“Price clustering in earning announcements and trading time in Hong Kong stock market”

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Abstract

The purpose of this study is to demonstrate that the rational approach based on investors with information asymmetry has an impact on price clustering even in an order-driven market. The authors proxy information asymmetry by the difference in trading time and earning announcements using a sample of Hong Kong stock market data. They show that price clustering is significant in whole numbers in the Hong Kong data. The authors then separate the trading time each day into 16 sessions and find that price clustering is strong in the 1st session (10:14:30), the 11th session (14:44:30), and the 16th session (15:59:30) of the day in the Hong Kong stock market. To investigate the information impact, the paper uses the earning announcement effects on price clustering before and after earning announcements. It demonstrates that earning announcements as a proxy for information asymmetry potentially have a significant impact on price clustering for the actively traded price ranges.

Keywords: price clustering, earning announcements and trading time.
JEL Classification: G1, G2.

Introduction

Based on the information before and after earning announcements, the purpose of this study is to investigate the effect of information asymmetry on price clustering according to the difference in trading volume with respect to different price ranges, and different time sessions in a day. It shows that the rational approach of price resolution hypothesis by Harris (1991) plays a role in Hong Kong stock market. The price resolution hypothesis suggests that when "negotiating cost" outweighs the benefit to resolve prices at their "finest" interval, less-informed investors make bids and offers at the round prices to enable their trades to consummate faster among themselves, thus lowering the "negotiating cost". On the other hand, it questions the validity of market maker collusion hypothesis by Christie and Shultz (1994, 1999) to explain the reason causing the asymmetric information.

Price clustering is the trend for transactions to occur with higher frequency at specific price than at other prices in financial markets. Clustering is usually found at some form of "round" number, such as odd eights that is opposed to even eights, and fractional prices that are opposed to whole numbers. There are many reasons of price clustering. The most controversial price clustering theory is related to the Nasdaq by Christie and Shultz (1994, 1999), they suggest that the irregularity of odd-eighths in the seventy stocks is because of market makers who want to keep the spreads large. But many other researches find that collusion may be impossible. After investigating the amount of price clustering in various financial markets, Grossman, Miller, Cone, Fischel, and Ross (1997) found that collusion was dubious on Nasdaq because the number of market makers in the financial markets were numerous and some hidden market makers exist, who can use the Internet to make order. Futhermore, price clustering is common in many financial markets so that clustering may not only result from market failure.

Ball, Torous, and Tschoegl (1985) show that the occurrence of price clustering in London Gold market may be a result of someone wants to get the optimal degree of price resolution. If round numbers are less expensive, the prices clustering will be found at the point of resolution in which marginal cost of introduction and information acquisition equals the marginal benefit. Ball et al. (1985) also suggest that if all people in trading accept the round prices, the expected value will become zero as their probability to benefit or lose on the rounding is the same. If someone trade in rounded number while the other requires precision, the latter one will gain. It was because he will only accept the rounded price when it is in his favor. However, if all the people in trading require precise prices, the expected value will become negative. They also suggest that high price fluctuation reflects low information precision that is information asymmetry, and the choice of clustering points depends on the price level. Moreover, Ball et al. (1985) suggest that the underlying value of securities may be made less valuable than its accurate pricing. It will mislead the traders to trade at round-number prices.

Harris (1991) in his study of NYSE (New York stock exchange), AMEX (American stock exchange) and Nasdaq stock prices suggests that investors use rounded prices to reduce the negotiation time based on the price resolution hypothesis which considers the cost, depending on trading rules, involved in searching for precise prices, which causes more price clustering. They find that traders use discrete price sets to decrease costs of negotiating. A small set limits the number of different bids and offers that can be made. Negotiations may therefore converge quicker since frivolous offers and counter-offers are restricted. A small set also limits the amount of information that must be exchanged between negotiating traders. It decreases the time it takes to strike a bargain and it decreases the probability which two traders will believe that they have traded at different prices. These savings can be significant if trading is active. So, different trading mechanisms in different markets may result as different levels of clustering.

Kandel, Sarig, and Wohl (2001) during their investigation of Israeli initial public offerings (IPOs) find that people are more likely to use whole numbers with ending in 0 or 5 than fractions so that price clustering in financial markets is psychological in nature that is the behavioral hypothesis. Behavioral hypothesis, in contrast with the information-based and price-resolution theory of Ball et al. (1985), suggests that the trading price may not only depend on time and money but also psychological. Other researchers, such as Cooney, Van Ness, and Van Ness (2001) also investigating NYSE limit orders find that people tend to use round number price, they also prefer even-eighth prices when they submit limit order; and Kahn, Pennacchi, and Sopranzetti (1999), using money market deposit account and retail certificate of deposit interest rate data from a sample of more than 500 U.S. deposit banks, find evidence that the underlying costs are based on "memory economizing" so that people are more likely to trade in rounder numbers.

In economics and contract theory, information asymmetry is about someone gets more or better information than others. Therefore, he/she can make a better decision in trading. This creates an imbalance of power and unfair situation in transactions which may benefit people with better information. Moral hazard and adverse selection are the problems in information asymmetry. Kim and Verrecchia (1991) find that in response to a public disclosure of information, situation, where people have different views and the pre-disclosure of information asymmetry level, is related to the change in trading volume. So, Kim and Verrecchia (1994) tested on the trading volume reaction to a public announcement in order to see if investors are different in the level of information asymmetry. We would also test the reactions of trading volume to earning announcements and want to find out information asymmetry in terms of price clustering.

Furthermore, Shiller and Pound (1989), Kim and Verrecchia (1994) suggest that because most foreign traders in Japan are institutional investors who not only have lower costs in information acquisition, but also better information processing ability, are better informed than non-institutional investors. Many studies (Cready, 1988; Lee, 1992; Kim et al., 1997) in the U.S. market find that institutional investors are more responsive to earning announcements and trade more on current information than non-institutional investors. Because most foreign traders in Hong Kong are institutional investors, trading volume reaction is positively related to the fraction of ownership held by foreigners granted that foreign investors in Hong Kong respond to public announcements in a similar way to those in the Japan and U.S. As a consequence, this paper arguably presents tests of the hypothesis that the level of information asymmetry created before and after earning announcements which induces a different level of price clustering is because the investors may react differently to this release of accounting information.

In Hong Kong, the stock market orders are executed by the automatic order matching and execution system. It is an order-driven rather than a market maker system. Granted Christie and Shultz (1994; 1999) is correct, price clustering would not be significant in Hong Kong's market. If it does, we would resort to the behavioral or psychological approach (Brown and Chua, 2002) to explain the reason leading to the price clustering. Our result demonstrates the contrary. Consistent with the price resolution hypothesis, asymmetric information among investors was found to be a contributing factor to price clustering in Hong Kong stock market. Thus, it demands an alternative explanation than the market maker collusion theory by Christie and Shultz (1994) defining who and why these investors with differential information continue to exist to cause price clustering at least in Hong Kong market. A complete theoretical investigation is the task of future research. This paper echos with Grossman, Miller, Cone, Fischel, and Ross (1997) begging for an alternative explanation for price clustering in the Hong Kong stock market. For a more detailed analysis, we also investigate in what specific time of a day the information asymmetry has its highest impact.

The rest of this paper is organized as follows. Section 1 discusses the sample data, the methodology and defines clustering. Section 2 presents results of price clustering in trading time and price ranges, whereas Section 3 discusses the results of price clustering before and after the earning announcement days. The last Section concludes.

1. Samples and methodology

1.1. Data. We use the Hang Seng Index constituent stock price data gathered by the Hong Kong Stock Exchange (HKEx) from 2001 to 2004. According to the listing requirement, the HKEx assigns stocks to two boards, one is the main board and other is the growth enterprise market (GEM) board. Stocks listed in the main board meet the strictest listing requirement from the HKEx, whereas those listed on the GEM board are usually the growth companies which require less stringent listing requirements of profitability and track record.

The main stock index in the main board is the Hang Seng Index. Hang Seng Index is a freefloat-adjusted market capitalization-weighted stock market index in Hong Kong. It is the main indicator to reflect overall Hong Kong stock market's performance and was used to record and monitor the daily changes of the largest companies of the main board. There were 33 companies under the Hang Seng Index, which were chosen by the Hang Seng Index services limited during the period.

The HKEx provides two continuous trading sessions in each trading day, one is in the morning from 10:00 a.m. to 12:30 p.m. and the other one is in the afternoon from 14:30 p.m. to 16:00 p.m. The only exception is some trading day before the public holidays, then the HKEx will only offer the morning session. Between 09:30 a.m. to 10:00 a.m., there are the call auction sessions to reflect the overnight news and set the opening price for the trading sessions.

