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The Inter-Temporal Behavior of Informed and Uninformed Traders

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Abstract. The purpose of this study is to investigate the inter-temporal trading behavior of informed and uninformed investors. We estimate a variation of the market microstructure model developed in Easley, Keifer, O'Hara, and Paperman (1996) and document the day-of-the-week pattern in informed and uninformed trading, as well as the probability of an information event and the probability of bad news. Using bootstrapped distributions, we show that the probability of trading against informed investors follows a U-shape pattern from Monday to Friday. Cross-sectional regression results suggest that inter-temporal patterns between informed and uninformed traders can generate observed patterns in liquidity provision costs.

Key words: informed trading, uninformed trading, market microstructure, stock exchange of Hong Kong

JEL Classification: G15

1. Introduction

The purpose of this study is to investigate the inter-temporal trading behavior of informed and uninformed investors. Numerous theoretical models posit the existence of differentially informed market participants and specify their competing trading behavior. Until recently, however, it was extremely difficult to produce empirical evidence of such behavior due to the lack of a credible trader identification method. The procedure proposed in Easley et al. (1996) generates estimates for the order arrival rates of both informed and uninformed traders. The estimated arrival rates can then be used to calculate the probability of trading against informed traders. This paper contributes to the capital markets literature in three primary areas. First, the general framework of Easley et al. (1996) is modified in order to produce parameter estimates that vary across the days of the week. Second, our model specification is used to document the inter-day trading patterns of the Hong Kong equity market. Third, we use a bootstrapping procedure to generate empirical distributions for the parameter estimates, instead of relying on point estimates alone. The results of such an investigation are useful to various market participants such as corporate managers and

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market makers, as well as to regulatory bodies including security exchanges and government agencies.

The Easley et al. (1996) model, hereafter referred to as EKOP (1996), is designed to capture the salient features of the trading process. Informed traders submit buy and sell orders conditional on the occurrence of a private information event and the observation of its good-versus-bad news content.[1] Uninformed traders are unaware of private information events and, therefore, do not observe the good-versus-bad news content (i.e., uninformed order flow is independent of private information). This asymmetric information model and its variants have been used to determine the probability of informed trading in high versus low volume stocks (EKOP (1996)), to extract the information content of trade size and test various market microstructure models (Easley, Keifer, and O'Hara (1997a, 1997b)), to analyze the effect of analysts' following on the level of informed and uninformed trading (Easley, O'Hara and Paperman, 1998), and to examine whether informed investors prefer to trade in the stock or options market (Easley, O'Hara and Srinivas, 1998). More recently, researchers have applied the EKOP (1996) model to non-U.S. exchanges with alternative market making systems (Brown, Thompson and Walsh, 1999; Brockman and Chung, 2000a), and have tested theoretical models of heterogeneous trading (Brockman and Chung, 2000b).

This study proposes a variation of the EKOP (1996) model that allows for inter-temporal parameter estimates. The standard EKOP (1996) formulation generates firm-specific estimates for (1) the probability of an information event, (2) the probability of bad (or good) news given the occurrence of an information event, (3) the order arrival rate of informed traders, (4) the order arrival rate of uninformed traders, and (5) the probability that any given trade is information based. With a simple modification, all five measures can be estimated on a company-by-company and day-of-the-week basis. Instead of point estimates per company, we generate (bootstrapped) estimated parameter distributions for each company on each day of the week (i.e., Monday,. . . , Friday). This estimation procedure allows the researcher to identify inter-temporal patterns in the trading behavior of informed and uninformed traders. Although this procedure may be applied to many empirical issues (discussed below), one specific application is to test for a day-of-the-week effect with respect to the probability of trading with informed traders.

In addition to investigating the inter-temporal variation in the probability of information trading, we posit that this same pattern underlies previously-documented inter-temporal variation in firm liquidity (e.g., bid-ask spreads). The hypothesized relation between the probability of information trading and firm liquidity is important because of the close connection between corporate liquidity and cost of capital (Amihud and Mendelson, 1986). Recent empirical evidence confirms that a corporation's required rate of return is significantly related to various liquidity proxies, such as turnover rates (Datar, Naik and Radcliffe, 1998), adverse selection costs (Brennan and Subrahmanyam, 1996), and amortized spreads (i.e., spread times share turnover, scaled by equity value) (Chalmers and Kadlec, 1998).

There are two primary benefits in applying the EKOP (1996) procedure to analyze the probability of informed trading and its relation to firm liquidity. First, this is the only widely-accepted methodology that generates firm-specific (and now, day-of-the-week) estimates for informed and uninformed order flow rates, as well as the probability that an arbitrary trade is information based. Second, various trading models predict that informed trading will increase or decrease over specific time periods. The benchmark against which the increase/decrease is to be measured, however, is not always clear from the model. For example, suppose there is twice as much informed trading today as there was yesterday, and that there is four times as much uninformed trading today as there was yesterday. Today's informed trading has increased relative to yesterday's informed trading, but today's informed-to-uninformed (or informed-to-total) trading has actually decreased relative to yesterday's informed-to-uninformed trading. Although disentangling these two measures in terms of theory is beyond the scope of this paper, we are able to distinguish between the two empirically by analyzing EKOP's (1996) parameter estimates.

