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The price impact of trading on the stock exchange of Hong Kong☆

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Abstract

In this paper I study the price formation process on the Stock Exchange of Hong Kong (SEHK). The estimation results reveal that the information effect is more important than the inventory effect in explaining the transaction price movement. The cross-sectional variation in market depth is positively related to the stocks' market capitalization, turnover rate, trading price, and trading noise. The price impact displays a U-shaped pattern over the trading day, which is in contrast to the downward sloping pattern discovered on the NYSE. Such differences seem to be caused by the variation in average trade size between the two markets. © 2000 Elsevier Science B.V. All rights reserved.

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1. Introduction

One of the most important aspects in the market microstructure literature is information-based trading. Trading by investors who possess superior information imposes significant liquidity costs on other market participants because of adverse selection. One measure of the adverse selection cost of trading is the price impact from trading, which is inversely proportional to Kyle's (1985) measure of market depth. Several studies on the U.S. quote-driven markets assess the behavior of price impact. For example, academics have discovered that the information effect is relatively more important than the inventory effect in influencing transaction prices (e.g., Madhavan and Smidt, 1991), that the price impact is negatively related to stocks' market value (e.g., Hasbrouck, 1991a,b) and trading activities (e.g., Glosten and Harris, 1988; Brennan and Subrahmanyam, 1995), and that the pattern of market depth exhibits a time-of-the-day effect (e.g., Madhavan et al., 1997). However, only limited studies examine the price formation process in securities markets outside the United States. In contrast to the dealership market under which dealers are obliged to post quotes, traders in pure limit order markets supply liquidity on a voluntary basis, and this may give rise to a different pattern of price impact for informed trading. Although the empirical studies based on the New York Stock Exchange (NYSE) fit with the theoretical prediction of Madhavan (1992) about the intraday behavior of adverse selection costs in quote-driven markets, whether a similar pattern applies to order-driven markets has not been tested.

In this paper I study the cross-sectional and time-of-the-day effects of price impacts in a limit order market. The Stock Exchange of Hong Kong (SEHK) is the eighth largest market in the world with a market capitaliz- ation exceeding US$270 billion at the end of 1995, the period during which I conduct my investigation. The empirical results show the sample stocks have statistically significant estimated parameters for both the adverse selection cost and inventory cost components. At the same time, there is evidence that information asymmetry is more important than inventory holding in determining security price movements. Furthermore, the cross-sectional analyses suggest that market depths are positively related to stocks' market value, turnover rate, trading price, and trading noise. These findings are generally in line with the U.S. stock markets. However, while the market usually becomes deeper as trading progresses on the U.S. exchanges, the price impact in the SEHK displays a U-shaped pattern over the trading day. I argue it is the difference in informed trading intensity that gives rise to such a difference in the time-of-the-day behavior.

The paper is organized as follows. The next section contains a brief discussion of the limit order trading mechanism on the SEHK. Section 3 presents a simple structural model for explaining the transaction price changes. Section 4 describes the data, while Section 5 explains the empirical results. Section 6 summarizes and concludes the paper.

2. Trading mechanism on the stock exchange of Hong Kong

Trading on the SEHK is done in an order-driven system in which security prices are determined solely by the submission of limit orders from public investors. The exchange is open five days a week and each trading day has two sessions separated by a lunch break. Under the exchange's 'Automated Order Matching and Execution System' (AMS), limit orders are matched and executed automatically on the basis of price/time priority. Brokers are permitted to cancel orders at any time before matching, and although they can decrease order size, they cannot increase an order already submitted. To facilitate the trading process, each stock is assigned a spread (size of one tick) that depends on the price at which the stock is being traded, such that the tick size is a step function of share price. For my empirical investigation period, the smallest spread is HK$0.001 for stocks in the price range of HK$0.01–HK$0.25, while the largest spread is HK$2.5 for stocks in the price range of HK$1,000–HK$9,995.[1]

The SEHK specifies a set of quotation rules that govern the posting of bid and ask prices. Under the opening quotation rule, the first bid (ask) entered into the trading system must be higher (lower) than or equal to the previous closing price minus (plus) four spreads. Quotations for buying and selling orders, other than the opening quotations, are governed by the intraday quotation rules. Generally speaking, a new bid price cannot be quoted at either (1) more than four spreads below the current best bid price (when there are existing bid prices quoted on the primary queue) or (2) more than four spreads below the current ask price (when there are no existing bid prices quoted on the primary queue). These rules are intended to prevent unrealistic price quotations. Furthermore, traders who demand immediate execution may also enter their bid orders at the current ask price. This is effectively equivalent to a 'marketable limit order'. Similar reasoning applies to the quotation of ask prices. Marketable limit orders are executed against the best price on the opposite side of the limit order book. Any excess that cannot be executed at that price remains as a quote at that price rather than executing the order at less favorable prices by walking up or down the limit order book. If an investor wishes to transact shares by walking through the book, he or she has to place appropriate limit orders. This institutional feature is identical to the one practiced on the Paris Bourse as described by Biais et al. (1995).

