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Information asymmetry, cluster trading, and market efficiency: Evidence from the Chinese stock market

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ABSTRACT

This study investigates the effect of asymmetry information and illiquidity related to cluster trading on information integration efficiency in the Chinese stock market. The results show that information asymmetry and illiquidity related to cluster trading both negatively affect market efficiency in the Chinese stock market. While the effect of information asymmetry on market efficiency dominates in the informational period, the effect of illiquidity related to cluster trading dominates in other periods, when trading is less concentrated. Noise trading has a positive effect on market efficiency by greatly reducing the illiquidity related to cluster trading; however, its effect on information asymmetry is not significant. Our results provide insight into investors' trading strategies.

1. Introduction

Since the contribution of Fama (1970), theoretical and empirical studies on market efficiency have attracted the attention of scholars and traders in stock markets. Empirical evidence shows that market efficiency is affected by several characteristics of individual stocks, such as market capitalization, price volatility, trading volume, institutional trading, and trading costs (Visaltanachoti and Yang, 2010). This study considers two types of trading costs: information asymmetry and illiquidity related to cluster trading.

The positive link between adverse selection and informed trading is extensively discussed in the market microstructure literature. Information asymmetry related to adverse selection arises whenever one party has superior information over its counterparty in the trading process. As a result, trading costs are likely to rise in the presence of information asymmetry. Admati and Pfleiderer (1988) show that liquidity traders and informed traders tend to trade together, and trading is concentrated, which is referred to in this study as cluster trading, because they prefer to trade when the market is "thick," which means that their trading has little effect on prices. Stocks with a higher level of cluster trading are less liquid and have a higher trading cost in the market (Duarte and Young, 2009). Therefore, stocks with higher information asymmetry and a higher level of cluster trading are expected to be less efficient.

Bloomfield et al. (2009) find that, although they consistently lose money by trading with informed traders, noise traders provide the market with additional liquidity and reduce trading costs by increasing the trading volume and market depth and reducing the price impact. In this context, this study considers the Chinese stock market. Although the significance of the Chinese stock market has increased over the past 25 years, some particular features of this market differ from those in American stock markets, such as the prevalence of speculative noise trading, and can have a significant impact on market efficiency.[1] Therefore, the following questions are of interest: (1) Do the information asymmetry and illiquidity related to cluster trading affect market efficiency in the Chinese stock market; and (2) does speculative noise trading affect market efficiency by reducing information asymmetry or by alleviating illiquidity related to cluster trading?[2]

Following Chordia et al. (2008) and Chung and Hrazdil (2010a, 2010b), this study adopts a two-stage regression approach to analyze market efficiency in the Chinese stock market. First, the methodology of Chordia et al. (2008) (i.e., the regression of 1-min returns on lagged order imbalances) is used to estimate the degree of market efficiency. Second, the study relates market efficiency to two variables of interest, information asymmetry and illiquidity related to cluster trading, to provide

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[1] The Chinese stock market was formed in the early 1990s. By the end of 2014, the Shanghai Stock Exchange ranked fourth in terms of global market capitalization, surpassing Euronext and the Stock Exchange of Hong Kong. The Shanghai Stock Exchange and the Shenzhen Stock Exchange ranked third and fourth, respectively, in terms of annual trading volume (World Federation of Exchanges monthly report).

[2] In the context of this study, market efficiency refers to weak-form market efficiency (Fama, 1970).

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evidence of the ways in which these factors affect market efficiency. Furthermore, this study investigates whether the prevalent speculative noise trading that is characteristic of the Chinese stock market influences market efficiency by affecting these two factors.

The empirical results suggest the following: (1) information asymmetry or illiquidity related to cluster trading becomes major force negatively affecting market efficiency over different horizons in the Chinese stock market; (2) while the effect of information asymmetry on market efficiency dominates in the period of intensive trading, the effect of illiquidity related to cluster trading dominates in other periods, when trading is less concentrated; (3) noise trading has a positive effect on market efficiency by greatly reducing illiquidity related to cluster trading; however, its effect on information asymmetry is not significant. Our results clearly show that, while investors concentrate their trading to exploit their information advantage in one period, the trading costs related to liquidity are their primary concern in their trading strategy in another period.