Our empirical results are based on intra-day data recorded at 30-second intervals for Hang Sang Index (HSI) firms traded on the Stock Exchange of Hong Kong (SEHK). The findings document variations across the days of the week for each parameter estimate. The estimated probability of bad news, for instance, shows that firms do not systematically withhold negative information during trading days and then release it over the weekend. The order arrival rates of informed and uninformed traders generally increase as the week progresses, and reach their maximum values on Friday. More significantly, the probability of trading against an informed trader follows a U-shape pattern across the week. Although both informed and uninformed order arrival rates are relatively low (high) on Mondays (Fridays), the informed arrival rates dominate and lead to an overall higher probability of trading against the informed. Cross-sectional regression results suggest that market participants are aware of these trading patterns and adjust bid-ask spreads accordingly.

The remainder of the paper is organized as follows. Section 2 examines the market microstructure of the SEHK's fully-automated, order-driven market and describes the intra-day data set. Section 3 provides the necessary background on the EKOP (1996) trading model, and Section 4 presents the empirical findings and analyzes their implications. And finally, Section 5 concludes the paper.

2. SEHK market microstructure and data

The SEHK is an electronic trading platform. This thoroughly continuous (i.e., no opening call market) order-driven market offers an ideal setting in which to analyze trading behavior because of its simplicity and transparency. While other exchanges possess some order-driven features, most use a hybrid form of trading mechanisms (e.g., the NYSE and AMEX). The SEHK, on the other hand, is about as pure an order-driven market as obtainable in practice. There are no designated dealers (specialists), no designated order processors (*saitori*), no switching from call to continuous markets, no inter- or intra-day price limits, no trading halts, and no mandatory versus non-mandatory quotation periods. The SEHK offers an interesting setting for applying the EKOP (1996) model because all order flow, whether originating from informed or uninformed traders, is displayed on computer terminals viewable by on- and off-Exchange investors.

Order entry and execution on the SEHK begins with the submission of a limit order, and limit orders are the only order type permitted on the Exchange (i.e., there are no market orders, at least in name). A buy limit order must state the bid price and number of shares to be purchased. A sell limit order must provide the asking price and number of shares to be sold. The limit order is entered into the Automatic Order Matching and Execution System (AMS) which prioritizes it first by price and then by time. Although order sizes are posted for each bid or ask price level, trade size is not a priority in execution. Bid prices are arranged in priority from highest to lowest, and ask prices are arranged from lowest to highest. The difference between the lowest ask price and the highest bid price represents the bid-ask spread. If a buyer (seller) requires an immediate fill (i.e., equivalent to a market order), then he will submit a limit bid (ask) price that is high (low) enough to touch the lowest (highest) posted ask (bid) price.

Trade depth, at the inside spread, is a function of the number of shares available at the lowest ask and highest bid prices. The number of shares available at the highest bid price represents the number of shares that a seller may sell without inducing a price decrease. The number of shares available at the lowest ask price represents the number of shares that a buyer may purchase without inducing a price increase. Actual and potential traders are able to observe all available bid prices and depths, ask prices and depths, along with the buying/selling broker's identity (i.e., the entire order book). Exchange members observe this trading information on floor-based and remote trading terminals, and non-Exchange members have access to the same information through (real-time) data providers. So, unlike the trading environment of the NYSE, AMEX, and Nasdaq, the SEHK's electronic order-driven mechanism is highly transparent with respect to limit order prices and depths. Informed and uninformed traders are able to observe the supply and demand schedules of all traders.

Our data set is obtained from the SEHK's Research and Planning Division and includes intra-day data recorded at 30-second intervals for the HSI constituent companies covering the period from May 1, 1996 to August 29, 1997.[2] Bid and ask prices, as well as transaction prices and volumes are compiled at thirty-second intervals throughout the trading day, including a morning session from 10:00 to 12:30 and an afternoon session from 14:30 to 15:55. Companies with incomplete trading information over the 16-month period (i.e., initial public offerings and delistings) are eliminated from the full sample. This reduces the sample to 32 firms (from 33 firms).

3. The trading model

The EKOP (1996) model provides a method for estimating the probability of a private information event (α), the probability of negative news given the occurrence of a private information event (δ), the order arrival rate of informed traders (μ), and the order arrival rate of uninformed traders (ε).[3] At the beginning of every trading day, nature selects whether an information event occurs (with probability α) or not (with probability $1 - \alpha$). On non-information days, only uninformed traders participate in the market, and buy order arrivals (with arrival rate ε) are equivalent to sell order arrivals (with arrival rate ε). On private-information event days, both informed and uninformed traders enter the market. If the information event represents bad news (with probability δ), then both informed and uniformed traders will issue sell orders (with arrival rate $\mu + \varepsilon$) but only uninformed traders will submit buy orders (with arrival rate ε). And if the information event represents good news (with probability $1 - \delta$), then both informed and uniformed traders will issue buy orders (with arrival rate $\mu + \varepsilon$) but only uninformed traders will submit sell orders (with arrival rate ε).