[1] Under the linked exchange rate system, the exchange rate between the U.S. dollar and the Hong Kong dollar has been pegged at US$1 = HK$7.8 since October 1983.

3. A simple structural model of price formation

In the SEHK, investors who are willing to wait for better prices supply liquidity to the market by posting the bid and ask prices they offer to trade. These investors are in effect serving as informal voluntary market makers. The structural price change equation adopted in this paper is a variant to that used by Glosten and Harris (1988) for the specialist market, after adjusting for the features relevant to trading in a pure limit order market. The model of transaction price movement is written as

$$\Delta P_t = \lambda q_{t-1} + \gamma(q_t - q_{t-1}) + \tfrac{1}{2}\omega(D_t - D_{t-1}) + \beta Q_t + \varepsilon_t, \tag{1}$$

where q_t denotes the number of shares traded, which carries a positive sign for a buyer-initiated trade and a negative sign for a seller-initiated trade; D_t is the trade direction indicator, which equals 1 if q_t is positive and -1 if q_t is negative; and ε_t is the serially uncorrelated public information shock. The Q_t variable represents the cumulative signed share volume of the trades since the last price change so that $Q_t = \sum_{i=1}^{m} q_{t-i}$ where m is the number of previous transactions that have the same sign and are at the same price as q_t.

In Eq. (1) λq_{t-1} measures the adverse selection component, while $\gamma(q_t - q_{t-1})$ and $1/2\omega(D_t - D_{t-1})$ measure the transitory component that causes the transaction price change. The one-period lag in belief updating (compared with Glosten and Harris, 1988) occurs because there are many liquidity suppliers; therefore, a trader would not have access to all the information in trade at time t.[2] Within the transitory component, γ can be interpreted as the inventory cost parameter, since it is related to the quantity liquidity suppliers are willing to trade at time t. To induce them to buy (sell) more from (to) the market, liquidity suppliers command lower (higher) prices to compensate for the extra risk incurred by early acquisition (depletion) of inventories. Last, ω represents the implicit bid–ask spread on the price schedule.

The adverse selection and transitory components together with the public information shock explain the transaction price changes if new liquidity suppliers place quotes after every trade. In reality, several incoming marketable limit orders may hit the prevailing quotes without causing any quote revision. However, there may still be changes in transaction prices if these accumulated incoming orders have exhausted all stale orders placed by the liquidity suppliers in the same price queue so that the best quote shifts from one set of passive limit orders to another. When the magnitude of cumulative incoming orders is larger,

[2] In deriving the transaction price change equation for the Paris Bourse, De Jong et al. (1996) also assume a one-period lag of the order flow as the updating variable.

the marginal incoming transaction is more likely to induce a large price change. The component βQ_t is thus created to capture the presence of such an effect.[3]

Because of the discrete nature of transaction prices, the dependent variable in Eq. (1) is interpreted and estimated under the ordered probit framework as suggested by Hausman et al. (1992). Larger positive (negative) values of the explanatory variables imply a higher probability of observing a larger positive (negative) price change.

4. Data

The transactions data used in this study, which cover all of 1995, are compiled by the Research and Planning Department of the SEHK. About 500 common stocks are included in the data set, and many of them are thinly traded. To cope with the manpower required for computation and yet cover both the heavily and moderately traded companies, I randomly select 100 sample stocks from the upper 40% of stocks most frequently traded. Only trades that were conducted through automatching during the official trading hours with transaction volume equal to one or multiples of round lots are included. I also treat trades conducted at the same transaction time and at the same price as a single trade. This is necessary because trades of this kind are most likely to be the result of a single incoming order hitting a certain number of smaller outstanding limit orders of the same price.[4] The number of transactions of individual sample stocks in the one-year period ranges from 89,702 trades to 3155 trades, with a median of 8320 trades.

I applied filtering on the number of states in the dependent variable before conducting the ordered probit estimation. Following the principle of the four-spread rule of price quotation on the SEHK and similar to what Hausman et al. (1992) adopt, I restrict the number of states to be equal to nine. This means the lowest extreme state refers to a price change of -4 ticks or less, the second

[3] Using five minutes as the minimum sampling interval, Huang and Stoll (1994) develop a transaction price change equation that incorporates the effect of cumulative signed share volume of the trades since the last observed trade. My logic for including the Q_t variable is similar although not exactly equal to the formulation of Huang and Stoll.