Investors can submit either limit orders or market orders to the HKEx. The trading volume of each order must be a multiple of the minimum trading unit specified by each listed company. Minimum trading units are either: 50, 100, 200, 400, 500, 1000, 2000, 5000 or 10000 shares. In the HKEx, most of the stocks are traded with a minimum trading unit such as 500, 1000 or 2000 shares.

The HKEx designs the minimum price increment, which is called as the tick size used for the price of orders. The tick size schedules vary with the price ranges. The price range between \$0.01 and \$0.25, the tick size is \$0.001. The price range between \$0.25 and \$0.50, the tick size is \$0.005. The price range between \$0.50 and \$2.00, the tick size is \$0.01. The price range between \$2.00 and \$5.00, the tick size is \$0.025. The price range between \$5.00 and \$30.00, the tick size is \$0.05. The price range between \$30.00 and \$50.00, the tick size is \$0.10. The price range between \$50.00 and \$100.00, the tick size is \$0.25. The price range between \$100.00 and \$200.00, the tick size is \$0.50. In our analysis, we focus on blue chip stocks in the Hang Seng Index to see whether there is the significant price clustering effect in the Hong Kong stock market.

The HKEx is a good example for the test of the price clustering because it is a pure order-driven market. The prices of securities are determined by both the buy and sell orders submitted by investors with none of designated market makers. Limited orders are placed through brokers and are consolidated into the electronic limit-order book and executed through an automated trading system, known as the automatic order matching and execution system (AMS) which is prioritized by price and then by time. There are no liquidity providers of last resort, no affirmative obligations to supply bid-ask quotations, no circuit breakers or other trading halts, no maximum price changes, and no exchange-designated order processors. The market opens as a continuous market and remains a continuous market up to and including the close of trading. Therefore, the Hong Kong market by default undermines collusions among market makers.

Our data set is acquired from the HKEx research and planning division which includes intra-day data for blue chip stocks covering a period from 2001 to 2004. Hang Seng Index services limited updates the blue chip stocks list in each quarter, there may be dropouts or new additions into the Hang Seng Index. Our analysis keeps track with the updated information over that period.

1.2. Clustering test. We use the Hang Seng Index blue chip stocks to test whether there is any information asymmetry effect on price clustering measured by the difference of trading time and a change of information content arising such as earning announcements. We use the historical transaction record of the 33 blue chip stocks to test the result covering the period from 2001 to 2004.

Most theories, tested position on price clustering, suggest that they occur at round numbers. In the financial market it is the tendency for transactions to occur with higher frequency at certain prices than the other prices. As early as the 1960s, researchers (Osborne, 1962; and Neiderhoffer, 1965 and 1966) focus on the price clustering at even eighths, quarters, halves, and whole numbers. Goodhart and Curio (1991) argue that investors have an attraction to certain integers like zero or five. Kandel, Sarig, and Wohl (2001) suggest that investors are more likely to use whole numbers ending in 0 or 5 than fractions.

As mentioned, the HKEx's tick size schedule has different price ranges which have different minimum tick sizes. Thus, we cannot use the same tick size as the U.S. stocks to divide all the HKEx's price ranges. We discretionarily choose our clustering points. Past research has focused on the price clustering at even eighths, quarters, halves and whole numbers. In our specific tick size schedules, we still use the halves and whole number as our clustering points, but for narrower price ranges we have to use 0.1 and 0.2 as our clustering points. Given the 33 blue chip stocks data, the HKEx's tick size schedules result in the following price ranges: those between \$0.50 and \$2.00, the tick size is \$0.01, we use 0.1 as a clustering point; those between \$2.00 and \$5.00, the tick size is \$0.025, we use 0.2 as a clustering point; those between \$5.00 and \$30.00, the tick size is \$0.05, we use 0.5 as a clustering point; those between \$30.00 and \$50.00, the tick size is \$0.10, we use 1 as a clustering point; those between \$50.00 and \$100.00, the tick size is \$0.25, we use 1 as a clustering point; those between \$100.00 and \$200.00, the tick size is \$0.50, we use 1 as a clustering point.

1.3. Method of analysis. Throughout the empirical analysis, we measure the even relative frequency (RF) in sixteen, fifteen minute trading sessions. The regression model is:

$$RF = \alpha + \sum_{k=1}^{15} \beta_k t_k + \varepsilon, \tag{1}$$

where α and β_k are respectively the intercept constant and the coefficients of the regression model, t_k is an indicator for the time interval at the k^{th} trading sessions, ε is the random errors. We define t_k as a dummy variable to see which session will show a higher degree of price clustering. Accordingly, trading session 1 (t_1) to trading session 16 (t_{16}) are represented by 10:14:30, 10:29:30, 10:44:30, 10:59:30, 11:14:30, 11:29:30, 11:44:30, 11:59:30, 12:14:30, 12:29:30, 14:44:30, 14:59:30, 15:14:30, 15:29:30, 15:44:30, and 15:59:30, respectively. The relative frequency is the ratio calculated by the mod function. In particular, we identify the even transactions by:

$$Mod\ (price,\ even\ base\ price), \tag{2}$$

where the even base price is the price preset at the clustering point according to their price ranges, and the price in the mod function represents the non-zero observed stock prices. The mod function is the scalar function returning the remainder of the division of elements of the first argument by elements of the second argument. Then if the remainder of the mod function is 0, it is the even price, we change it to 1. On the other hand, if the remainder is not the even price, we change it to 0[1].

[1] For example, X_1 = mod (10, 3) is 1; X_2 = mod (1.7 , 0.1) is 0.

After their value changes, we sum all the even prices. We also keep a record of the total number of transactions. Hence, RF is calculated as follows,

$$\frac{Total\ number\ of\ even\ prices}{Total\ number\ of\ transactions} = RF\ . \tag{3}$$

2. Testing clustering in trading time and price ranges

Based on the historical transaction record of the 33 blue chip stocks over a period from 2001 to 2004, Figures 1 to 4 show the price clustering in different price ranges. Clustering is not significant in the price range of \$2-\$5 (Figure 1, see Appendix), where we cannot find an outstanding clustering point. However, in the price ranges of \$5-30 (Figure 2, see Appendix) and \$30-50 (Figure 3, see Appendix), trading volume in whole number and multiple of 0.5 is abnormally high suggesting that clustering exists. For the price range of \$50-\$100 (Figure 4, see Appendix), we can further find that people are more likely to trade in the whole number and multiple of 5. Moreover, we find that in the price ranges of \$3 to \$5, \$16 to \$30, \$33 to \$50, \$50 to \$80 and \$96 to \$100, the trading volume is much less than those in the price ranges from \$2 to \$3, \$5 to \$16, \$30 to \$33, and \$80 to \$96. This is a peculiar feature of the stock price data we selected over the specified period.

After the testing for clustering in different price ranges, we conclude that price clustering occurs in Hong Kong stock market. So, we further test the clustering in different trading time sessions.

Figures 5 to 9 (see Appendix) show the clustering level in terms of trading volume in different time intervals given the various price ranges. In the \$2 to \$5 price range, Figure 5 (see Appendix) only shows that clustering occurs at the first and the eleventh sessions. However, in all the other price ranges, we can find in Figures 6 to 9 that the trading volume is always very high in the first interval (10:14:30), the eleventh interval (14:44:30), and the last interval (15:44:30). But the clustering level decreases slowly after the first interval and the eleventh interval. It increases again at about the fourteenth interval (15:29:30) and reaches the peak at the end.

It may be because the information asymmetry in terms of clustering is very strong before the stock market begins its operation everyday. After starting the operation, the level of information asymmetry decreases and becomes the lowest at the tenth interval (12:29:30) and so the level of price clustering falls. After lunch time, information asymmetry increases again and so the clustering increases. Then, it falls initially but subsequently increases and reaches its peak when toward the end of the day.

3. Testing clustering before and after the earning announcement days

We further test the difference in the clustering level before and after the earning announcement days. Since information asymmetry is strong before the announcement day and it may reach its peak just before the announcement, we are going to test the clustering level before and after earning announcements to further study how different market participants evaluate and utilize the differential private information of earning announcements. Since we are testing the flow of asymmetric information into the stock market over a day, we minimize the outlier effect of t_{16} in Figures 5 to 9 (see Appendix) by including only t_1 to t_{15} into our regression models, thus leaving the effect of t_{16} to be determined by that of the intercept.