The arrival of buys (B) and sells (S) within the trading day is modeled as a combined Poisson process. In total, three such processes are specified (i.e., one for each information structure corresponding to a non-event day, a bad news day, and a good news day). The probabilities of observing B buys and S sells on a non-event day, a bad news day, and a good news day, respectively, are given by

$$e^{-\varepsilon}\frac{\varepsilon^B}{B!}e^{-\varepsilon}\frac{\varepsilon^S}{S!} \tag{1}$$

$$e^{-\varepsilon}\frac{\varepsilon^B}{B!}e^{-(\varepsilon+\mu)}\frac{(\varepsilon+\mu)^S}{S!} \tag{2}$$

$$e^{-(\varepsilon+\mu)}\frac{(\varepsilon+\mu)^B}{B!}e^{-\varepsilon}\frac{\varepsilon^S}{S!}\,. \tag{3}$$

The probability of a non-event day is $1-\alpha$, the probability of a bad news day is $\alpha\delta$, and the probalility of good news day is $\alpha(1-\delta)$. Combining these probabilities with the Poisson processes in (1), (2), and (3) yields the following likelihood function:

$$\begin{aligned} L((B,S)\mid\alpha,\delta,\varepsilon,\mu) = {} & (1-\alpha)e^{-\varepsilon}\frac{\varepsilon^B}{B!}e^{-\varepsilon}\frac{\varepsilon^S}{S!} + (\alpha\delta)e^{-\varepsilon}\frac{\varepsilon^B}{B!}e^{-(\mu+\varepsilon)}\frac{(\mu+\varepsilon)^S}{S!} \\ & + \alpha(1-\delta)e^{-(\mu+\varepsilon)}\frac{(\mu+\varepsilon)^B}{B!}e^{-\varepsilon}\frac{\varepsilon^S}{S!}\,. \end{aligned} \tag{4}$$

Parameter estimates for the probability of informed trading (α), the probability of bad news (δ), the order arrival of informed traders (μ), and the order arrival of uninformed traders (ε) are obtained by maximizing the likelihood funtion:

$$L(D\mid\alpha,\delta,\varepsilon,\mu) = \prod_{i=1}^{N} L(\alpha,\delta,\varepsilon,\mu\mid B_i,S_i)\,. \tag{5}$$

The data set, D, requires only the number of buys (B) and sells (S) compiled on a daily basis over a total of N days. The overall derivation assumes that B and S are independent across trading days. This assumption is consistent with an informationally efficient market that fully impounds news events by the close of the trading day (recall that information events occur at the beginning of the trading day). Although the independence assumption may be violated in practice, the value of the EKOP (1996) model lies in its ability to predict trading behavior and not in the reasonableness of its underlying assumptions.

4. Empirical results and analysis

4.1. Descriptive statistics

Table 1 presents summary statistics for the sample of 32 companies covering the sample period of 330 trading days. Reported values refer only to the ordinary shares (i.e., no

Table 1. Selected market statistics on trading activities of sample companies over the period from May 1, 1996 to August 29, 1997[a]

Number of companies in the sample	32
Average market capitalization per company (HK$)	$68,620,600,000
Average daily trading volume per company in number of shares	4,562,597
Average daily trading volume per company in total dollar volume (HK$)	$126,294,675
Average percentage of trading days (over the sample period) with one or more shares traded	99.92%
Average percentage of five-minute intervals with one or more shares traded	81.14%
Average percentage of thirty-second intervals with one or more shares traded	29.35%
Average share price in five-minute intervals	$33.497
Average absolute bid-ask spread in five-minute intervals (HK$)	$0.12276
Average relative bid-ask spread in five-minute intervals	0.00452
Average volume depth in five-minute intervals	387,413
Average dollar depth in five-minute intervals (HK$)	$10,399,887

The sample is made up of all constituent stocks of the Hang Seng Index at August 29, 1997 as compiled by HSI Services Limited. One company is eliminated from the sample as it was not listed on the Stock Exchange of Hong Kong (SEHK) throughout the entire sample period.

[a]Two trading days (October 14, 1996 and December 12, 1996) are not included in the 330-day sample period because data on the bid and ask quotes on these two particular days were not available from the SEHK.

convertibles, preferred stock, or warrants) of the respective firms. The average HSI market capitalization, price, and daily trading volume are $68,620,600,000, $33.497, and 4,562,597 shares, respectively.[4] Average daily dollar volume per company is $126,294,675. The typical HSI company is traded during 99.92% of all available trading days, 81.14% of all five-minute intervals, and 29.35% of all thirty-second intervals. The descriptive statistics provided in Table 1 confirm that our sample HSI companies are large and actively traded. These firms represent approximately 63% of the SEHK's total market value, along with 34% of its total turnover. The SEHK typically ranks among the top ten stock exchanges in the world by market capitalization, and second in Asia behind Japan.

Average dollar (or absolute) bid-ask spreads (i.e., ask price minus bid price) are $0.12276 and average relative bid-ask spreads (i.e., absolute bid-ask spread divided by the bid-ask midpoint) are 0.00452, or less than one-half of one percent of the stock's price. Depth, a second dimension of liquidity, may be measured simply as the number of shares at the highest bid price plus the number of shares at the lowest ask price, or the number of shares at the highest bid and lowest ask price times their respective prices. The first measure is referred to as volume depth and the second is referred to as dollar depth. Both measures show that the average HSI company is relatively liquid with a volume depth of 387,413 shares and dollar depth of $10,399,887.