[4] Of course, it is always possible that I could miscalculate the trade size when adopting this correction method, since some of these trades could be hit by more than one incoming order. To mitigate the effect of such a miscalculation, whenever the refined volume of these trades exceeds 200 round lots (which is the maximum order size that a broker can enter into the AMS for a single transaction during the investigation period), I convert the refined trade size into 200. In fact, few observations in the refined data set have a trade size larger than 200 lots. Of the 100 sample stocks, 83 have none or less than 0.1% of observations with a trade size of over 200 lots,10 have less than 0.2%, and the remaining 7 have less than 1% of such observations.

lowest state refers to a price change of -3 ticks, and so on, so that the highest extreme state refers to a price change of $+4$ ticks or more. By grouping the observations with an absolute number of ticks greater than or equal to 4 into the extreme states, I can keep the number of states to a manageable proportion while using all the trading information as well as filtering out large price changes due to data entry errors.[5]

Transactions also need to be classified as buyer initiated or seller initiated. Because the SEHK data set does not contain information on bid-ask quotes, the quote-based approach cannot be applied to sign the trades.[6] As a result I use the 'tick test' as described by Lee and Ready (1991) to infer the trade direction from the price-only data. Under the tick test, each trade is classified into one of the following categories: an uptick, a downtick, a zero uptick, or a zero downtick. A trade is an uptick (downtick) if the price is higher (lower) than the price of its immediate past trade. A zero tick occurs when the price is the same as the immediate past trade. In this case, the trade is classified as a zero uptick if the last price change was an uptick, or a zero downtick if the last price change was a downtick. Finally, a transaction is classified as buyer initiated if it occurs on an uptick or a zero uptick; otherwise, it is classified as seller initiated.

5. Empirical results

5.1. Ordered probit estimation results

To capture the average return between transactions, I include the intercept in the ordered probit estimation of Eq. (1). Table 1 portrays the cross-sectional summary statistics of the parameter estimates.

The estimates of the information asymmetry parameter λ for the 100 sample stocks all have the expected positive sign and are statistically significant at the 0.01 level. This indicates the magnitude of an immediate past trade exerts a positive effect on the current transaction price change. At the same time, the estimated value of the inventory cost parameter γ is generally smaller than that of λ for the same stock, and 96 of the 100 sample stocks exhibit this pattern. Thus, the price impact from information asymmetry is more serious than that

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[5] Since the four-spread rule only applies to price quotation and the SEHK does not impose any rule to govern the maximum price variation, the transaction price change can be more than 4 ticks. In the data set, 97 of the 100 sample stocks contain less than 1% of observations with a price change of 5 ticks or more before the adjustment. The other 3 stocks have 1.4% to 1.6% of such observations.

[6] The SEHK has recently launched a new data set that provides intraday bid and ask information. However, this new data set only contains snapshots at 30 s or longer intervals, and available information starts at May 1996, which is beyond the investigation period of this study.

Table 1
Cross-sectional summary statistics of the estimated parameters from the ordered probit regressions

The estimated equation is: $\Delta P_t = \lambda q_{t-1} + \gamma(q_t - q_{t-1}) + (1/2)\omega(D_t - D_{t-1}) + \beta Q_t$ where q_t is the signed order flow, D_t is the trade indicator variable that equals 1 for a buyer-initiated trade and -1 for a seller-initiated trade, and Q_t is the accumulated past trade volume transacted in the same price queue. The above equation is estimated using the ordered probit method for each of the 100 sample stocks from January 3, 1995 to December 29, 1995. Using the likelihood ratio test, the null hypothesis that all the slope terms are zero is rejected at the 0.01 significance level for all 100 ordered probit regressions.

	Intercept	λ ($\times 10^5$)	γ ($\times 10^5$)	ω	β ($\times 10^6$)
Mean	5.1443	1.0706	0.6930	3.1015	0.3687
Standard deviation	1.1312	1.5572	0.9171	0.6635	0.8334
Median	5.0029	0.6461	0.4365	2.9340	0.1435
Minimum	3.3687	0.1965	0.1873	2.1519	− 0.3802
Maximum	8.4792	13.8300	7.9400	5.1786	6.8521

from inventory holding for a given trading volume. This is reasonable since liquidity suppliers on the SEHK provide immediacy for the incoming orders on a voluntary basis and therefore face relatively little inventory pressure from stock trading.

For the parameter β, which captures the effect of the exhaustion of stale limit orders, 64 of the 100 sample stocks have positive estimated values of β, which are statistically significant at the 0.05 level. Many of these stocks are actively traded, so that when more stale limit orders have been exhausted, the probability of observing a transaction price change is greater. For the remaining 36 stocks, 33 have a statistically insignificant β parameter and 3 have negative parameter estimates, which are statistically significant at the 0.05 level. A negative β value is possible if a short queue of stale limit orders at the prevailing price occurs more often than a long queue (which is true for thinly traded stocks). In this case, when the value of Q_t is smaller, a price change is more likely.