3.1. Data. We choose data which were five working days before the announcement day and five working days after the announcement day. For any given HKEx's stock, there are usually two announcement days in one year. Therefore, we will get a total of 20-day trading record for each stock in one year. Some companies may announce annual report at afternoon, some may announce after the market was closed in the announcement day. If companies announces at noon, it would affect information asymmetry level before and after noontime. However, if companies announce after the market was closed, it would not affect information asymmetry level during that trading day. Therefore, it is hard to classify whether the announcement day should take a before or after announcement value. Consequently, we will delete the trade record in the announcement day, because we cannot clearly categorize it either into as a pre-announcement or a post-announcement day, justified by its informational content or by its watershed classification time point.

3.2. Regression model with announcements. We add the announce as a dummy variable to the regression model above. Thus,

$$RF = \alpha + \sum_{k=1}^{15} \beta_k t_k + \gamma \, Announce \, + \varepsilon \,, \qquad (4)$$

where γ is the coefficient to the regression variable announce. The dummy variable announce is constructed based on the assumption that before the annual report earning announcement, the market got less information about that company. After the announcement, the investors know more about the company. If the investors get more information, therefore they can more precisely evaluate the value of that stock, and hence investors would trade at a better informed price. If investors do not know, they should trade at a price which is only a rough estimate. Because each transaction would become a reference of the later transaction, as information of the transaction prices accumulates, the price of later transaction would be closer to the informed price. As the information asymmetry decreases, the spread of trade would decrease, so is clustering level. In defining the announce dummy variable, we set the five working days before the announcement day as 1, and the five working days after the announcement day as 0.

We have seen information release level would affect the clustering level of each time interval in Table 1 and Figures 5 to 9 (see Appendix). After the trading started, the numbers of transactions increase resulting in more observations for reference. Therefore, information imbalance decreases. As the result, the price clustering level decreases. If we assume that the annual report release is a form of information release, we would expect that the clustering level would be affected. For the same analysis before, we segregate data into intraday sessions for comparison.

Before the announcement day, all investors got less information about company performance, so they may overestimate or underestimate the value of the companies. On the other hand, we assume that institutional investors always got more information than non-institutional investor before the announcement day. It creates an opportunity for institutional investors to take advantage of this differential information (Cready, 1988; Lee, 1992; Kim et al., 1997) to make profit. Hence, we would expect that the pre-announcement clustering level should be higher than that of the post-announcement period.

3.3. Results of the 5-day model. From the regression result in the Table 2 (see Appendix), we show from the F-statistic that the regression model is not significant at the significance level of 5% except the price range \$5-\$30. The R-square are less than 0.01 in all the regressions, it means less than 0.1% of observations can be explained by the regression model. The parameter estimates of *Announce* in the price ranges \$2-\$5, \$5-\$30, \$30-\$50, \$50-\$100 and all the price ranges together are -2.616, 1.898, and -2.943, -2.511, -0.333, respectively. The probability value of the t-statistics of the *Announce* in \$2-\$5, \$5-\$30, \$30-\$50, \$50-\$100 and all price ranges together are 0.007, < 0.0001, < 0.0001, 0.0146, and 0.289, respectively. In the all prices together ranges, *Announce* is statistically insignificant. Nevertheless, the announcement effect is significant at 5% level in all the other price ranges. Therefore, information asymmetry is potentially more pronounced in these price ranges. It is interesting to see the coefficient is positive in the $5-$30 price range suggesting information asymmetry is highest before earning announcement, but vice versa for the other price ranges.

3.4. Further analysis of 2-day model. As a robustness check, we re-define the dummy variable *Announce* based on the announcement data which were two working days prior to the announcement day and two working days after. There are two annual announcements in one year. Therefore, we will get a total of 8 days trading record of each stock in one year.

3.5. Result of the 2-day model. We use the regression model given in equation (4) above. From the regression result in the Table 3 (see Appendix), we show from F-statistic that the regression model in equation (4) is not significant at the significance level of 5%. However, in terms of probability value, the model in the price range $5-$30 is more significant than the others. The parameter estimate the time intervals of *Announce* in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all price ranges together are -2.787, 1.314, and -2.163, -2.549, 0.120, respectively. Their associated probability values based on the t-statistics for the *Announce* in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all price ranges together are 0.0311, 0.013, 0.0453, 0.1028 and 0.7877, respectively. Except for the price range $50-$100, the results are consistent with those of the 5-working days announcement effect.

3.6. Other results. In Tables 4 to 9 (see Appendix), we further investigate the regression models in equation (4) including only the time session dummy variables t_1, t_2, t_{11}, and t_{12} which are shown to have stronger price clustering as suggested in Figures 5 to 9 (see Appendix). The F-statistics of the 5-day regression models in Tables 4, 6 and 8 (see Appendix) are significant in most of the price ranges. By comparison, the 2-day models in Tables 5, 7 and 9 are less significant. This is a result similar to that in Tables 2 and 3 (see Appendix). All in all, the coefficient of Announce in the price range $5-$30 is significantly positive at 5% level in all Tables 2 to 9 (see Appendix).

Conclusions

To conclude, using a sample of Hong Kong stock market data, we investigate the different level of price clustering caused by information asymmetry. We use the difference in information content to various market participants before and after earning announcements to proxy information asymmetry. Based on the Hong Kong Hang Seng Index constituent stock price data from HKEx between the years 2001-2004, we find that price clustering is significant in whole numbers. While there are numerous studies investigating price clustering and earning announcements, there are hardly any studies that relate them together. To identify what exactly the cause of price clustering in Hong Kong market would take another research endeavor, the suggestion that institutional investors play a role of course needs to be thoroughly elaborated. However, the use of the earning announcements as proxy for investors using asymmetric information helps us to unravel if rational explanation to price clustering still exists in a seemingly competitive trading system as in the Hong Kong stock market.

Hong Kong adopted a pure order-driven system through which submitted limit orders are electronically matched and executed through an automated trading system called the automatic order matching and execution system (AMS). Therefore, the market maker collusion theory and findings by Christie and Shultz (1994, 1999) from Nasdaq is not important in the Hong Kong stock market. While Brown and Chua (2002) demonstrate that cultural influence is important to explain price clustering in the Asian stock markets, in this paper we demonstrate that the rational approach based on information asymmetry, time and cost consideration still plays a role in determining price clustering at least in Hong Kong stock market.

We separate the trading time every day into 16 sessions and find that the price clustering is strong in the 1^{st} session (10:14:30), the 11^{th} session (14:44:30), and the 16^{th} session (15:59:30) of the day. However, their strength in price clustering level decreases slowly thereafter as shown by the relative frequency of even prices. Therefore, it suggests that information asymmetry is the strongest at those sessions. One explanation for the clustering at the 16^{th} session is that some investors such as insiders may have the specific or private information, which will be announced after the end of trading day. These investors will use the information to make the transaction before the market closed. So, the clustering at the end of trading is the strongest. For the clustering in the 1^{st} session, investors who got the information from the announcement before the beginning of the trading day may make the transactions at the very beginning of the following trading day leading to strong price clustering in the 1^{st} session. For the clustering in the 11^{th} session, some information may be announced or some private information may be gained during the lunch time. So, we also expect strong price clustering after the lunch time at the 11^{th} session.

To support the argument that the level of price clustering in the Hong Kong's stock market data at least is partly induced by information asymmetry, we regress price clustering against trading time and earning announcements. The use of the earning announcements is because it is a specific form of private information, which is to be announced to the market. We perform the 2-day and 5-day before and after earning announcement tests. Although the R-squares of the 5-day and 2-day models are all less than 0.02, the F-statistics of the models and the t-statistics to the dummy variable of earning announcements for the more actively traded price range \$2-\$5 is statistically significant when we split the trading day into 16 time sessions. This potentially is a further evidence that earning announcements, and hence information asymmetry affects the Hong Kong stock market investors' behavior over the trading day for those price ranges.