4.2. *Model estimation and results*

In the original EKOP (1996) formulation, parameter estimates for Eq. (5) are made at the firm level. This would produce 32 sets of α, δ, μ, and ε estimates, or one set per company in the sample. In this paper, we estimate model parameters for separate day-of-the-week samples. Maximum likelihood estimation is carried out to estimate Eq. (5) (i.e., EKOP's (1996) trade process model) and to generate bootstrapped distributions of the model parameters for every sample firm in each day-of-the-week sample. Five day-of-the-week samples are formed such that the first sample ($j = 1$) includes only Mondays, the second sample ($j = 2$) only Tuesdays, the third sample ($j = 3$) only Wednesdays, the fourth sample ($j = 4$) only Thursdays, and the fifth sample ($j = 5$) only Fridays over the sample period. The bootstrapping procedure is implemented on a firm-by-firm basis by randomly selecting 40 days from each day-of-the-week sample and repeating this process 200 times to generate an empirical distribution containing 200 observations.[5]

For each set, the Newton-Raphson method with a line search algorithm is used to obtain the parameter estimates that maximize the natural log of the likelihood function

$$\prod_{i=1}^{40}\left[\begin{array}{l}(1-\alpha_j)\,e^{-\varepsilon_j}\,\dfrac{\varepsilon_j{}^{B_{ij}}}{B_{ij}!}\,e^{-\varepsilon_j}\,\dfrac{\varepsilon_j{}^{S_{ij}}}{S_{ij}!}+\alpha_j\,\delta_j\,e^{-\varepsilon_j}\,\dfrac{\varepsilon_j{}^{B_{ij}}}{B_{ij}!}\,e^{-(\mu_j+\varepsilon_j)}\,\dfrac{(\mu_j+\varepsilon_j)^{S_{ij}}}{S_{ij}!}\\ +\,\alpha_j(1-\delta_j)\,e^{-(\mu_j+\varepsilon_j)}\,\dfrac{(\mu_j+\varepsilon_j)^{B_{ij}}}{B_{ij}!}\,e^{-\varepsilon_j}\,\dfrac{\varepsilon_j{}^{S_{ij}}}{S_{ij}!}\end{array}\right] \tag{6}$$

where α_j, δ_j, μ_j, and ε_j are the Poisson process parameters representing, with respect to the jth day-of-the-week sample, the probability of an information event, probability of the information being bad news, arrival rate of informed trades, and arrival rate of uninformed trades respectively. B_{ij} and S_{ij} are the number of buys and the number of sells, respectively, on the ith trading day for the jth day-of-the-week sample. Transaction and bid-ask data on all the sample firms are compiled at 30-second intervals throughout the trading days. For each interval, trades are identified as a buy if the transaction price is at the posted ask and trades are identified as a sell if the transaction price is at the posted bid. On purely order-driven exchanges such as the SEHK, transactions cannot occur within the spread. The total number of buys and the total number of sells for each day are then determined for each sample firm-day. Following EKOP (1996), we restrict α_j and δ_j to (0,1) through a logit transformation, and μ_j, and ε_j to (0, ∞) through a logarithmic transformation of the unrestricted parameters. Starting values are determined based on an extensive grid search over the parameter space for each firm to ensure that the global maximum is reached.

The bootstrapped results are presented in Table 2. For each firm, the 200 estimates obtained for each parameter generate a bootstrapped distribution. Panel A shows the median measures across all sample firms of the mean and median statistics of the bootstrapped parameter distributions. Panel B shows the median measures of the standard deviation and interquartile range of the bootstrapped parameter distributions across the sample firms. Although we report mean values, our discussion focuses on median values as they tend to provide a better measure of central tendency (i.e., the bootstrapped distributions are not assumed to be normally distributed).

As observed in Panel A (1st column), the probability of an information event for the typical firm on any given day of the week is approximately 50%. The median probability of an information event (α_j) is highest on Mondays (0.5163) and lowest on Tuesdays (0.4734). The relatively high Monday α_j's are rather intuitive as one expects that information accumulated over the weekend will be impounded into prices during Monday's trading hours. The median