5.2. Cross-sectional analysis of the determinants of price impact

Based on previous studies (e.g., Glosten and Harris, 1988; Brennan and Subrahmanyam, 1995), I select four variables to explain the cross-sectional determinants of price impact of trading. These four variables are: (1) *MKTCAP*: the stock's market capitalization as of June 30, 1995; (2) *TURN*: the stock's turnover rate, which is calculated by dividing the number of shares traded during all of 1995 by the number of shares outstanding as of June 30, 1995; (3) *AVGP*: the stock's mean transaction price of all trades during all of 1995; and

(4) *NOISE*: the stock's trading noise, which is proxied by the variance of trade volume as a percentage of total number of shares outstanding.[7]

I cannot directly compare the ordered probit coefficients across different stocks because these coefficients do not represent the simple marginal effect of changes in regressors on the dependent variables. In fact, the ordered probit parameter estimates show the regressors' effect on the probability of observing ΔP_t in different states. Furthermore, the marginal effect of a particular regressor also depends on the magnitudes of all other estimated parameters as well as the values of all explanatory variables. Therefore, I conduct the cross-sectional comparison by simulating the expected transaction price changes for each stock by assigning imaginary values to the explanatory variables. To calculate the price impact due to adverse selection and to see whether the result is robust to different order sizes, I take q_{t-1} to equal a buy order of either (1) HK\$100,000, (2) HK\$200,000, (3) HK\$300,000, (4) HK\$400,000, (5) HK\$500,000, (6) the corresponding stock's mean transaction volume, or (7) the corresponding stock's mean plus one standard deviation of the transaction volume. In each of these cases I also assume $(q_t - q_{t-1})$ equals zero, $(D_t - D_{t-1})$ equals zero, and Q_t equals the stocks mean positive Q_t. After plugging all of these imaginary values into the ordered probit regression, I can calculate the expected price change (in ticks) and call this variable '*PT*'. I then regress the natural logarithm of *PT* on the set of explanatory variables (also after taking the natural logarithm).

Panel A of Table 2 shows the results of these cross-sectional regressions with all standard errors corrected by the White asymptotic estimator. Although the explanatory variables are related to each other, the multicollinearity problem should not be serious since the largest condition index (intercept adjusted) bears a safety value of 9.6765.

The *MKTCAP* and *TURN* variables are negative and statistically different from zero in all seven cross-sectional regressions. The *NOISE* variable is less robust, showing significantly negative estimates in the first five regressions and significantly positive estimates in the last two regressions. The results support the prediction of market microstructure models that large, actively and noisily traded stocks suffer less from information asymmetry.

The estimated coefficients for the *AVGP* variable are either positive or not statistically significant. However, recall that the tick size on the SEHK varies with the price range in which the stock is trading. When the trading price of a stock is higher, the tick is smaller in terms of the percentage of the trading price. Therefore, another indicator of market depth is to calculate the price

[7] I thank an anonymous referee for suggesting this measure to me.

impact in terms of percentage price change ('*PP*' variable), which is defined as:

$$\frac{\textit{Expected value of ticks} \times \textit{Tick size at mean price of stock}}{\textit{Mean price of stock}}.$$

The cross-sectional regression results using *PP* as the dependent variable are presented in Panel B of Table 2. All the *AVGP* estimates are now significantly negative, while the estimated coefficients of the other explanatory variables are generally in line with the previous regression results. This means that percentage price impact is actually inversely related to stock price. I provide the following explanation for the change of signs in the *AVGP* estimates between the tick change (*PT*) regressions and the percentage price change (*PP*) regressions. There are two effects associated with *AVGP* and *PT*: (1) a negative relation between *AVGP* and *PP*, and (2) a negative relation between *AVGP* and the tick size as a percentage of the stock price. Although stocks with a higher trading price produce lower percentage price impact, the effect on tick changes is ambiguous since the percentage price change may (or may not) be translated into a larger number of ticks because of the second effect.

5.3. Time-of-the-day effect on price impact

To assess the time-of-the-day pattern, I first divide each trading day into eight trading intervals. The first seven trading intervals each have a trading time of 30 min, and the last trading interval runs from 3:30 p.m. until the end of the SEHK's official trading hours, which is either 15 min (January–August) or 25 min (September–December). The price change equation (Eq. (1)) for each stock is then estimated for each trading interval. The obtained parameter estimates are plugged back into the equation to calculate the expected price impact. Similar to the procedure followed in the above section, I assume q_{t-1} equals a buy order of either HK\$100,000 or the stock's mean transaction volume in that trading interval.