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Appendix

Table 1. Summary of the tables of relative frequency of clustering

Price ranges	\$2-\$5	\$5-\$30	\$30-\$50	\$50-\$100	All prices
Observations	320	1023	351	211	1311
Degree of freedom (DF)	15	15	15	15	16
Sum of squares	1864.30392	5517.52597	1342.94870	1195.10821	5937.00719
Mean square	124.32693	367.83506	89.52991	79.67388	395.80048
F value	2.28	7.84	2.51	1.59	9.87
Pr > F	<.0045	<.0001	<.0015	<.0785	<.0001
Dependent variable of relative frequency of clustering of the model					
Root MSE	7.38015	6.84915	5.96927	7.07330	6.33099

Table 1 (cont.). Summary of the tables of relative frequency of clustering

Price ranges	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Dependent mean	3.98018	6.19273	5.08540	5.63787	5.55502
R-square	0.1009	0.1045	0.1009	0.1086	0.1026
Adjusted R-square	0.0567	0.0912	0.0607	0.0404	0.0922
Parameter estimates (t-value)	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Intercept	11.97304 (7.43)	13.50400 (15.77)	11.13943 (8.75)	12.88038 (6.57)	12.23206 (17.5)
Parameter estimate(t_1)	-5.53430 (-2.4)	-4.70054 (-3.88)	-3.75076 (-2.08)	-3.94688 (-1.42)	-4.25365 (-4.30)
Parameter estimate(t_2)	-8.34167 (-3.62)	-6.99511 (-5.76)	-5.89955 (-3.28)	-7.57448 (-2.78)	-6.44169 (-6.52)
Parameter estimate(t_3)	-8.75422 (-3.8)	-8.08208 (-6.68)	-6.60081 (-3.67)	-8.21715 (-3.02)	-7.29378 (-7.38)
Parameter estimate(t_4)	-8.66134 (-3.76)	-8.25001 (-6.81)	-6.80525 (-3.78)	-8.21715 (-2.95)	-7.56906 (-7.66)
Parameter estimate(t_5)	-9.39476 (-4.07)	-8.71984 (-7.20)	-6.70979 (-3.73)	-8.76594 (-3.16)	-8.01694 (-8.11)
Parameter estimate(t_6)	-9.52883 (4.13)	-9.03236 (-7.46)	-7.76865 (-4.32)	-8.79387 (-3.17)	-8.31004 (-8.40)
Parameter estimate(t_7)	-9.41395 (-4.08)	-9.10948 (-7.52)	-7.52668 (-4.18)	-9.32204 (-3.36)	-8.39684 (-8.49)
Parameter estimate(t_8)	-9.40641 (-4.08)	-9.31501 (-7.69)	-7.72936 (-4.29)	-9.01434 (-3.31)	-8.43200 (-8.53)
Parameter estimate(t_9)	-9.82709 (-4.26)	-9.37066 (-7.74)	-7.8151 (-4.34)	-9.42936 (-3.46)	-8.56874 (-8.67)
Parameter estimate(t_{10})	-9.66221 (-4.19)	-9.12886 (-7.54)	-7.75301 (-4.31)	-8.71549 (-3.14)	-8.32360 (-8.42)
Parameter estimate(t_{11})	-6.26998 (-2.72)	-5.7126 (-4.72)	-5.12623 (-2.85)	-4.80952 (-1.73)	-5.02572 (-5.08)
Parameter estimate(t_{12})	-7.57493 (-3.29)	-7.74524 (-6.40)	-6.69658 (-3.72)	-7.55788 (-2.72)	-6.93516 (-7.01)
Parameter estimate(t_{13})	-8.41601 (-3.65)	-7.67602 (-6.34)	-6.07186 (-3.37)	-7.57736 (-2.73)	-6.93305 (-7.01)
Parameter estimate(t_{14})	-8.82365 (-3.83)	-7.14288 (-5.90)	-6.1632 (-3.42)	-7.16226 (-2.58)	-6.68832 (-6.76)
Parameter estimate(t_{15})	-8.6761 (-3.76)	-5.9996 (-4.96)	-4.44766 (-2.47)	-6.4057 (-2.31)	-5.64410 (-5.71)

Table 2. Results of the 5-day regression

Price ranges	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Observations	3126	12792	4477	3157	24062
Degree of freedom (DF)	16	16	16	16	16
Sum of squares	14356	19540	15041	19243	11139
Mean square	897.24383	1221.25754	940.07279	1202.69457	696.18758
F value	1.22	2.98	1.59	1.44	1.17
Pr > F	0.2413	<.0001	0.0637	0.1154	0.2806
Dependent variable of relative frequency of clustering of the model					
Root MSE	27.08822	20.23696	24.33829	28.94353	24.35777
Dependent mean	12.80229	10.05707	12.31222	27.16758	13.30729
R-square	0.0062	0.0037	0.0056	0.0072	0.0008
Adjusted R-square	0.0011	0.0025	0.0021	0.0022	0.0001
Parameter estimates (t-value)	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Intercept	14.90077(7.51)	9.72315(13.26)	13.12681(8.79)	28.38808(13.43)	13.73416(21.29)
Parameter estimate (t_1)	0.88145(0.32)	1.89797(1.74)	1.24467(0.61)	3.01455(1.04)	1.85602(2.10)
Parameter estimate (t_2)	-4.83412(-1.78)	1.75166(-0.76)	1.30400(0.64)	2.38529(0.82)	-0.47563(-0.54)
Parameter estimate (t_3)	0.32232(0.12)	-0.76701(-0.15)	1.07447(0.52)	-1.46047(-0.50)	-0.07535(-0.09)
Parameter estimate (t_4)	0.60903(0.22)	-0.15126(-0.71)	2.72978(1.33)	-0.75422(-0.26)	0.20615(0.23)
Parameter estimate (t_5)	-0.23686(-0.09)	-0.71083(-1.25)	2.19579(1.07)	0.82433(0.28)	-0.13696(-0.15)
Parameter estimate (t_6)	0.04195(0.02)	-1.26592(0.29)	-0.09362(-0.05)	-3.52809(-1.21)	-0.32245(-0.36)

Table 2 (cont.). Results of the 5-day regression

Price ranges	\$2-\$5	\$5-\$30	\$30-\$50	\$50-\$100	All prices
Parameter estimate (t_7)	0.87077(0.32)	0.29115(-0.35)	0.54826(0.27)	-4.09783(-1.41)	-0.49245(-0.55)
Parameter estimate (t_8)	-0.65889(-0.24)	-0.35016(-0.33)	-0.16798(-0.08)	0.37594(0.13)	-0.27694(-0.31)
Parameter estimate (t_9)	-3.35715(-1.23)	-0.33443(-0.82)	-0.15688(-0.08)	-0.02484(-0.01)	-0.89919(-1.01)
Parameter estimate(t_{10})	-0.85930(-0.32)	-0.82442(-1.13)	2.17135(1.06)	-2.20908(-0.76)	-0.61257(-0.69)
Parameter estimate(t_{11})	-1.38789(-0.51)	-1.13949(-0.92)	1.17940(0.57)	3.14868(1.08)	0.08305(0.09)
Parameter estimate(t_{12})	-3.96549(-1.45)	-0.92817(-1.20)	0.50042(0.24)	1.49744(0.52)	-0.60250(-0.68)
Parameter estimate(t_{13})	0.28596(0.10)	-1.21643(-1.36)	-0.45755(-0.22)	2.49044(0.86)	-0.39928(-0.45)
Parameter estimate(t_{14})	-0.85857(-0.31)	-1.37663(-1.35)	-1.23791(-0.60)	-0.26280(-0.09)	-1.13561(-1.28)
Parameter estimate(t_{15})	0.15819(0.06)	-1.36013(-1.30)	-0.61089(-0.30)	-1.01356(-0.35)	-0.93021(-1.05)
Announce	-2.61570(-2.71)	1.89797 (5.31)	-2.94267(-4.05)	-2.51063(-2.44)	-0.33288(-1.06)
Pr > |t|	0.0068	<.0001	<.0001	0.0146	0.2890

Notes: The observations in the price ranges \$2-\$5, \$5-\$30, \$30-\$50, \$50-\$100 and all the price ranges together are 3126, 12792, 4477, 3157 and 24062, respectively. The R-squares are less than 0.008 in all the regressions, it means less than 0.8% of observations can be explained by the regression model. The parameter estimates of *Announce* in the price ranges \$2-\$5, \$5-\$30, \$30-\$50, \$50-\$100 and all the price ranges together are -2.616, 1.898, and -2.943, -2.511, -0.333, respectively. The probability value of the t-statistics of the *Announce* in \$2-\$5, \$5-\$30, \$30-\$50, \$50-\$100 and all price ranges together are 0.0068, < 0.0001, < 0.0001, 0.0146, and 0.289, respectively. In the price range \$50-\$100 and all price ranges together, *Announce* is statistically insignificant. Nevertheless, the announcement effect is significant at 5% level in the price ranges of \$2-\$5, \$5-\$30, \$30-\$50 and \$50-\$100.