Table 2. Estimates of model parameters for the separate day-of-the-week samples

	Median (mean) of the bootstrapped distribution of the estimated parameters				
	Probability of information event α_j	Probability of information being bad news δ_j	Arrival rate of informed traders μ_j	Arrival rate of uninformed traders ε_j	Probability of information-based trading $PINF_j$
Panel A					
Monday sample,	0.5163	0.5125	48.7560	41.7831	0.2340
$j = 1$	(0.5134)	(0.5124)	(48.6623)	(41.8556)	(0.2330)
Tuesday sample,	0.4734	0.5354	49.4823	42.1664	0.2207
$j = 2$	(0.4744)	(0.5410)	(49.4043)	(42.0956)	(0.2212)
Wednesday sample,	0.5160	0.4353	51.3017	42.0820	0.2217
$j = 3$	(0.5189)	(0.4349)	(50.8351)	(42.2051)	(0.2213)
Thursday sample,	0.5110	0.5287	48.1091	43.4557	0.2208
$j = 4$	(0.5086)	(0.5315)	(48.4832)	(43.4667)	(0.2207)
Friday sample,	0.5096	0.4504	54.1567	43.6164	0.2358
$j = 5$	(0.5075)	(0.4432)	(53.9766)	(43.7044)	(0.2322)
	Interquartile range [standard deviation] of the bootstrapped distribution of the estimated parameters				
Panel B					
Monday sample,	0.0787	0.0882	5.9354	2.3538	0.0297
$j = 1$	[0.0593]	[0.0706]	[4.6934]	[1.7196]	[0.0223]
Tuesday sample,	0.0921	0.1056	6.4634	2.1352	0.0304
$j = 2$	[0.0664]	[0.0794]	[4.7933]	[1.5623]	[0.0236]
Wednesday sample,	0.0905	0.0972	6.1420	2.1162	0.0313
$j = 3$	[0.0654]	[0.0731]	[4.7998]	[1.6834]	[0.0235]
Thursday sample,	0.0756	0.1048	6.2937	2.0159	0.0276
$j = 4$	[0.0590]	[0.0777]	[4.8169]	[1.5381]	[0.0206]
Friday sample,	0.0771	0.0981	7.1542	2.1506	0.0312
$j = 5$	[0.0619]	[0.0763]	[5.3113]	[1.6760]	[0.0245]

Maximum likelihood estimation is carried out to estimate the Easley et al. (EKOP) (1996) trade process model and to generate bootstrapped distributions of the model parameters for every sample firm in each day-of-week sample. Five day-of-the-week samples are formed such that the first sample ($j = 1$) includes only the Mondays, the second sample ($j = 2$) only the Tuesdays, the third sample ($j = 3$) only the Wednesdays, the fourth sample ($j = 4$) only the Thursdays, and the fifth sample ($j = 5$) only the Fridays over the sample period. The bootstrapping procedure is implemented on a firm-by-firm basis by randomly selecting 40 days from each day-of-the-week sample and repeating this process 200 times to generate 200 sets of data. For each set, the Newton-Raphson method with the line search algorithm is used to obtain the parameter estimates that maximize the natural log of the likelihood function

$$\prod_{i=1}^{40}\left[(1-\alpha_j)e^{-\varepsilon_j}\frac{\varepsilon_j{}^{B_{ij}}}{B_{ij}!}e^{-\varepsilon_j}\frac{\varepsilon_j{}^{S_{ij}}}{S_{ij}!}+\alpha_j\delta_j e^{-\varepsilon_j}\frac{\varepsilon_j{}^{B_{ij}}}{B_{ij}!}e^{-(\mu_j+\varepsilon_j)}\frac{(\mu_j+\varepsilon_j)^{S_{ij}}}{S_{ij}!}\right.$$
$$\left.+\alpha_j(1-\delta_j)e^{-(\mu_j+\varepsilon_j)}\frac{(\mu_j+\varepsilon_j)^{B_{ij}}}{B_{ij}!}e^{-\varepsilon_j}\frac{\varepsilon_j{}^{S_{ij}}}{S_{ij}!}\right]$$

where α_j, δ_j, μ_j, and ε_j are the Poisson process parameters representing, with respect to the jth day-of the-week sample, the probability of an information event, probability of the information being bad news, arrival rate of

(*Continued on next page.*)

standard deviation of α_j estimates, reported in Panel B, are relatively low on Mondays, increase on Tuesdays and Wednesdays, and then taper off over the remainder of the week. The 2nd column reports the probability that the information event is bad news (δ_j). The median probability of bad news is highest on Tuesdays (0.5354) and lowest on Wednesdays (0.4353). Although no obvious trends appear in the bad news estimates, our evidence suggests that firms do not systematically release negative news over the weekend (i.e., a possible explanation for the Monday effect) since the median Monday δ_j estimate (0.5125) is not particularly large.

The median arrival rate of informed traders (μ_j) is highest on Fridays (54.1567) and lowest on Thursdays (48.1091). With the exception of Thursdays' relatively low estimates, there is a general trend of increasing levels of informed trading during the week. The same pattern applies to the bootstrapped standard deviations in Panel B (i.e., values increase over the days of the week). The median arrival rate of uninformed traders (ε_j) is highest on Fridays (43.6164) and lowest on Mondays (41.7831). The pattern of uninformed traders' arrival rates parallels that of informed traders. Both arrival rates are relatively low at the beginning of the week and generally increase until reaching their maximum values on Fridays. This finding is consistent with the notion that informed traders attempt to conceal their information by trading when the market is relatively thick.[6] We also note that there is considerably more variation in the arrival rates for informed traders than for uninformed traders (see Panel B). The economic interpretation is that uninformed trading (in the aggregate) arrives in a more uniform manner than information-based trading.