Table 3 presents the time-of-the-day pattern of expected price impact of trading. To isolate the market capitalization effect, I divide the sample of 100 stocks into 10 equal deciles according to market capitalization, where decile 1 contains the 10 largest stocks and decile 10 contains the 10 smallest stocks. The arithmetic average of the stocks' expected price changes in each decile are computed, revealing similar patterns for different order sizes. For illustration purposes, Fig. 1 graphs the price impact of a buy order for HK\$100,000.

I find a U-shaped pattern in price impact within the trading day for most deciles. The morning opening session always has the largest price impact, while the session before closing has either the second or third largest price impact of the day. The observation that the beginning session has the largest price impact is not difficult to explain and conforms to other microstructure findings. Private

Table 2
Cross-sectional regression results of the determinants of the price impact from trading

The ordered probit parameter estimates for the following price change equation:

$$\Delta P_t = \lambda q_{t-1} + \gamma(q_t - q_{t-1}) + (1/2)\omega(D_t - D_{t-1}) + \beta Q_t$$

are plugged into the equation using different imaginary values of q_{t-1} to calculate the expected price changes, assuming $(q_t - q_{t-1})$ equals zero, $(D_t - D_{t-1})$ equals zero, and Q_t equals the stock's mean positive Q_t. The expected price change in ticks and expected price change as a percentage of the mean price (both in natural logarithm) of each stock are then regressed on their market capitalization, turnover rate, average price, and trading noise to arrive at the cross-sectional regression results.

The explanatory variables in the cross-sectional regressions are defined as follows: MKTCAP is the natural logarithm of the stock's market capitalization as of June 30, 1995; TURN is the natural logarithm of turnover rate, which is calculated by dividing the number of shares traded during all of 1995 by the number of outstanding shares as of June 30, 1995; AVGP is the natural logarithm of the mean transaction price of all trades during all of 1995; and NOISE is the natural logarithm of trading noise, which is proxied by the variance of trading volume as a percentage of total number of shares outstanding.

The first figure in each cell is the estimate of the respective parameter. The figures in parenthesis represent the standard error of the parameter estimate adjusted by the White asymptotic estimator. *** denotes estimated parameter significance at the 0.01 level, ** denotes significance at the 0.05 level and * denotes significance at the 0.10 level.

Size of q_{t-1}	Intercept	MKTCAP	TURN	AVGP	NOISE	Adj R^2
Panel A: Dependent variable as measured by expected price change in ticks						
Buy order of HK$100,000	14.0287***	– 0.9037***	– 0.4537***	0.0682	– 0.2178***	0.7827
	(1.5152)	(0.0958)	(0.0754)	(0.0768)	(0.0655)	
Buy order of HK$200,000	17.7967***	– 1.0834***	– 0.5019***	0.0213	– 0.2940**	0.8263
	(1.7687)	(0.1119)	(0.0841)	(0.0869)	(0.0732)	
Buy order of HK$300,000	19.9972***	– 1.1816***	– 0.5230***	0.0135	– 0.3288***	0.8565
	(1.8705)	(0.1185)	(0.0864)	(0.0870)	(0.0751)	
Buy order of HK$400,000	21.6060***	– 1.2518***	– 0.5285***	0.0325	– 0.3504***	0.8784
	(1.9281)	(0.1226)	(0.0870)	(0.0850)	(0.0769)	

Buy order of HK$500,000	22.8409*** (1.9712)	– 1.3043*** (0.1261)	– 0.5282*** (0.0877)	0.0634 (0.0840)	– 0.3640*** (0.0794)	0.8901
Stock's mean transaction volume	5.7455*** (0.9775)	– 0.3676*** (0.0630)	– 0.4290*** (0.0558)	0.2335*** (0.0535)	0.1250*** (0.0486)	0.6191
Stock's mean plus one standard deviation of transaction volume	6.5364*** (1.0370)	– 0.3533*** (0.0657)	– 0.4711*** (0.0576)	0.2468*** (0.0541)	0.1599*** (0.0485)	0.6430
Panel B: Dependent variable as measured by expected price change as a percentage of mean price						
Buy order of HK$100,000	7.4574*** (1.5424)	– 0.7767*** (0.1043)	– 0.4962*** (0.0717)	– 0.3117*** (0.0671)	– 0.1450* (0.0755)	0.8954
Buy order of HK$200,000	11.2253*** (1.7518)	– 0.9564*** (0.1169)	– 0.5444*** (0.0792)	– 0.3585*** (0.0770)	– 0.2211*** (0.0813)	0.9090
Buy order of HK$300,000	13.4258*** (1.8366)	– 1.0546*** (0.1221)	– 0.5655*** (0.0812)	– 0.3663*** (0.0800)	– 0.2559*** (0.0831)	0.9183
Buy order of HK$400,000	15.0346*** (1.8879)	– 1.1248*** (0.1255)	– 0.5710*** (0.0813)	– 0.3473*** (0.0803)	– 0.2776*** (0.0842)	0.9262
Buy order of HK$500,000	16.2695*** (1.9247)	– 1.1773*** (0.1280)	– 0.5706*** (0.0811)	– 0.3165*** (0.0809)	– 0.2911*** (0.0853)	0.9304
Stock's mean transaction volume	– 0.8259 (1.1026)	– 0.2406*** (0.0807)	– 0.4715*** (0.0556)	– 0.1463*** (0.0480)	0.1978*** (0.0652)	0.8500
Stock's mean plus one standard deviation of transaction volume	– 0.0350 (1.1122)	– 0.2263*** (0.0793)	– 0.5135*** (0.0535)	– 0.1330*** (0.0461)	0.2328*** (0.0611)	0.8574