Table 3. Results of the 2-day regression

Price ranges	\$2-\$5	\$5-\$30	\$30-\$50	\$50-\$100	All prices
Observations	1284	7173	1964	1258	11906
Degree of freedom (DF)	16	16	16	16	16
Sum of squares	11317	12530	7627.56892	19139	13550
Mean square	707.33166	783.14616	476.72306	1196.17984	846.84473
F value	1.30	1.56	0.83	1.54	1.42
Pr > F	0.1858	0.0709	0.6563	0.0786	0.1196
Dependent variable of relative frequency of clustering of the model					
Root MSE	23.28818	22.40659	24.01905	27.87602	24.38029
Dependent mean	9.70293	10.13694	11.56815	26.92260	12.40260
R-square	0.0160	0.0035	0.0067	0.0192	0.0019
Adjusted R-square	0.0037	0.0012	-0.0014	0.0067	0.0006
Parameter estimates (t-value)	\$2-\$5	\$5-\$30	\$30-\$50	\$50-\$100	All prices
Intercept	10.45821(3.97)	10.62975(9.82)	12.01804(5.39)	23.48743(7.31)	12.32483(13.45)
Parameter estimate (t_1)	1.96697(0.54)	1.30162(0.88)	4.49200(1.47)	11.80299(2.69)	3.30063(2.63)
Parameter estimate (t_2)	0.92901(0.26)	-1.96743(-1.32)	3.08876(1.01)	10.06131(2.28)	0.43960(0.35)
Parameter estimate (t_3)	5.05742(1.39)	-2.22461(-1.49)	1.64889(0.54)	4.63548(1.05)	-0.02854(-0.02)
Parameter estimate (t_4)	6.05964(1.67)	-2.06812(-1.39)	1.62944(0.53)	8.94806(2.02)	0.79242(0.63)
Parameter estimate (t_5)	3.67578(1.01)	-3.43886(-2.30)	1.41466(0.46)	5.34909(1.21)	-0.85785(-0.68)
Parameter estimate (t_6)	1.50847(0.42)	-1.29016(-0.86)	-1.53741(-0.50)	1.24600(0.28)	-0.81944(-0.65)
Parameter estimate (t_7)	1.53108(0.42)	-1.10120(-0.74)	0.35856(0.12)	-0.14228(-0.03)	-0.46901(-0.37)
Parameter estimate (t_8)	-2.84855(-0.78)	-1.14138(-0.76)	-0.60215(-0.20)	8.01813(1.82)	-0.25550(-0.20)
Parameter estimate (t_9)	-0.64675(-0.18)	-1.16211(-0.78)	-0.49874(-0.16)	3.06452(0.70)	-0.59160(-0.47)
Parameter estimate(t_{10})	0.08608(0.02)	-2.59858(-1.75)	1.63771(0.53)	0.61721(0.14)	-1.35929(-1.08)
Parameter estimate(t_{11})	-0.27431(-0.08)	-0.01223(-0.01)	-1.59770(-0.52)	6.44101(1.46)	0.52269(0.42)
Parameter estimate(t_{12})	-4.16654(-1.15)	0.13879(0.09)	0.72772(0.24)	3.64517(0.82)	0.46447(0.37)
Parameter estimate(t_{13})	-0.17888(-0.05)	-0.41467(-0.28)	0.67024(0.22)	7.59052(1.72)	0.69102(0.55)
Parameter estimate(t_{14})	-1.03879(-0.29)	-1.44967(-0.97)	-1.62411(-0.53)	2.52245(0.57)	-1.08241(-0.86)
Parameter estimate(t_{15})	-1.50765(-0.41)	-0.96334(-0.65)	0.03760(0.01)	1.46287(0.33)	-0.52109(-0.41)
Announce	-2.78684(-2.16)	1.31374(2.49)	-2.16260(-2.00)	-2.54933(-1.63)	0.12025(0.27)
Pr > |t|	0.0311	0.0130	0.0453	0.1028	0.7877

Notes: The observations in the price ranges \$2-\$5, \$5-\$30, \$30-\$50, \$50-\$100 and all the price ranges together are 1284, 7173, 1964, 1258 and 11906, respectively. The R-squares are less than 0.02 in all the regressions, it means less than 2% of observations can be explained by the regression model. The parameter estimate of time intervals of *Announce* in the price ranges \$2-\$5, \$5-\$30, \$30-\$50, \$50-\$100 and all price ranges together are -2.787, 1.314, and -2.163, -2.549, -0.120, respectively. Their associated probability values based on the t-statistics for the *Announce* in the price ranges \$2-\$5, \$5-\$30, \$30-\$50, \$50-\$100 and all price ranges together are 0.0311, 0.013, 0.0453, 0.1028 and 0.7877, respectively.

Table 4. Results of the 5-day regression (t_1, t_2, t_{11}, t_{12})

Price ranges	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Observations	3137	12803	4488	3168	24073
Degree of freedom (DF)	5	5	5	5	5
Sum of squares	11744	16488	10092	11894	8362.09232
Mean square	2348.87030	3297.57112	2018.45976	2378.85129	1672.41846
F value	3.21	8.05	3.41	2.84	2.82
Pr > F	0.0068	<.0001	0.0045	0.0145	0.0150
Dependent variable of relative frequency of clustering of the model					
Root MSE	27.05607	20.23416	24.33112	28.93336	24.35458
Dependent mean	12.80229	10.05707	12.31222	27.16758	13.30729
R-square	0.0051	0.0031	0.0038	0.0045	0.0006
Adjusted R-square	0.0035	0.0027	0.0027	0.0029	0.0004
Parameter estimates (t-value)	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Intercept	14.59632(19.90)	9.01289(33.15)	13.62390(24.71)	27.59053(35.22)	13.31189(55.76)
Parameter estimate (t_1)	1.18309(0.59)	2.46249(3.31)	0.74656(0.49)	3.81407(1.79)	2.27876(3.50)
Parameter estimate (t_2)	-4.53247(-2.26)	-0.05618(-0.08)	0.80589(0.53)	3.18482(1.49)	-0.05288(-0.08)
Parameter estimate(t_{11})	-1.08628(-0.54)	-0.21734(-0.29)	0.68131(0.45)	3.94822(1.84)	0.50579(0.77)
Parameter estimate(t_{12})	-3.66389(-1.82)	-0.50560(-0.68)	0.00232(0.00)	2.29699(1.07)	-0.17976(-0.27)
Announce	-2.60998(-2.70)	1.89681(5.30)	-2.94062(-4.05)	-2.51461(-2.45)	-0.33382(-1.06)
Pr > |t|	0.0069	<.0001	<.0001	0.0144	0.2876

Notes: The observations in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all the price ranges together are 3137, 12803, 4488, 3168 and 24073, respectively. The R-squares are less than 0.01 in all the regressions, it means less than 1% of observations can be explained by the regression model. The parameter estimate of time intervals of announce in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all price ranges together are -2.6100, 1.8968, and -2.941, -2.5146, -0.3338, respectively. Their associated probability values based on the t-statistics for the *Announce* in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all price ranges together are 0.0069, < 0.0001, < 0.0001, 0.0144 and 0.2876, respectively.

Table 5. Results of the 2-day regression (t_1, t_2, t_{11}, t_{12})

Price ranges	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Observations	1295	7184	1975	1269	11917
Degree of freedom (DF)	5	5	5	5	5
Sum of squares	4740.53334	8064.35870	5719.19384	9936.40847	10013
Mean square	948.10667	1612.87174	1143.83877	1987.28169	2002.68814
F value	1.75	3.21	1.99	2.56	3.37
Pr > F	0.1210	0.0067	0.0771	0.0260	0.0048
Dependent variable of relative frequency of clustering of the model					
Root MSE	23.29831	22.40331	23.97223	27.88527	24.37512
Dependent mean	9.70293	10.13694	11.56815	26.92260	12.40260
R-square	0.0067	0.0022	0.0050	0.0100	0.0014
Adjusted R-square	0.0029	0.0015	0.0025	0.0061	0.0010
Parameter estimates (t-value)	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Intercept	11.42900(11.59)	9.14492(22.73)	12.27787(14.99)	27.11090(22.70)	11.95118(35.13)
Parameter estimate (t_1)	0.99079(0.37)	2.78493(2.54)	4.23090(1.90)	8.19049(2.54)	3.67506(3.98)
Parameter estimate (t_2)	-0.04731(-0.02)	-0.48414(-0.44)	2.82765(1.26)	6.44867(1.99)	0.81404(0.88)
Parameter estimate (t_{11})	-1.25062(-0.47)	1.47105(1.34)	-1.85879(-0.83)	2.82852(0.87)	0.89712(0.97)
Parameter estimate (t_{12})	-5.14285(-1.92)	1.62208(1.47)	0.46662(0.21)	0.03267(0.01)	0.83891(0.90)
Announce	-2.77580(-2.15)	1.31683(2.49)	-2.16004(-2.01)	-2.57101(-1.65)	0.11866(0.27)
Pr > |t|	0.0318	0.0127	0.0451	0.1000	0.7904

Notes: The observations in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all the price ranges together are 1295, 7184, 1975, 1269 and 11917, respectively. The R-squares are less than 0.01 in all the regressions, it means less than 1% of observations can be explained by the regression model. The parameter estimate of time intervals of *Announce* in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all price ranges together are -2.7758, 1.3168, and -2.1600, -2.5710, 0.1187, respectively. Their associated probability values based on the t-statistics for the *Announce* in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all price ranges together are 0.0318, 0.0127, 0.0451, 0.1000 and 0.7904, respectively.