Although we have presented some potentially interesting inter-temporal patterns for the α_j, δ_j, μ_j, and ε_j estimates, the focus of this study is to investigate inter-temporal patterns in the probability of trading against informed traders. This is significant because changes in the probability of trading against informed traders can lead to changes in the costs of liquidity provision. So far, the results show that both informed and uninformed investors trade with increasing intensity as the week progresses. Although there are fewer informed traders in absolute terms at the beginning of the week, there are also fewer uninformed traders at this time. What is needed is a measure that incorporates the relationship between informed and uninformed trading, along with the likelihood of information events. EKOP

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(*Continued.*) informed trades, and arrival rate of uninformed trades respectively. B_{ij} and S_{ij} are the number of buys and the number of sells, respectively, on the ith trading day for the jth day-of-the-week sample. Transaction and bid-ask data on all the sample firms are compiled at 30-second intervals throughout the trading days. For each interval, trades are identified as a buy if the transaction price is at the posted ask and trades are identified as a sell if the transaction price is at the posted bid. The total number of buys and the total number of sells for each day are then determined for each sample firm. Following EKOP (1996), we restrict α_j and δ_j to (0,1) through a logit transform and μ_j, and ε_j to $(0, \infty)$ through a logarithmic transform of the unrestricted parameters. Starting values are determined based on an extensive grid search over the parameter space for each firm to ensure that the global maximum is reached. The probability of informed trading is a function of the estimated model parameters and is derived as $\hat{\alpha}_j\hat{\mu}_j(\hat{\alpha}_j\hat{\mu}_j + 2\hat{\varepsilon}_j)^{-1}$ for the jth day-of-the-week sample. For each firm, the 200 estimates obtained for each parameter form the bootstrapped distribution of the estimated parameter. Panel A shows the median measures across all sample firms of the median and mean statistics of the bootstrapped parameter distributions. Panel B shows the median measures of the interquartile range and standard deviation of the bootstrapped parameter distributions across the sample firms.

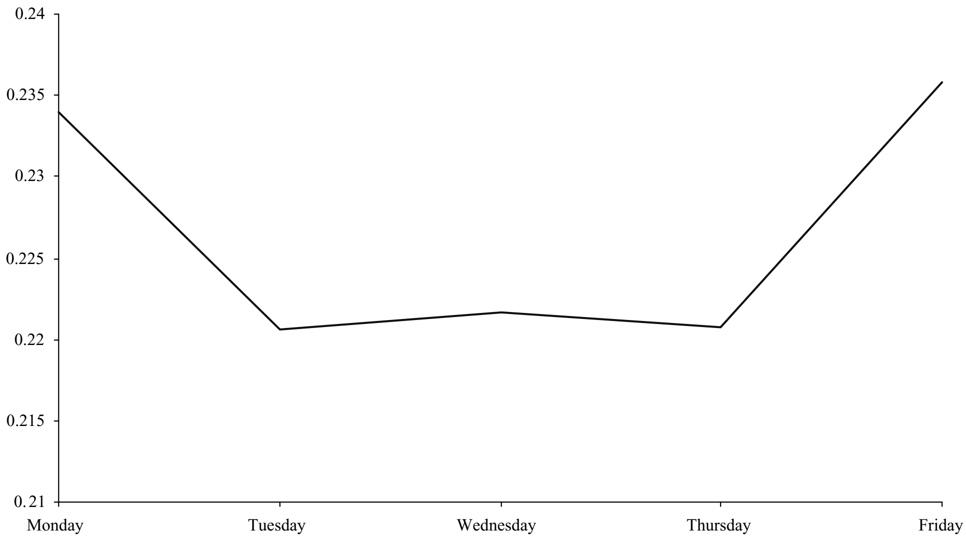

Figure 1. Inter-day pattern of median estimated probability of information-based trading (*PINF*).

(1996) define the probability of informed trading as

$$\frac{\alpha\mu}{(\alpha\mu + 2\varepsilon)}, \tag{7}$$

where α, μ, and ε are defined above. This measure uses informed and uninformed arrival rates, combined with the probability of a private information event, to construct the probability that any given trade is information based.

The last column of Table 2 reports the estimated probability of informed trading ($PINF_j$) across the days of the week. The median probability of information-based trading is highest on Fridays (0.2358) and lowest on Tuesdays (0.2207). More significantly, median $PINF_j$ values follow a U-shape pattern across the week, as seen in Figure 1. This U-shape pattern is similar to that reported for liquidity measures such as bid-ask spreads (e.g., Brockman and Chung (1998)).

In Table 3, we test for differences in $PINF_j$ means and medians using the bootstrapped distributions of the estimated parameters. We use parametric and non-parametric tests to confirm the significance of the U-shape pattern across the weekdays focusing on the decline at the beginning of the week between Monday and Tuesday, and the rise at the end of the week between Thursday and Friday. Panel A shows the summary results of the parametric t-test for difference in the means of the bootstrapped distributions. Panel B shows the summary results of the non-parametric Wilcoxon Rank Sum test for difference in the medians of the bootstrapped distributions. Both panels confirm that Mondays and Fridays experience significantly higher probabilities of trading against informed traders. Under the null hypothesis, we expect only 5% of the firms to show a significant difference between

Table 3. Test for differences in mean and median of the bootstrapped distributions of the estimated parameters for the probability of information-based trading