This study contributes to the literature in the following ways. First, while the factors affecting market efficiency are comprehensively investigated in developed markets, we still lack solid empirical evidence in developing countries, where the research concentrates mainly on the effect of market microstructure change, such as market deregulation (Hung, 2009), split-share reform in China (Beltratti et al., 2016), and so on, on market efficiency. A weak cross-correlation between market efficiency and trading volume is found in three emerging markets in Asia (Sukpitak and Hengpunya, 2016). The relation between trading costs and market efficiency is also confirmed in the Chinese stock market (Chen et al., 2009). This study first investigates the effects of two types of specific trading costs, information asymmetry and illiquidity related to cluster trading, on market efficiency in the Chinese stock market to contribute to the literature.

Second, while Bloomfield et al. (2009) use laboratory data and find that noise trading actually has a positive effect on market efficiency and lower trading costs by providing the market with additional liquidity and greater depth, they do not clearly indicate the channel of trading costs through which noise trading affects market efficiency. We fill this gap by investigating noise trading's effect on information asymmetry and illiquidity related to cluster trading.

Third, speculative noise trading as a characteristic of the Chinese stock market is largely confirmed and recognized (Mei et al., 2009), but few studies are dedicated to investigating its effect on market quality. Fong (2009) indicates that the superior performance of A-shares is more likely due to a return bias caused by speculation, rather than risk compensation.[3] Ding and Cheng (2011) find that the price bubble in the Stock Exchange of Hong Kong during the period of the Hong Kong "through-train scheme" is caused by speculative noise trading from mainland Chinese investors who were allowed to invest directly in Hong Kong market.[4] This study contributes to the existing literature on noise trading by investigating the effects on market efficiency of speculative noise trading, which is specific to the Chinese stock market.

Fourth, in the literature, the information motivation model argues that, driven by private information that they receive, the investors' trading incorporates information into prices and entails a problem of information asymmetry, which goes back to Grossman and Stiglitz (1980) and Kyle (1985). The liquidity motivation model, however, focuses on the management of trading to reduce trading costs related to liquidity (Vayanos, 1999). We provide supporting evidence for both models and insight into which motivation is the dominant force behind investor trading.

Finally, it extends the findings of Chordia et al. (2008) by studying market efficiency in a stock market using the measure of order imbalance with high-frequency data in a developing country. The characteristic of Chinese stock market is different from that of US stock market with domination of institutional traders. The Chinese stock market, where individual investors make up the majority of the total number of investor accounts, provides us an ideal case to study the effect of noise trading on market efficiency. Moreover, while the literature of market microstructure mostly focuses on the quote-driven market, the mechanism of the order-driven market is not thoroughly analyzed in the literature. As the importance of Chinese stock market, which is a typical order-driven market, is increasing, it is of empirical interest to provide evidence on the mechanism of the Chinese stock market.

This study is consistent with Klein et al. (2017), who suggest that traders in stock markets have two kinds of trading motives—an information-based motive and a liquidity-based motive—based on which the trading activities may significantly differ. This study corroborates the findings of Bloomfield et al. (2009), who indicate that noise trading actually has a positive effect on market efficiency and lowers trading costs by providing the market with additional liquidity and greater depth.

The remainder of this paper is organized as follows. Section 2 provides a brief description of the Chinese stock market. Section 3 presents the theoretical considerations. Section 4 describes the data and the methods of analysis. Section 5 empirically explores the effect of information asymmetry and illiquidity related to cluster trading on market efficiency as well as the effect of speculative noise trading on these two factors, and Section 6 provides concluding remarks.

2. Market structure in China

In early 1991, the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) were formed, and trading began. Since then, the two exchanges have expanded rapidly in terms of the number of listed securities and market value.