Table 3
Time-of-the-day pattern of price impact from trading and stocks' normalized trade size

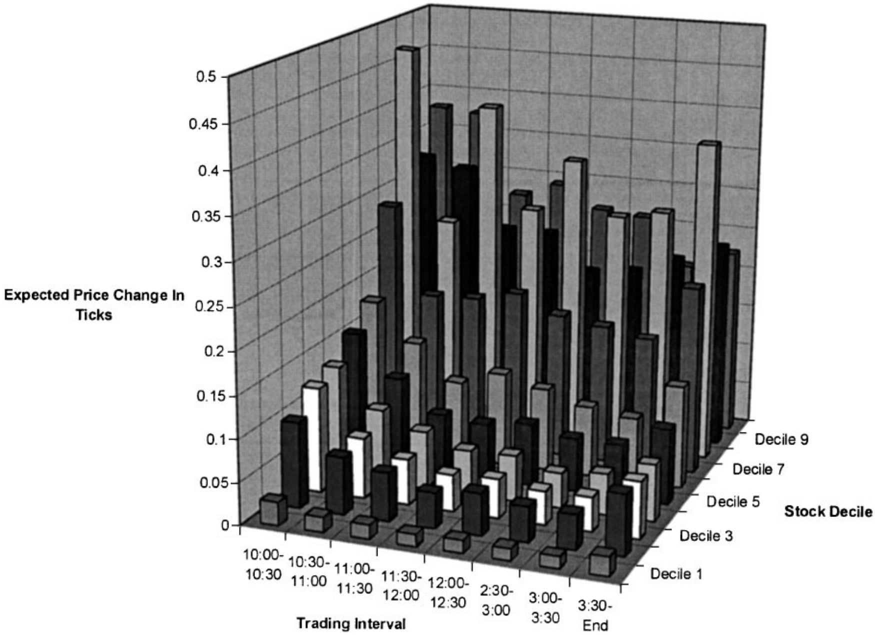
Each trading day is divided into eight trading intervals. For each of the 100 sample stocks the following intraday price change equation is estimated with the ordered probit procedure during each trading interval:

$$\Delta P_t = \lambda q_{t-1} + \gamma(q_t - q_{t-1}) + (1/2)\omega(D_t - D_{t-1}) + \beta Q_t$$

The estimated parameters are then plugged back into the above equation using different imaginary values of q_{t-1} to calculate the expected price changes, assuming $(q_t - q_{t-1})$ equals zero, $(D_t - D_{t-1})$ equals zero, and Q_t equals the stock's mean positive Q_t during that trading interval. The first figure is the cross-sectional average of price impact of the 100 sample stocks during that particular trading interval. Figures in parenthesis represent the cross-sectional standard error of the price impact.

Normalized trade size is calculated by dividing each stock's mean transaction volume within each of the eight trading intervals by its mean transaction volume in the first trading interval. The first figure is the cross-sectional average and the figure in parenthesis is the standard error of the cross-sectional average.

Trading interval	Price impact from trade				Stocks' average normalized trade size
	Assume q_{t-1} equals a buy order of HK$100,000		Assume q_{t-1} equals the stock's mean transaction volume during that particular trading interval		
	Expected price change in ticks	Expected price change as a percentage of the mean price	Expected price change in ticks	Expected price change as a percentage of the mean price	
10:00–10:30	0.2180 (0.0251)	0.2050 (0.0290)	0.1085 (0.0065)	0.0841 (0.0056)	1.0000 (0.0000)
10:30–11:00	0.1616 (0.0201)	0.1512 (0.0209)	0.0785 (0.0052)	0.0612 (0.0043)	1.0395 (0.0085)
11:00–11:30	0.1465 (0.0221)	0.1390 (0.0204)	0.0686 (0.0045)	0.0562 (0.0043)	1.0919 (0.0117)
11:30–12:00	0.1340 (0.0184)	0.1291 (0.0184)	0.0629 (0.0043)	0.0520 (0.0043)	1.1049 (0.0119)
12:00–12:30	0.1322 (0.0188)	0.1261 (0.0187)	0.0670 (0.0045)	0.0543 (0.0042)	1.1447 (0.0145)
2:30–3:00	0.1201 (0.0158)	0.1179 (0.0185)	0.0604 (0.0039)	0.0493 (0.0039)	1.1428 (0.0143)
3:00–3:30	0.1162 (0.0164)	0.1168 (0.0195)	0.0605 (0.0036)	0.0499 (0.0040)	1.2154 (0.0173)
3:30–End	0.1512 (0.0192)	0.1486 (0.0226)	0.0872 (0.0050)	0.0716 (0.0055)	1.2626 (0.0260)