	Number of firms with significant result at 0.05 level	Percent of firms with significant result at 0.05 level (%)
Panel A: Test for difference in means of the bootstrapped parameter distributions		
Between Monday and Tuesday		
H_a : *mean*($PINF_1$) > *mean*($PINF_2$)	18	56
Between Thursday and Friday		
H_a: *mean*($PINF_4$) < *mean*($PINF_5$)	17	53
Panel B: Test for difference in medians of the bootstrapped parameter distributions		
Between Monday and Tuesday		
H_a: *median*($PINF_1$) > *median*($PINF_2$)	18	56
Between Thursday and Friday		
H_a: *median*($PINF_4$) < *median*($PINF_5$)	16	50

Parametric and non-parametric tests are performed to confirm the significance of the U-shape pattern across the weekdays focusing on the decline at the beginning of the week between Monday and Tuesday and the rise at the end of the week between Thursday and Friday. Panel A shows the summary results of the parametric t-test for difference in the means of the bootstrapped distributions. Panel B shows the summary results of the non-parametric Wilcoxon Rank Sum test for difference in the medians of the bootstrapped distributions.

the days of the week (i.e., Monday versus Tuesday, and Thursday versus Friday). However, the empirical findings reveal that between 50–56% of our HSI firms exhibit a significant $PINF_j$ reduction from Monday to Tuesday, and a significant $PINF_j$ increase from Thursday to Friday.

4.3. *Probability of informed trading and spreads*

As mentioned above, the U-shape probability of trading against an informed trader is similar to other U-shape patterns documented in the market microstructure literature. We hypothesize that liquidity patterns, in particular, can be generated by the inter-temporal trading patterns of informed and uninformed traders documented above. When the probability of trading against an informed trader is high, bid-ask spreads will widen in order to reflect the increase in adverse selection costs.

We test the empirical relation between bid-ask spreads and the probability of information-based trading using regression analysis. Following Benston and Hagerman (1974) and others, we include price, volume, and volatility as control variables in the following model specification:

$$Spread_i = \alpha + \beta\, PINF_i + \delta_1\, Volume_i + \delta_2\, Price_i + \delta_3\, Volatility_i + \varepsilon_i \tag{8}$$

$Spread_i$ is the bid-ask spread and is measured by either $ASpread_i$ or $RSpread_i$. $ASpread_i$ is a measure of the average absolute dollar spread of a sample firm over a trading day i and is calculated as the mean of all absolute dollar spreads recorded thirty seconds apart during the day. $RSpread_i$ is the relative spread averaged across all thirty-second intervals over the trading day i. $PINF_i$ is the probability of information-based trading for the firm and is measured by the median of the bootstrapped parameters obtained for the particular day of the week to which the trading day i belongs. $Volume_i$ is the total trading volume during the trading day. $Price_i$ is the average of all transaction prices recorded thirty seconds apart over the trading day. $Volatility_i$ measures the variance of returns over the trading day and returns are calculated by taking the logarithms of bid-ask midpoint relatives thirty seconds apart. The variables $ASpread_i$, $RSpread_i$, $Volume_i$, $Price_i$ and $Volatility_i$ are all transformed by taking natural logarithms. The t-statistics are adjusted for arbitrary cross-correlations, serial correlation and heteroskedasticity using Hansen's (1982) generalized method of moments (GMM) with the Newey and West (1987) procedure.

The regression results are reported in Table 4, for both absolute and relative spreads. The estimated coefficients for the control variables are all statistically significant and consistent

Table 4. Regression of bid-ask spread on probability of information-based trading controlling for the effects of price, volume and volatility

		Absolute spread $Spread_i = Aspread_i$		Relative spread $Spread_i = RSpread_i$	
		Estimated coefficient	t-stat.	Estimated coefficient	t-stat.
Intercept	α	−1.8535	−2.18*	−1.8676	−2.20*
PINF	β	0.2067	2.45**	0.2068	2.45**
Volume	δ_1	−0.0481	−10.44**	−0.0479	−10.41**
Price	δ_2	0.7175	159.90**	−0.2826	−62.99**
Volatility	δ_3	0.1848	2.59**	0.1837	2.57**
Number of observations		10,551		10,551	
Adjusted R^2		0.8156		0.4200	
F-statistic (d.f. = 4 and 10,546)		11,665.74**		1,911.01**	

$$Spread_i = \alpha + \beta PINF_i + \delta_1 Volume_i + \delta_2 Price_i + \delta_3 Volatility_i + \varepsilon_i$$

$Spread_i$ is the bid-ask spread and is measured by either $ASpread_i$ or $RSpread_i$. $ASpread_i$ is a measure of the average absolute dollar spread of a sample firm over a trading day i and is calculated as the mean of all absolute dollar spreads recorded thirty seconds apart during the day. $RSpread_i$ is the relative spread averaged across all thirty-second intervals over the trading day i. $PINF_i$ is the probability of information-based trading for the firm and is measured by the median of the bootstrapped parameters obtained for the particular day of the week to which the trading day i belongs. $Volume_i$ is the total trading volume during the trading day. $Price_i$ is the average of all transaction prices recorded thirty seconds apart over the trading day. $Volatility_i$ measures the variance of returns over the trading day and returns are calculated by taking the logarithms of bid-ask midpoint relatives thirty seconds apart. The variables $ASpread_i$, $RSpread_i$, $Volume_i$, $Price_i$ and $Volatility_i$ are all transformed by taking natural logarithms. The t-statistics are adjusted for arbitrary cross-correlations, serial correlation and heteroskedasticity using Hansen's (1982) generalized method of moments (GMM) with the Newey and West (1987) procedure. Significance is indicated at the 0.05 and 0.01 levels by one and two asterisks respectively.