In China, stocks can be listed either on the SHSE or the SZSE but not both. The Chinese stock market is divided into three boards. The main board was created in 1991. It is the most important board and has the most stringent listing requirements. The Small and Medium-Size Enterprise (SME) board was created as a transitional board in 2004 and is regarded as midway between the main board and the ChiNext board. The latter was created in 2009 with relatively lower listing requirements. Both the SHSE and SZSE operate the main board, while the SZSE also runs the SME and the ChiNext boards.

The trading mechanism of the stock market in mainland China is similar to that of the Hong Kong or Tokyo Stock Exchanges. Both SHSE and SZSE run a pure order-driven trading mechanism on electronic systems without official market makers. Both are open five days a week except on holidays. Two trading systems are used to match orders: (i) a periodic auction at market opening 9:15–9:25 a.m. and (ii) a continuous discriminating auction 9:30–11:30 a.m. The afternoon session includes only one continuous trading period 13:00–15:00. The periodic auction incorporates all orders submitted during the pre-trading session and results in a single opening price, for each stock, that maximizes that stock's volume traded. The continuous auction system employed thereafter uses a time and priority scheme to match orders. Unmatched orders remain in the system until they are executed or cancelled, or for a maximum of one day if not executed beforehand. Only limit orders and market orders are allowed in both exchanges. Floor trading among brokers is prohibited. The limit of price change for each trading day is $\pm 10\%$ of the previous closing price. The quantity of stock purchased must be in round lots of 100 while there is no requirement on the quantity of sales.

Compared with the US stock market, the Chinese stock market is characterized by the dominance of individual investors (Lee et al., 2010), who engage mainly in speculative noise trading (Wang et al., 2006; Mei

[3] A-shares are shares purchased and traded on the SHSE and the SZSE that are denoted in renminbi.

[4] The "Share Investment Through-Train Scheme to Hong Kong" was announced on August 20, 2007. Under the scheme, mainland authorities initially allowed individual mainland investors to purchase Hong Kong stocks directly. However, in a speech on November 3, 2007, the Chinese prime minister said that the scheme would have to be reassessed because of concerns that excess fund flows could affect market stability. The scheme was not suspended but has made no progress since then.

et al., 2009). This speculative noise trading is the result of strict short-sale constraints and the presence of less experienced individual investors who hold heterogeneous beliefs about stock prices (Mei et al., 2009). Such investors are more concerned with short-term price fluctuations than long-term stock returns. Therefore, the stock market in China offers an ideal environment for investigating the effect of speculative noise trading.

3. Theoretical considerations

3.1. Trading costs related to information asymmetry

The hypothesis on the positive link between adverse selection and informed trading is extensively discussed in the market microstructure literature. Early on, researchers focused on the interaction between competitive market makers and informed traders who have access to private information about asset values. Facing an adverse selection problem, market makers have an incentive to adjust bid–ask spreads or the price impact to account for the presence of information-based trading activity (Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985; Easley and O'Hara, 1987). These models argue that informed traders improve market efficiency by exploiting their informational advantage and thus contribute to a more rapid adjustment of prices toward fundamental values. In turn, the liquidity provider faces adverse selection by having to trade with unidentified informed traders hidden among many uninformed traders. Information asymmetry allows informed traders to earn extra returns at the expense of uninformed traders. The higher the probability of informed trading, the higher the transaction costs and the lower the liquidity.

More recently, research has been extended to the behavior of strategic liquidity suppliers, who submit limit orders to exploit market conditions or possibly private signals about orders of other market participants. In this setting, the marginal cost and markup of supplying liquidity increase with the degree of adverse selection (Glosten, 1994; Bernhardt and Hughson, 1997; Biais et al., 2000). Regardless of changes in market structure and trading mechanisms over time, a central tenet remains: an adverse selection problem arises whenever one party has superior information over its counterparty (information asymmetry) in the trading process. As a result, trading costs are likely to rise with information asymmetry in the presence of adverse selection (Chang and Wang, 2015). Our first hypothesis is as follows:

Hypothesis 1. Market efficiency is negatively related to the trading cost of information asymmetry resulting from adverse selection.