Table 6. Results of the 5-day regression (t_1, t_{11})

Price ranges	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Observations	3139	12805	4490	3170	24075
Degree of freedom (DF)	3	3	3	3	3
Sum of squares	6004.22018	16300	9923.47311	9257.98007	8315.27648
Mean square	2001.40673	5433.45781	3307.82437	3085.99336	2771.75883
F value	2.73	13.27	5.59	3.69	4.67
Pr > F	0.0425	<.0001	0.0008	0.0115	0.0029
Dependent variable of relative frequency of clustering of the model					
Root MSE	27.08124	20.23294	24.32647	28.93860	24.35360
Dependent mean	12.80229	10.05707	12.31222	27.16758	13.30729
R-square	0.0026	0.0031	0.0037	0.0035	0.0006
Adjusted R-square	0.0016	0.0029	0.0031	0.0025	0.0005
Parameter estimates (t-value)	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Intercept	14.00956(19.93)	8.97304(34.46)	13.68118(25.91)	27.98244(37.27)	13.29533(58.13)
Parameter estimate (t_1)	1.76945(0.89)	2.50234(3.39)	0.68901(0.46)	3.42193(1.62)	2.29534(3.54)
Parameter estimate(t_{11})	-0.49992(-0.25)	-0.17749(-0.24)	0.62376(0.41)	3.55608(1.67)	0.52237(0.80)
Announce	-2.60917(-2.70)	1.89681(5.30)	-2.94006(-4.05)	-2.51415(-2.45)	-0.33387(-1.06)
Pr > |t|	0.0070	<.0001	<.0001	0.0144	0.2875

Notes: The observations in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all the price ranges together are 3139, 12805, 4490, 3170 and 24075, respectively. The R-squares are less than 0.01 in all the regressions, it means less than 1% of observations can be explained by the regression model. The parameter estimate of time intervals of *Announce* in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all price ranges together are -2.6092, 1.8968, and -2.9401, -2.5142, -0.33387, respectively. Their associated probability values based on the t-statistics for the *Announce* in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all price ranges together are 0.0070, < 0.0001, < 0.0001, 0.0144 and 0.2875, respectively.

Table 7. Results of the 2-day regression (t_1, t_{11})

Price ranges	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Observations	1297	7186	1977	1271	11919
Degree of freedom (DF)	3	3	3	3	3
Sum of squares	2730.84174	6820.39973	4797.03370	6850.58702	9139.13923
Mean square	910.28058	2273.46658	1599.01123	2283.52901	3046.37974
F value	1.67	4.53	2.78	2.93	5.13
Pr > F	0.1706	0.0035	0.0396	0.0325	0.0015
Dependent variable of relative frequency of clustering of the model					
Root MSE	23.31359	22.40405	23.96984	27.90685	24.37458
Dependent mean	9.70293	10.13694	11.56815	26.92260	12.40260
R-square	0.0039	0.0019	0.0042	0.0069	0.0013
Adjusted R-square	0.0016	0.0015	0.0027	0.0045	0.0010
Parameter estimates (t-value)	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Intercept	11.05555(11.70)	9.22550(23.93)	12.51182(15.95)	27.57697(24.07)	12.06932(37.03)
Parameter estimate (t_1)	1.36508(0.51)	2.70417(2.48)	-2.15646(1.80)	7.72550(2.41)	3.55654(3.87)
Parameter estimate (t_{11})	-0.87631(-0.33)	1.39030(1.28)	3.99518(-0.94)	2.36353(0.73)	0.77861(0.85)
Announce	-2.77752(-2.15)	1.31716(2.49)	-2.09448(-2.00)	-2.57314(-1.65)	0.11941(0.27)
Pr > |t|	0.0319	0.0127	0.0454	0.1000	0.7891

Notes: The observations in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all the price ranges together are 1297, 7186, 1977, 1271 and 11919, respectively. The R-squares are less than 0.01 in all the regressions, it means less than 1% of observations can be explained by the regression model. The parameter estimate of time intervals of *Announce* in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all price ranges together are -2.7775, 1.3172, and -2.0945, -2.5731, 0.1194, respectively. Their associated probability values based on the t-statistics for the *Announce* in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all price ranges together are 0.0319, 0.0127, 0.0454, 0.1000 and 0.7891, respectively.

Table 8. Results of the 5-day regression (t_2, t_{12})

Price ranges	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Observations	3139	12805	4490	3170	24075
Degree of freedom (DF)	3	3	3	3	3
Sum of squares	11236	11865	9846.11002	6757.39144	948.28659
Mean square	3745.36569	3955.03572	3282.03667	2252.46381	316.09553

Table 8 (cont.). Results of the 5-day regression (t_2, t_{12})

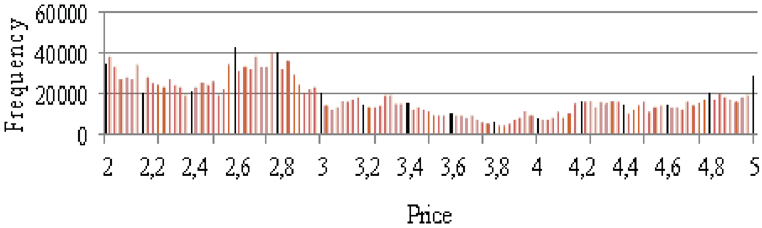
Price ranges	$2-$5	$5-$30	$30-$50	$50-$100	All prices
F value	5.12	9.65	5.55	2.69	0.53
Pr > F	0.0016	<.0001	0.0009	0.0449	0.6598
Dependent variable of relative frequency of clustering of the model					
Root MSE	27.05045	20.24150	24.32683	28.95223	24.35989
Dependent mean	12.80229	10.05707	12.31222	27.16758	13.30729
R-square	0.0049	0.0023	0.0037	0.0025	0.0001
Adjusted R-square	0.0039	0.0020	0.0030	0.0016	-0.0001
Parameter estimates (t-value)	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Intercept	14.60480(20.80)	9.17414(35.22)	13.72602(26.00)	28.14720(37.48)	13.51224(59.08)
Parameter estimate (t_2)	-4.54024(-2.28)	-0.21720(-0.29)	0.70383(0.47)	2.62862(1.24)	-0.25305(-0.39)
Parameter estimate (t_{12})	-3.67164(-1.83)	-0.66662(-0.90)	-0.09974(-0.07)	1.74079(0.82)	-0.37993(-0.58)
Announce	-2.61143(-2.71)	1.89635(5.30)	-2.94075(-4.05)	-2.51556(-2.45)	-0.33421(-1.06)
Pr > |t|	0.0068	<.0001	<.0001	0.0144	0.2871

Notes: The observations in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all the price ranges together are 3139, 12805, 4490, 3170 and 24075, respectively. The R-squares are less than 0.01 in all the regressions, it means less than 1% of observations can be explained by the regression model. The parameter estimate of time intervals of *Announce* in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all price ranges together are -2.6114, 1.8964, and -2.9408, -2.5156, -0.3342, respectively. Their associated probability values based on the t-statistics for the *Announce* in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all price ranges together are 0.0068, < 0.0001, < 0.0001, 0.0144 and 0.2871, respectively.