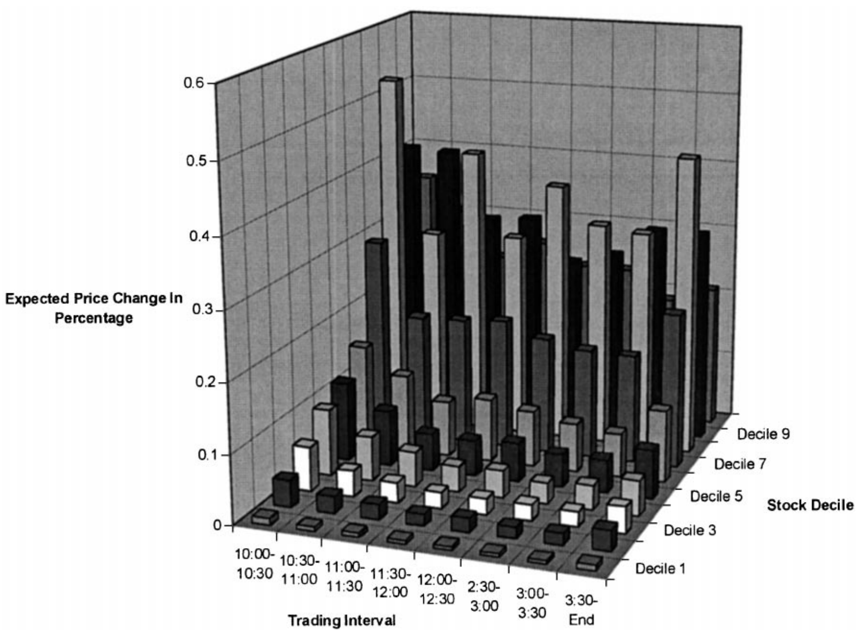


Fig. 1. Time-of-the-day pattern of price impacts from trading. (Top) Expected price change in ticks at time t for a buy order of HK\$100,000 at time $t-1$. (Bottom) Expected price change in percentage at time t for a buy order of HK\$100,000 at time $t-1$.

information collected by informed traders after the market's close on the previous trading day has yet to be revealed through trading. As more information is impounded into the price during trading, the magnitude of information asymmetry is gradually resolved and leads to a lower price impact. But it is not as clear why the price impact rebounds before the market's close. Clues can be found by looking at the changes in the stocks' average trade size across different trading intervals. I divide each stock's mean transaction volume within each of the eight trading intervals by its mean transaction volume in the first interval. This is called 'normalized trade size', which can be compared among stocks. These figures are given in the last column of Table 3.

The average normalized trade size displays an upward trend over the day. It is reasonable to assert that trading at a large volume is more likely to be associated with informed trading. Lin et al. (1995) find that the adverse information component of the effective spread increases monotonically with trade size. Barclay and Warner (1993) find most of the NYSE stocks' cumulative price changes occur on medium size trades, which is consistent with the hypothesis that most of the informed trades are of medium size rather than small size. Therefore, the higher average trade size in the latter trading intervals of the SEHK indicates that informed trading is more prevalent before market close so that the price impact due to adverse selection also becomes higher.[8]

5.4. Differences in market depth patterns between the SEHK and other markets

I compare the price impact pattern found on the SEHK with those found on other stock exchanges. My comparisons are mainly between the SEHK and the NYSE since related studies focus on the U.S. stock markets far more than any other markets.

First, my empirical results indicate the intraday stock price movement is due to the information effect more than to the inventory effect. De Jong et al. (1996) find the presence of adverse selection costs and weak evidence of an inventory effect on the Paris Bourse. Madhavan and Smidt (1991) make a similar finding for NYSE stocks. Therefore, the relative importance of adverse selection is evident in both limit order and specialist markets.