3.2. Trading costs related to cluster trading

Admati and Pfleiderer (1988) develop a model to analyze the intraday trading pattern in the stock market by including a discretionary liquidity trader. Their results show that liquidity traders tend to trade together, and the trading is concentrated because they prefer to trade when the market is "thick," which means that their trading has little effect on prices. Moreover, more informed trading generally intensifies the forces leading to the concentration of trading because informed traders compete with one another to lower the liquidity traders' trading costs. With more liquidity trading in a given period, more informed traders trade, and this makes it even more attractive for liquidity traders to trade in that period. Foster and Viswanathan (1990) indicate that because of the presence of discretionary liquidity traders and the private information being revealed publicly, informed trading is concentrated in certain periods in which private information comes to the market. They also imply that the intensity of informed trading decreases after the information is gradually integrated into prices.

Therefore, the trading, which is not smooth in the timeline, is concentrated in certain periods, especially when informed trading is intensive, and it becomes less concentrated in other periods. In the period of incoming information (hereafter referred to as the informational period), information trading and liquidity trading are both concentrated, with a higher trading volume, especially when private/public information comes into the stock market. In the other period of non-incoming information (hereafter referred to as the non-informational period), trading intensity is reduced, with a lower trading volume, which raises the trading cost. This is characterized as cluster trading, which introduces another trading cost to the market.

When cluster trading exists, the investor faces a trade-off between waiting, perhaps for some time, for a period of high trading volume, when the stock will be more liquid and when his trade can presumably be crossed with another trade, or trading immediately and involving a liquidity provider at additional cost. Thus, stocks with prevalent cluster trading tend to be among the least liquid in the market (Duarte and Young, 2009). Therefore, stocks with higher cluster trading are effectively less liquid, with a higher trading cost. Our second hypothesis is as follows:

Hypothesis 2. Market efficiency is negatively related to the level of cluster trading.

3.3. Different trading strategies: information asymmetry and illiquidity related to cluster trading

Different motivations for strategic trading can be traced in a range of models. In the first group of models, the trading is primarily information motivated. Informed investors spread their trades over time in order to conceal their private information and manage the permanent price impact their trades have on the stock price (Kyle, 1985; Glosten and Milgrom, 1985). In the second group of models, the trading is basically liquidity motivated ("allocational" motives in Vayanos (2001)]) and trading motives comprise portfolio rebalancing and risk sharing. Aware of their trading impact on stock prices, investors manage to balance between immediacy of execution and the cost related to immediate execution without any information motivations for trading.

On the one hand, according to information-based theories, informed traders try to trade more rapidly because of the information competition, which leads to a "rat-race" effect. Therefore, while the information is gradually incorporated into prices through the trading activities of informed traders, informed traders speed their trading and try to outrun other informed traders to exploit their informational advantage, which is reduced with the integration of information into prices.[5] On the other hand, liquidity-based theories argue that, aware of the possible depletion of liquidity, which results in a higher price impact and increased trading costs, traders decrease their trading frequency, which extends the trading horizon, if they know that other investors are trading in the same direction at the same time. In liquidity-induced trades, the price impact moves prices away from fundamental values and creates benefits from waiting and holding out until some point in the future, when the market has learned the true information content of trades and prices have reverted to fundamental values (Klein et al., 2017).

Based on our analysis above, we can describe the trading process as follows. The trading process can be divided into two trading periods: an informational period and a non-informational period. During an informational period, when information is coming into the market, informed traders compete in a "rat race" to exploit their information advantage, and information asymmetry is most prevalent. The trading cost of information asymmetry induced by adverse selection is most obvious and negatively affects market efficiency. At the same time, the trading volume increases, and the elevated trading intensity resulting from cluster trading could also enhance the integration of information. Klein et al. (2017) find that, in

[5] See also Foster and Viswanathan (1994, 1996), who investigate the case in which the signals of two competing insiders are not perfectly correlated. Then the prediction mentioned above holds only for the common component of insiders' signals. Back et al. (2000) show that the "rat-race" effect obtains only if the signals of different insiders are sufficiently correlated. Important extensions of this framework allow for the possibility that information is disclosed (Huddart et al., 2001) and that it becomes stale (Bernhardt and Miao, 2004).

most cases, trades are completed more quickly if insiders are more likely to be informed. More importantly, competition from other insiders reduces trade duration for all classifications of informed trades. This result is in line with the predictions of the information-based models of Back et al. (2000), Foster and Viswanathan (1994, 1996), Holden and Subrahmanyam (1992), and Kaniel and Liu (2006).

