)				Difference in Abnormal Integer Price Frequency (%, Ask – Bid)				Difference (%, Buy – Sell)	
Stock Class		Best Queue	2nd & 3rd Queues	4th & 5th Queues	All Queues	Best Queue	2nd & 3rd Queues	4th & 5th Queues	All Queues	Abnormal Even Freq.	Abnormal Integer Freq.
Class 1		3.76***	2.63***	1.99***	3.42***	3.76***	2.63***	1.99***	3.42***	0.67^{+}	0.67*
Class 2		5.77***	4.71***	2.47***	4.87***	6.80***	7.13***	6.09***	7.92***	1.20*	1.12**
Class 3		1.72***	2.05***	1.83***	1.99***	1.99***	2.38***	0.46	2.09***	-0.24	-0.11
Stock Class	Price Group (Tick Size)										
1	2 (\$0.005)	3.46***	3.05***	2.33***	3.63***	3.46***	3.05***	2.33***	3.63***	0.04	0.04
	5 (\$0.05)	4.21***	1.42***	1.02	2.68***	4.21***	1.42***	1.02	2.68***	1.81*	1.81**
	8 (\$0.5)	11.01***	6.65	4.90	8.25	11.01***	6.65	4.90	8.25	10.54	10.54
2	4 (\$0.025)	6.28***	4.61***	2.53***	4.92***	6.76***	7.16***	6.24***	7.96***	1.36*	1.12**
	7 (\$0.25)	-1.98	6.21	1.56	4.03	7.43**	6.77	3.65	7.41	-0.96	1.13
3	1 (\$0.001)	0.96	0.45	0.66	0.72**	1.82**	-0.32	-4.66***	-0.36	0.25	-0.85**
	3 (\$0.01)	1.79***	2.69***	2.31***	2.44***	1.71***	3.23***	1.98***	2.79***	-0.44	-0.01
	6 (\$0.1)	4.04**	-0.27	-1.44	0.37	6.93***	5.27**	-1.13	3.49**	1.23	2.60**

Table 11 Short Sale Prohibition and the Imbalance in Quote and Trade Price Clustering between the Buy and Sell sides

This table reports the cross-sectional means and medians of the difference in abnormal even price frequencies (as a percentage) between the ask and bid quote prices (Panel A) and between buy and sell transactions (Panel B) for sub-samples based on tick sizes and shorts sale restrictions. Class 1 stocks have a tick size of \$0.005 or \$0.05. Class 2 stocks have a tick size of \$0.025 or \$0.25. Class 3 stocks have a tick size of \$0.001, \$0.01, or \$0.1. The p-values from t-test (for means) or the Wilcoxon two-sample sign test (for medians) for the null hypothesis –that the statistic is not different from zero – are in parentheses.

Panel A: Imbalance in Quote Price Clustering between Ask and Bid

Stock Class		'No Short Sale' (Short Sales Prohibited)	'Short Sale' (Short Sales Permitted)	P-value from Wilcoxon Two Sample Median Test
Class 1	Mean	3.94 (0.00)	0.44 (0.40)	0.00
	Median	3.78 (0.00)	0.98 (0.03)	
	N	139	84	
Class 2	Mean	5.63 (0.00)	1.82 (0.10)	0.00
	Median	5.81 (0.00)	1.95 (0.22)	
	N	59	43	
Class 3	Mean	2.08 (0.00)	0.93 (0.04)	0.00
	Median	1.74 (0.00)	0.48 (0.06)	
	N	337	104	

Panel B: Imbalance in Trade Price Clustering between Buy and Sell

Class 1	Mean	0.72 (0.14)	0.11 (0.80)	0.08
	Median	1.54 (0.01)	-0.13 (0.94)	
	N	139	84	
Class 2	Mean	1.59 (0.03)	1.01 (0.29)	0.32
	Median	1.50 (0.05)	0.51 (0.39)	
	N	59	43	
Class 3	Mean	-0.02 (0.95)	-0.53 (0.04)	0.80
	Median	0.10 (0.89)	0.486 (0.72)	
	N	337	104	

Table 12 OLS Regression of Bid-Ask Imbalance in Quote Price
Clustering with Short Sale Restriction Dummy

This table reports the results from cross-sectional regressions of the difference in abnormal even price frequencies between the ask side and bid side of the order book. The difference in abnormal even price frequencies is calculated from quotes on all five queues combined. Independent variables include the natural log of average daily order volume (ln(ov)), the natural log of the daily number of orders, the natural log of the market value of equity (ln(mv)), and the dummy variable for short sale restrictions (shortsale), which takes the value of 1 if short sales are allowed for the stock and 0 otherwise. Class 1 stocks have a tick size of \$0.005 or \$0.05. Class 2 stocks have a tick size of \$0.025 or \$0.25. Class 3 stocks have a tick size of \$0.001, \$0.01, or \$0.1. *, **, and *** indicate that the coefficients are different from zero at the 10, 5, and 1 percent levels respectively.