Table 9. Results of the 2-day regression (t_2, t_{12})

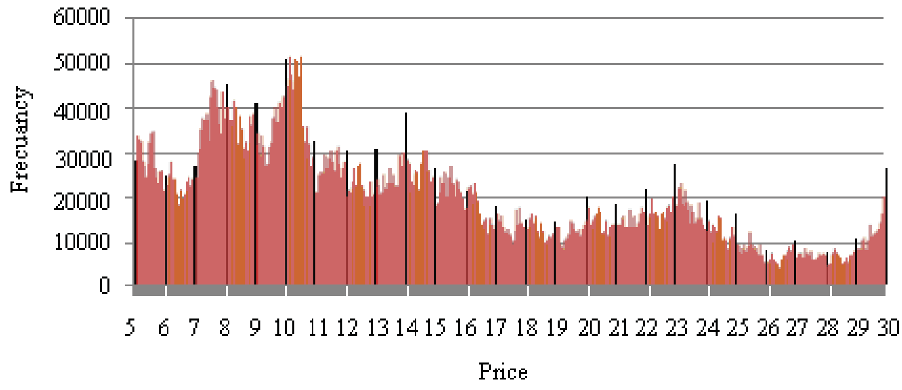
Price ranges	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Observations	1297	7186	1977	1271	11919
Degree of freedom (DF)	3	3	3	3	3
Sum of squares	4532.18696	4165.24374	3108.68017	4575.40878	363.25430
Mean square	1510.72899	1388.41458	1036.22672	1525.13626	121.08477
F value	2.79	2.76	1.80	1.95	0.20
Pr > F	0.0395	0.0404	0.1450	0.1191	0.8940
Dependent variable of relative frequency of clustering of the model					
Root MSE	23.28379	22.41230	23.98764	27.93891	24.38968
Dependent mean	9.70293	10.13694	11.56815	26.92260	12.40260
R-square	0.0064	0.0012	0.0027	0.0046	0.0001
Adjusted R-square	0.0041	0.0007	0.0012	0.0022	-0.0002
Parameter estimates (t-value)	$2-$5	$5-$30	$30-$50	$50-$100	All prices
Intercept	11.41185(12.10)	9.45177(24.52)	12.44863(15.87)	27.89943(24.32)	12.28215(37.68)
Parameter estimate (t_2)	-0.02856(-0.01)	-0.79073(-0.73)	2.65437(1.19)	5.65400(1.75)	0.48374(0.52)
Parameter estimate (t_{12})	-5.12411(-1.92)	1.31549(1.20)	0.29339(0.13)	-0.76208(-0.23)	0.50860(0.55)
Announce	-2.77899(-2.15)	1.31629(2.49)	-2.15501(-2.00)	-2.55871(-1.64)	0.11732(0.26)
Pr > |t|	0.0315	0.0128	0.0457	0.1023	0.7929

Notes: The observations in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all the price ranges together are 1297, 7186, 1977, 1271 and 11919, respectively. The R-squares are less than 0.01 in all the regressions, it means less than 1% of observations can be explained by the regression model. The parameter estimate of time intervals of *Announce* in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all price ranges together are -2.7790, 1.3163, and -2.1550, -2.5587, 0.1173, respectively. Their associated probability values based on the t-statistics for the *Announce* in the price ranges $2-$5, $5-$30, $30-$50, $50-$100 and all price ranges together are 0.0315, 0.0128, 0.0457, 0.1023 and 0.7929, respectively.



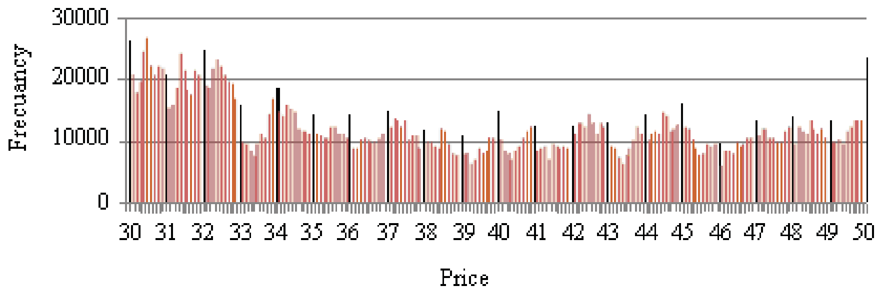
Notes: Figure 1 shows the clustering in price range from $2 to $5. The x-axis is the price and the y-axis is the frequency. The higher number of frequency represents the higher level of clustering. The black bars represent the even prices of $2, $2.2, $2.4 to $5. Clustering is the strongest at $2, $2.6, and $2.8. In the price range from $3 to $5, the clustering is not as strong as in the range from $2 to $3. However, it shows that the clustering in most integer prices is relative higher than others.

Fig. 1. Clustering in $2-$5 price range



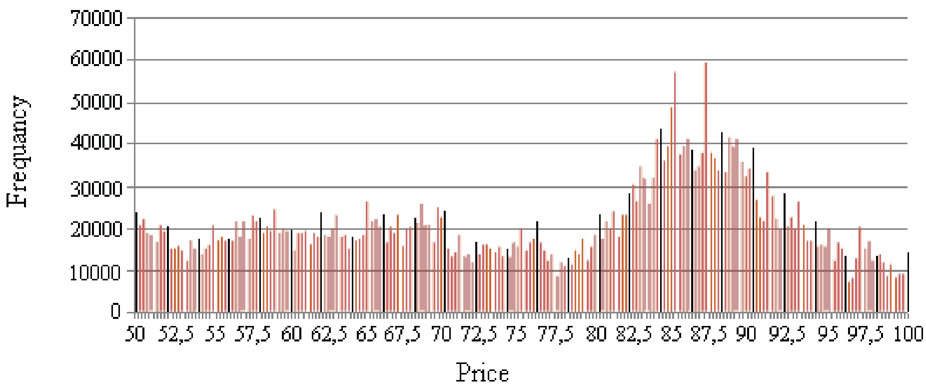
Notes: Figure 2 shows the clustering in price range from $5 to $30. The x-axis is the price and the y-axis is the frequency. The higher number of frequency represents the higher level of clustering. The black bars represent the even prices of $5, $6, $7 to $30. Clustering is the strongest at $7.5, $8, $8.5, $9, $10 and $10.5. In the price range from $17 to $30, the frequency is not as much as in the range from $5 to $16. However, it shows that the clustering in most integer prices is relative higher than others. Most black bars are taller in the picture above, while the light grey bars are usually shorter. Furthermore, clustering is also very strong in multiple of 0.5 such as $5.5, $7.5, $10.5, $12.5, $15.5, $20.5 etc. It shows that people are more likely to trade in the price of the multiple of 0.5 in this price range of $5-$30. This result is more significant than that in the price range from $2-$5.

Fig. 2. Clustering in $5-$30 price range



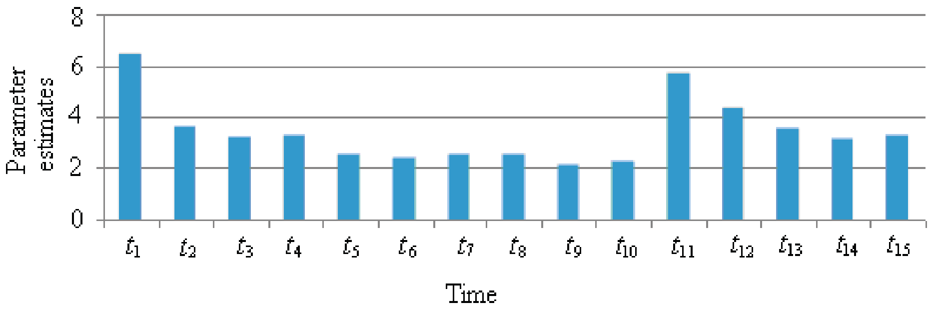
Notes: Figure 3 shows the clustering in price range from $30 to $50. The x-axis is the price and the y-axis is the frequency. The higher number of frequency represents the higher level of clustering. The black bars represent the even prices of $30, $31, $32 to $50. Clustering is the strongest at $30, $30.5, $31.5, $32, and $50. In the price range from $33 to $50, the frequency is not as much as in the range from $30 to $33. However, it shows that the clustering in most integer prices is relative higher than others. Most black bars are taller in the picture above, while the light grey bars are usually shorter. Furthermore, clustering is also very strong in multiple of 0.5 such as $30.5, $31.5, $32.5, $35.5, $42.5 etc. It shows that people are more likely to trade in the price of the multiple of 0.5 in this price range of $30-$50. This result is more significant than that in the price range from $2-$5.