With the information gradually integrated into the price and the trading intensity decreased, trading enters a non-informational period in which the trading cost resulting from information asymmetry greatly decreases and loses this effect on market efficiency. With a greatly decreased trading volume and increased price impact of trading, some investors postpone their trading to profit from the low price impact in the next informational period, which greatly slows the speed of information integration. Klein et al. (2017) find strong evidence for their liquidity-time hypothesis: that insiders respond to changes in market liquidity by avoiding low-liquidity days and trading more on days on which liquidity is high. Collin-Dufresne and Fos (2015) analyze the trading strategy of activist investors (Schedule 13D filers) and document liquidity-timing trading behavior. Therefore, the illiquidity related to cluster trading becomes the dominant force that negatively affects market efficiency. The illiquidity in a non-informational period is a result of cluster trading in which trading is concentrated with incoming information. Therefore, our third hypothesis is as follows:

Hypothesis 3. The effect of information asymmetry on market efficiency is most obvious during the informational period; and the effect of illiquidity related to cluster trading on market efficiency is most obvious during the non-informational period.

3.4. Effect of noise trading on market efficiency

Bloomfield et al. (2009) use a laboratory market to investigate the behavior of different traders: informed traders, liquidity traders, and uninformed (noise) traders in the stock market. Their results show that the role of noise trading in the stock market is not unique. On the one hand, although they consistently lose money by trading with informed traders, noise traders provide the market with additional liquidity and reduce trading costs by increasing trading volume and market depth and reducing the price impact. On the other hand, noise trading generated by uninformed (noise) traders harms market efficiency because the uninformed traders' contrarian strategies keep prices from adjusting to new information when prices are far from their true values. However, their results also suggest that noise trading increases market efficiency when stock prices are not extreme because of the additional liquidity provided by noise trading.

Wang (2010) extends the model proposed by Kyle (1985) to analyze trading dynamics by including noise trading. The results of his dynamic model show that, although the noise imparted by noise trading eventually reduces the informativeness of prices, aggressive information trading by informed traders actually accelerates the integration of information into prices. Empirical evidence also suggests that greater noise trading resulting from more individual investor participation induces the informed trader to engage in more aggressive transactions and renders prices more informative (Ahn et al., 2014). Wang (2010) also indicates that market liquidity is enhanced (or, equivalently, the trading cost is lowered) due to aggressive noise trading from noise traders.

However, the effect of noise trading on trading costs remains a mystery. Bloomfield et al. (2009) do not clearly indicate that noise trading increases market efficiency by reducing trading costs. In our research, we focus on trading costs related to asymmetric information and to cluster trading.

The presence of noise traders trading with informed traders highly increases trading volume, provides greater market depth, reduces the price impact, and therefore reduces the influence of adverse selection. This effect is most obvious during the informational period, when the information asymmetry problem is most prevalent. Moreover, speculative noise trading provides informed traders with the camouflage necessary to conceal their information trading, which also reduces the adverse selection problem (Wang, 2010).

Foster and Viswanathan (1990) show that, because they are deterred by the trading costs resulting from adverse selection, uninformed traders (discretionary liquidity traders) do not actively participate in trading with informed traders. In our study, we do not characterize noise traders, who are mostly individual investors, as discretionary liquidity traders; the latter are mostly large traders, such as financial institutions, whose trades reflect their clients' need for liquidity or who trade for portfolio-balancing reasons (Admati and Pfleiderer, 1988). Therefore, as noise traders are not deterred by trading costs related to adverse selection, noise trading speeds information integration by reducing information asymmetry.