Panel A: Class 1 Stocks

	Group 2 (Tick Size = \$0.005)			Group 5 (Tick Size =\$0.05)		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	2.93 **	4.83 *	10.14 ***	4.91 ***	9.49 ***	6.93 **
ln(ov)	0.23			-0.50		
ln(on)		-0.14			-0.87 *	
ln(mv)			-1.19 **			-0.46
shortsale	-5.19 ***	-4.96 ***	-3.97 ***	-2.33 **	-2.01 *	-1.35
Adj. R^2(%)	10.89	10.63	13.57	9.83	12.00	8.83
Sample Size	156	156	156	64	64	64

Panel B: Class 2 Stocks

	Group 4 (Tick Size = \$0.025)			Group 7 (Tick Size =\$0.25)		
	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	7.59 ***	15.44 ***	11.89 ***	15.63 **	33.11 **	29.71
ln(ov)	-0.68			-2.05		
ln(on)		-1.50 ***			-3.08	
ln(mv)			-1.04 *			-1.55
shortsale	-2.94 ***	-2.09 *	-1.51	-8.95	-7.22	-11.11 *
Adj. R^2(%)	10.36	15.23	11.73	47.06	58.48	46.22
Sample Size	91	91	91	7	7	7

Panel C: Class 3 Stocks

	Group 1 (Tick Size = \$0.001)			Group 3 (Tick Size =\$0.01)		
	(13)	(14)	(15)	(16)	(17)	(18)
Intercept	3.53 ***	6.01 ***	2.07	1.69 **	3.12 *	6.38 ***
ln(ov)	-0.54 ***			0.21		
ln(on)		-0.81 ***			-0.12	
ln(mv)			-0.19			-0.78 ***
shortsale	-3.65 ***	-3.38 **	-4.04 ***	-1.67 ***	-1.30 **	-0.57
Adj. R^2(%)	12.67	12.45	6.44	1.63	1.34	3.62
Sample Size	111	111	111	313	313	313

Table 13 The Percentage of Orders Submitted at a Near Integer Price

This table presents the cross-sectional means and medians of the percentages of limit orders and limit order volume placed at the prices that end with \$0.001 or \$0.009 for Group 1 stocks (tick size = \$0.001) and at the prices that end with \$0.01 or \$0.09 for Group 3 stocks (tick size = \$0.01). The table also presents the difference between the mean and median percentages of orders and order volume placed at the ask and the bid. The p-values from the conventional t-test (for means) and the sign-test (for medians) for the null hypothesis that the difference is zero is presented in the last column.

Last Digit Price			\$0.001				\$0.009			
			Ask	Bid	Ask-Bid	p-value	Ask	Bid	Ask-Bid	p-value
Group 1 (N=128)	Number of Orders	Mean	5.251	6.568	-1.318	0.000	7.878	6.145	1.733	0.000
		Median	5.616	7.437	-1.456	0.000	8.227	6.258	1.393	0.000
	Order Volume	Mean	6.124	6.211	-0.087	0.899	8.708	6.816	1.892	0.023
		Median	5.282	6.788	-0.959	0.000	8.428	6.248	1.108	0.000

Last Digit Price			\$0.01				\$0.09			
			Ask	Bid	Ask-Bid	p-value	Ask	Bid	Ask-Bid	p-value
Group 2 (N=418)	Number of Orders	Mean	8.742	11.531	-2.790	0.000	7.616	6.748	0.868	0.000
		Median	8.021	9.369	-1.650	0.000	8.053	7.219	0.794	0.000
	Order Volume	Mean	9.130	12.594	-3.464	0.000	7.515	6.924	0.592	0.002
		Median	8.110	9.627	-1.570	0.000	7.865	7.291	0.368	0.001