Fig. 3. Clustering in $30-$50 price range



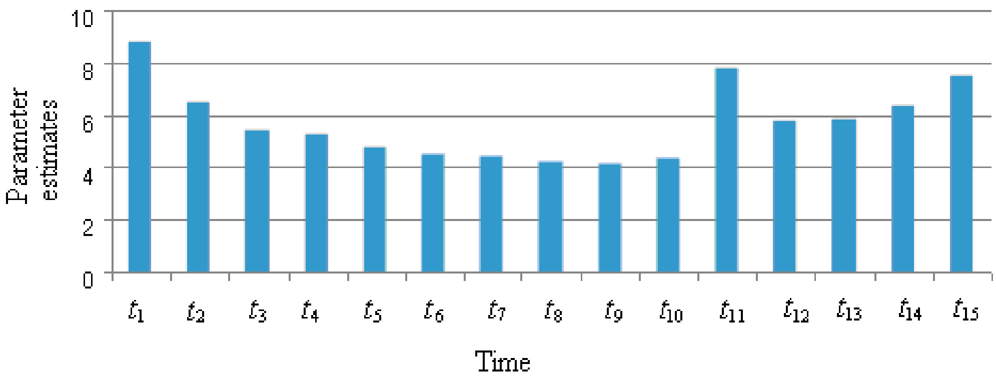
Notes: Figure 4 shows the clustering in price range from $50 to $100. The x-axis is the price and the y-axis is the frequency. The higher number of frequency represents the higher level of clustering. The black bars represent the even prices of $50, $52, $54, 56 to $100. Clustering is the strongest at $84, $85, $87, $88, and $90-they are all integer numbers. In the price range from $50 to $82 and $92-$100, the frequency is not as much as in the range from $82 to $92. However, it shows that the clustering in most integer prices is relative higher than others, especially for $50, $55, $65, $75, $80, $85, $90. It shows that people are more likely to trade in the multiple of 5 in the price range of $50-$100.

Fig. 4. Clustering in $50-$100 price range



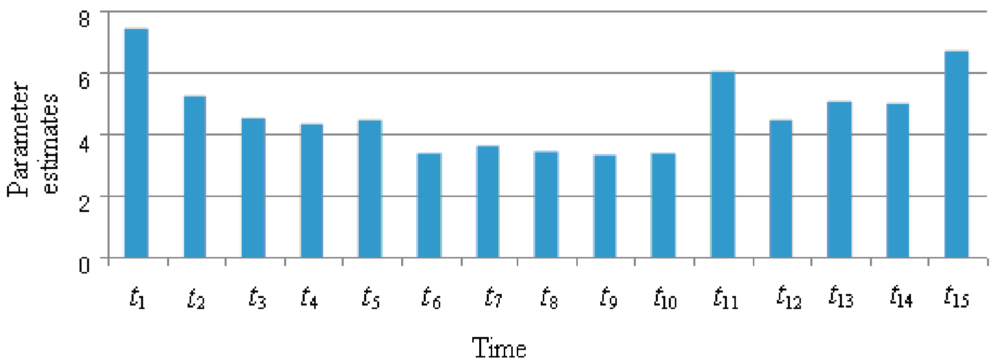
Notes: Figure 5 shows the clustering level in \$2-\$5 price range in the sixteen different time sessions from t_1 to t_{16}. Each session is fifteen minutes. The x-axis is the different trading sessions while the y-axis is the parameter estimates $\hat{\beta}_k$ of the regression model $RF = \sum_{k=1}^{16} \beta_k t_k + \varepsilon$. We can see that the clustering level is strong in t_1 (10:14:30), t_{11} (14:44:30). The clustering level is decreasing from t_2 (10:29:30) to t_{10} (12:29:30). But after lunch time, the clustering level increases sharply in t_{11} (14:44:30), then it decreases again from t_{12} (14:59:30) to t_{15} (15:44:30).

Fig. 5. Clustering in different time intervals: \$2-\$5 price range



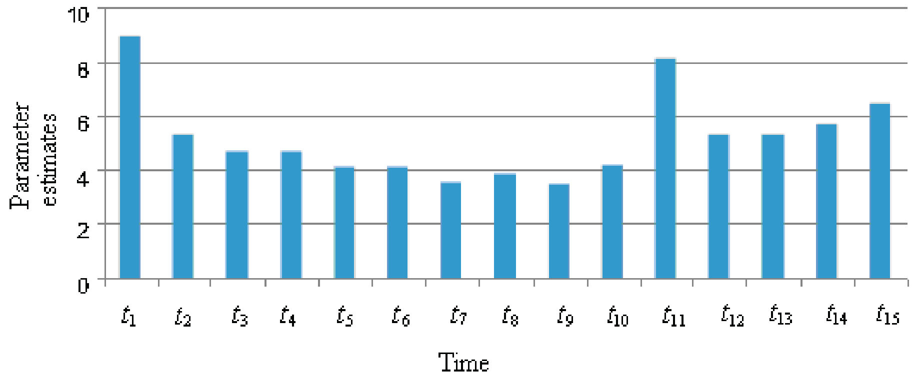
Notes: Figure 6 shows the clustering level in \$5-\$30 price range in the sixteen different time sessions from t_1 to t_{16}. The x-axis is the different trading sessions while the y-axis is the parameter estimates $\hat{\beta}_k$ of the regression model $RF = \sum_{k=1}^{16} \beta_k t_k + \varepsilon$. We can see that the clustering level is strong in t_1 (10:14:30), t_{11} (14:44:30). The clustering level decreases slowly from t_2 (10:29:30) to t_{10} (12:29:30). After lunch time, the clustering level increases sharply in t_{11} (14:44:30) and gradually from t_{12} (14:59:30) to t_{15} (15:44:30).

Fig. 6. Clustering in different time intervals: \$5-\$30 price range



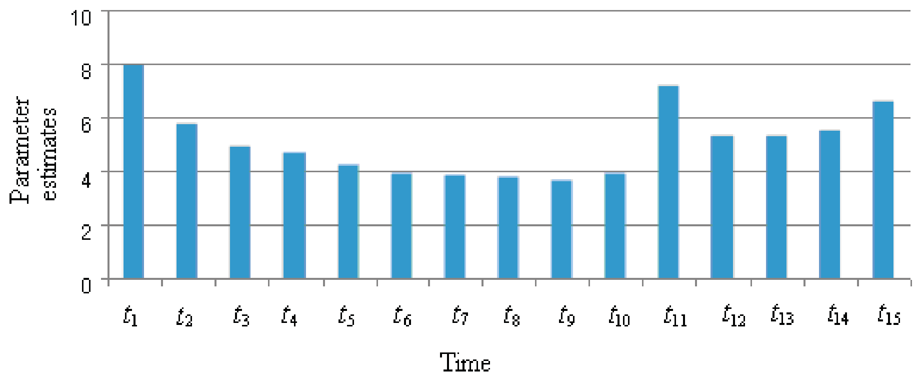
Notes: Figure 7 shows the clustering level in \$30-\$50 price range in the sixteen different time sessions from t_1 to t_{16}. The x-axis is the different trading sessions while the y-axis is the parameter estimates $\hat{\beta}_k$ of the regression model $RF = \sum_{k=1}^{16} \beta_k t_k + \varepsilon$. We can see that the clustering level is strong in t_1 (10:14:30), t_{11} (14:44:30), t_{15} (15:44:30). The clustering level decreases slowly from t_2 (10:29:30) to t_{10} (12:29:30). After the lunch time, the clustering level increases in t_{11} (14:44:30), gradually from t_{12} (14:59:30) to t_{15} (15:44:30).

Fig. 7. Clustering in different time intervals: \$30-\$50 price range



Notes: Figure 8 shows the clustering level in \$50-\$100 price range in the sixteen different time sessions from t_1 to t_{16}. The x-axis is the different trading sessions while the y-axis is the parameter estimates $\hat{\beta}_k$ of the regression model $RF = \sum_{k=1}^{16} \beta_k t_k + \varepsilon$. We can see that the clustering level is strong in t_1 (10:14:30), t_{11} (14:44:30). The clustering level decreases slowly from t_2 (10:29:30) to t_{10} (12:29:30). After the lunch time, the clustering level increases sharply in t_{11} (14:44:30), gradually from t_{12} (14:59:30) to t_{15} (15:44:30).

Fig. 8. Clustering in different time intervals: \$50-\$100 price range



Notes: Figure 9 shows the clustering level of all price range in the sixteen different time sessions from t_1 to t_{16}. The x-axis is the different trading sessions while the y-axis is the parameter estimates $\hat{\beta}_k$ of the regression model $RF = \sum_{k=1}^{16} \beta_k t_k + \varepsilon$. We can see that the clustering level is strong in t_1 (10:14:30), t_{11} (14:44:30). The clustering level decreases slowly from t_2 (10:29:30) to t_{10} (12:29:30). After the lunch time, it increases sharply again in t_{11} (14:44:30), and remains from t_{12} (14:59:30) to t_{13} (15:14:30). But it increases sharply again from t_{14} (15:29:30).

Fig. 9. Clustering in different time intervals: all price range