with previous findings. Bid-ask spreads are negatively related to trading volume ($\delta_1 = -0.0481$ and -0.0479) since order processing costs include both fixed and variable costs. The fixed cost portion is reduced on a per unit basis with higher volumes. Absolute bid-ask spreads are positively related to price levels ($\delta_2 = 0.7175$) since inventory holding costs are an increasing function of share price. However, relative bid-ask spreads are inversely related to price levels ($\delta_2 = -0.2826$) due to economies of scale in inventory and order processing costs. And lastly, spreads exhibit a positive relation to volatility ($\delta_3 = 0.1848$ and 0.1837) because of the increase in inventory costs associated with volatile, uncertain security prices. The most significant finding in Table 4, however, is the positive and significant relation between spreads and $PINF_i$ ($\beta = 0.2067$ and 0.2068). This finding confirms the posited relation between the probability of trading against informed investors and firm liquidity. While these results should be considered preliminary in nature, they certainly suggest that inter-temporal patterns in informed and uninformed trading give rise to (previously-documented) inter-temporal patterns in firm liquidity.

5. Conclusion

The purpose of this study is to investigate the inter-temporal trading behavior of informed and uninformed investors. To date, relatively little empirical evidence has been presented that identifies such patterns. We adopt the general framework of Easley et al. (1996) but modify the estimation procedure in order to produce day-of-the-week parameter estimates for (1) the probability of an information event, (2) the probability of bad news given the occurrence of an information event, (3) the order arrival rate of informed traders, (4) the order arrival rate of uninformed traders, and (5) the probability that any given trade is information based. In addition to providing a more complete picture of inter-day informed and uninformed trading, the results suggest that these same trading patterns might be the underlying cause of other market microstructure regularities such as U-shaped liquidity costs.

More specifically, the findings show that the probability of an information event displays considerable variation across the days of the week, implying that the dissemination of private information is not uniformly distributed. The estimated probability of bad news demonstrates that firms do not systematically withhold negative information, only to be released when the market is closed over the weekend. The order arrival rates of informed and uninformed traders generally increase as the week progresses, until reaching their maximum values on Fridays. More significantly, the probability of trading against an informed trader follows a U-shape pattern across the week. Although both informed and uninformed order arrival rates are relatively low (high) on Mondays (Fridays), the informed arrival rates dominate and lead to an overall higher probability of trading against the informed. Market participants are apparently aware of this pattern and adjust bid-ask spread accordingly.

The method of analysis employed herein can also be used to test theoretical models of investor behavior, or to investigate the relationship between trading behavior and pricing dynamics. Calendar-day or seasonal anomalies, for example, have been documented at daily (Harris, 1986), weekly (French, 1980), monthly (Ariel, 1987), and yearly (Rozeff and Kinney, 1976) intervals. There also exists considerable empirical evidence of a holiday effect in which pre-holiday returns are abnormally large. Lakonishok and Smidt (1988), for example, show that pre-holiday returns are more than 23 times larger than average non-holiday returns and account for approximately 50 percent of the Dow Jones Industrial Average (DJIA) total yearly return. Future research can investigate the role played by informed and uninformed arrival rates in generating these pricing patterns simply by re-calibrating Eq. (6) to the specific time interval of interest.

Notes

1. Easley, O'Hara and Paperman (1998) define a private information event as (p. 178) "the occurrence of a signal that is not publicly observable about the future value of the asset where the signal may be good news or bad news." The signal could be generated from inside information or superior information processing of public information. Regardless of the signal source, the distinguishing feature of private information events is that they affect trading activity. Public information events can affect prices, but they have little or no affect on trading activity. Consistent with this distinction, Easley, O'Hara and Paperman (1998) argue that (p. 179) "To the extent that seemingly public information events affect trade, they have a private component (such as understanding how to use this particular information) and we classify them as private information events."
2. Minor adjustments are made to the time-of-day for the first eight months of the sample period due to an internal clock misalignment in the original data capturing process. These adjustments are made based on information provided by SEHK's Research and Planning officials and verified by our program filters.
3. Although all versions of the EKOP (1996) model are based on the same underlying trade process, this section specifically describes the recent Easley, O'Hara and Paperman (1998) version.
4. All $ values refer to Hong Kong dollars. The Hong Kong dollar is officially pegged at 7.8 per U.S. dollar, and remained very close to this rate during the period under investigation.
5. We also generate bootstrapped estimates using 500 and 1000 iterations for a subsample of firms, and find no significant differences from those reported herein. In addition, we change the number of days in each iteration from 40 to 60 and repeat the same estimation procedures. Again, no significant differences are found.
6. Informed traders must also take into consideration a possible reduction in the value of private information by waiting for the market to thicken. The informed trader's timing decision will depend on the trade-off between the benefits of waiting (i.e., market thickness) and the costs of waiting (i.e., information depreciation). We thank an anonymous referee for pointing out the cost side of deferred information trading.

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