The presence of noise traders alleviates the illiquidity related to cluster trading by providing the market with additional liquidity in the non-informational period. Therefore, our fourth and fifth hypotheses are as follows:

Hypothesis 4. Noise trading has a positive effect on market efficiency by reducing the influence of information asymmetry on market efficiency.

Hypothesis 5. Noise trading has a positive effect on market efficiency by reducing the influence of illiquidity related to cluster trading on market efficiency.

4. Methods of analysis and data

4.1. Measure of information asymmetry and illiquidity related to cluster trading

The empirical evidence of Collin-Dufresne and Fos (2015) suggest that neither high-frequency measures (the Kyle lambda, the effective spread, the realized spread, etc.) nor low-frequency measures (Amihud (2002)] illiquidity, the daily bid-ask spread and the probability of informed trade [*pin*] introduced by Easley et al. (1996)]) correctly capture information asymmetry resulting from adverse selection because insiders make extensive use of limit orders, and they trade on days when liquidity is high (cluster trading). The traditional measures of trading costs related to information asymmetry are distorted by the abnormal trading volume that results from cluster trading.

Therefore, we use the adjusted-PIN model developed by Duarte and Young (2009), which takes into account information asymmetry and cluster trading at the same time, to calculate the levels of information asymmetry and illiquidity related to cluster trading. Their model specifies the structure of the trading process as follows. The probability that a private information event will occur during a particular period is α. When it occurs, the probability that an informed trader will receive a positive signal is δ. If the signal is positive, the arrival rate of buyer-initiated and seller-initiated order flow follows independent Poisson distributions with the intensity parameter $\varepsilon_b + \mu$ and ε_s, respectively. μ is the arrival rate of informed trades. ε_b and ε_s are the arrival rates of noise traders' buy and sell orders, respectively. The adjusted-PIN model accounts for the pervasive positive correlation between buys and sells by allowing a simultaneous increase in buy and sell orders on days with no private information (cluster trading). θ is the probability of such an increase. The additional arrival rate of both buys and sells is measured by Δ.

We estimate the parameters for each firm $\Theta = (\alpha, \delta, \mu, \varepsilon_b, \varepsilon_s, \theta, \Delta)$ using the maximum likelihood technique. The likelihood function is:

$$
\begin{aligned}
L(\Theta|B,S) = {} & (1-\alpha)(1-\theta)\left(e^{-\varepsilon b}\varepsilon_b^B/B!\right)\left(e^{-\varepsilon s}\varepsilon_s^S/S!\right) + \alpha\delta\left(e^{-(\mu+\varepsilon b)}(\mu+\varepsilon_b)^B/B!\right) \\
& \times \left(e^{-\varepsilon s}\varepsilon_s^S/S!\right) + \alpha(1-\delta)\left(e^{-\varepsilon b}\varepsilon_b^B/B!\right)\left(e^{-(\mu+\varepsilon s)}(\mu+\varepsilon_s)^S/S!\right) \\
& + (1-\alpha)\theta\left(e^{-(\Delta+\varepsilon b)}(\Delta+\varepsilon_b)^B/B!\right)\left(e^{-(\Delta+\varepsilon s)}(\Delta+\varepsilon_s)^S/S!\right)
\end{aligned}
\tag{1}
$$

where B and S are, respectively, the number of buyer- and seller-initiated trades for a given period. An adjusted-PIN (*AdjPIN*) measure and a PSOS (probability of symmetric order flow shock) measure are then calculated for each stock as follows:

$$AdjPIN = \alpha\mu/(\alpha\mu + 2(1-\alpha)\theta\Delta + \varepsilon_b + \varepsilon_s) \tag{2}$$

$$PSOS = 2(1-\alpha)\theta\Delta/(\alpha\mu + 2(1-\alpha)\theta\Delta + \varepsilon_b + \varepsilon_s) \tag{3}$$

According to Duarte and Young (2009), *AdjPIN* is a good proxy for the degree of information asymmetry, while *PSOS* measures illiquidity related to cluster trading. A larger *AdjPIN* indicates greater information asymmetry. A larger *PSOS* shows greater illiquidity related to cluster trading. We also construct our measure of noise trading as follows:

$$Noise = (\varepsilon_b + \varepsilon_s)/(\alpha\mu + 2(1-\alpha)\theta\Delta + \varepsilon_b + \varepsilon_s) \tag{4}$$