Second, my cross-sectional regression results are parallel to the findings on the NYSE and American Stock Exchange (AMEX). Brennan and Subrahmanyam (1995) show that the adverse selection cost is negatively related to trading activities, trading noise, and market value. In addition, they find that the

[8] According to the Members Transaction Survey 1996 conducted by the SEHK, about 30% of market turnovers are caused by overseas institutional investors, 40% of which are European funds. Because of the time zone effect, these European investors (who should be more informed) tend to place their orders in the afternoon trading session.

marginal cost for transacting a given dollar transaction is decreasing in the share price. Hasbrouck (1991a,b) also discovers that the price impact and the extent of information asymmetry appear to be more significant for firms with smaller market value on the NYSE and AMEX. Similarly, my cross-sectional regressions suggest that the price impact from a given dollar volume is inversely related to stocks' market capitalization, turnover rate, trading price, and trading noise.

Despite the above similarities, the time-of-the-day pattern of adverse selection costs differs between the SEHK and the NYSE. There is evidence that the adverse selection cost of trading on the NYSE is highest at the market opening and declines thereafter (e.g., Hasbrouck, 1991b; Lin et al., 1995; Madhavan et al., 1997). This is in contrast with the SEHK where the price impact of trading displays a U-shaped pattern. While Madhavan et al. (1997) document a continual drop in average trade size over the trading day, I find average trade size tends to increase as trading progresses. Market microstructure models suggest that traders learn about fundamental asset value through the trading process. If at the same time the degree of adverse selection is more severe for larger trade sizes, the downward-sloping pattern of the adverse selection cost on the NYSE is understandable. However, the larger average trade size on the SEHK during the afternoon trading session would also lead to a larger price impact as traders become more cautious about informed trading before the market closes. Therefore, the interaction between the evolution of information asymmetry and the variation of average trade size gives rise to different intraday patterns (i.e., U-shaped or monotonic declining) of the price impact of trading.

6. Summary and conclusion

In this paper I study the price formation process on the SEHK. The ordered probit estimation results for a sample of 100 stocks during 1995 indicate the estimated parameters for the adverse selection cost and the inventory cost are statistically significant with expected signs. Since the estimated parameter for the adverse selection cost is always larger than that for the inventory cost, it appears information asymmetry is more important in determining price changes than inventory holding for a given transaction volume.

The cross-sectional regressions show that the percentage price impact is inversely related to market capitalization, turnover rate, trading price, and trading noise of the respective stock. For the time-of-the-day effect in market depth, I find the price impact from trading varies in different periods during the trading day. Price impact is at its highest at the market's opening in the morning, then levels off gradually and rebounds before the market's close. This U-shaped pattern for the adverse selection cost is not observed in the U.S. stock markets. I attribute the difference to the variation in informed trading intensity.

However, whether this observed pattern is also related to differences in the trading mechanism has yet to be investigated and is left for future research.

On the whole, the price impact of trading, which is well documented for other stock exchanges, is also influential on the SEHK. For the price formation process, this study provides further empirical evidence for stock markets that rely purely on limit order trading.

References

Barclay, M., Warner, J., 1993. Stealth trading and volatility: Which trades move prices. Journal of Financial Economics 34, 281–305.

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

Brennan, M., Subrahmanyam, A., 1995. Investment analysis and price formation in securities markets. Journal of Financial Economics 38, 361–381.

De Jong, F., Nijman, T., Roell, A., 1996. Price effects of trading and components of the bid-ask spread on the Paris Bourse. Journal of Empirical Finance 3, 193–213.

Glosten, L., Harris, L., 1988. Estimating the components of the bid/ask spread. Journal of Financial Economics 21, 123–142.

Hasbrouck, J., 1991a. Measuring the information content of stock trades. Journal of Finance 46, 179–207.

Hasbrouck, J., 1991b. The summary informativeness of stock trades. An econometric analysis. Review of Financial Studies 4, 571–595.

Hausman, J., Lo, A., MacKinlay, A., 1992. An ordered probit analysis of transaction stock prices. Journal of Financial Economics 31, 319–379.

Huang, R., Stoll, H., 1994. Market microstructure and stock return predictions. Review of Financial Studies 7, 179–213.

Kyle, A., 1985. Continuous auction and insider trading. Econometrica 53, 1315–1336.

Lee, C., Ready, M., 1991. Inferring trade direction from intraday data. Journal of Finance 46, 733–746.

Lin, J., Sanger, G., Booth, G., 1995. Trade size and components of the bid-ask spread. Review of Financial Studies 8, 1153–1183.

Madhavan, A., 1992. Trading mechanism in securities market. Journal of Finance 47, 607–642.

Madhavan, A., Richardson, M., Roomans, M., 1997. Why do security prices change? A transaction-level analysis of NYSE stocks. Review of Financial Studies 10, 1035–1064.

Madhavan, A., Smidt, S., 1991. A Bayesian model of intraday specialist pricing. Journal of Financial Economics 30, 99–134.