However, as *Noise* is closely correlated with *AdjPIN* and *PSOS*, we construct another measure of noise trading, *Accnum*, which is the quarterly average number of active trading accounts. In our study, *AdjPIN* and *PSOS* are estimated with data from different time intervals from one to 60 min in order to analyze their effect on market efficiency for different horizons. We have convergence for almost all the estimations, except those for 40- and 60-min intervals. Therefore, we have a slightly smaller sample size in our cross-sectional analysis for 40- and 60-min intervals. In Section 5, we do not present the results for 40- and 60-min intervals in some cases because they are qualitatively the same as the results for 30-min interval.

Although adjusted-PIN theory assumes that a market maker discovers information relevant to an asset price in a quote-driven market, its application in an order-driven market, such as the Chinese stock market, is also justified. Back and Baruch (2007) have proven the equivalence of the limit-order market and floor exchanges, such as the Chicago Board Options Exchange (CBOE), under suitable regularity assumptions. Kubota and Takehara (2009) estimate *PIN* in the electronic, order-driven market of the Tokyo Stock Exchange and claim that the limit orders, which are sent mainly by professional investors in large volumes, are proxies for the quotes sent by market makers. Gençay and Gradojevic (2013) estimate the intraday *PIN* using a hypothetical market maker in an electronic, order-driven market without established market makers. Moreover, the PIN model is also proven to be viable in the Chinese stock market with intraday data analysis (Copeland et al., 2009; Lai et al., 2014).

4.2. Methods of analysis

Griffin et al. (2010) show that empirical efficiency measures necessarily rely on partial information sets. A careful choice of market efficiency measures is crucial in market efficiency research. The information that gives investors the opportunity to earn greater returns is incorporated into prices by the trading of informed investors and is reflected in excess buying or excess selling pressure (abnormal order flow) (Cullen et al., 2010; Grossman and Stiglitz, 1980). Therefore, the imbalance in trading, which is a reflection of information, will push prices to reflect this information. The method proposed by Chordia and Subrahmanyam (2004) aims to measure market efficiency by analyzing the relation between stock returns and the lagged order imbalance, which makes it an appropriate method for our research purposes.

This study computes order imbalance and stock return measures for all stocks.[6] Following Chordia et al. (2008), we compute stock returns over 1-min intervals using the bid-ask midpoints quoted at the end of the intervals. This study computes the order imbalance for each 1-min interval *t*. The following model is used to assess the degree of market efficiency:

$$Return_t = \alpha + \beta_1 OrderImbalance_{t-1} + \beta_2(OrderImbalance_{t-1} {}^* ILD_t) + \varepsilon_t \tag{5}$$

where $Return_t$ is the stock midpoint return over the 1-min interval t, and $OrderImbalance_{t-1}$ is the order imbalance over the 1-min interval $t-1$. This study uses an *adjusted* R^2 as the primary measure of market efficiency throughout (Chordia et al., 2008; Chung and Hrazdil, 2010a). Following Chordia et al. (2008), we include the interaction variable $OrderImbalance_{t-1}$ and ILD_t to control for the effects of liquidity changes on market efficiency. We code the dummy variable ILD_t with a value of one for all intervals on a day if the value-weighted average effective spread for the day is at least one standard deviation above the mean spread calculated for a surrounding period (−60, +60), and zero otherwise.

Eq. (5) is estimated for each firm on a daily basis at 1-min intervals. The *adjusted* R^2 is collected from the estimation and used as the measure for market efficiency. In a multiple regression framework, the ways in which market efficiency is associated with each variable are examined. Thus:

$$\begin{aligned} Efficiency_i = {} & \alpha_i + \beta_1 Cap_i + \beta_2 Volatility_i + \beta_3 Volume_i + \beta_4 Insholding_i \\ & + \beta_5 Accnum_i + \beta_6 Noise_i + \beta_7 AdjPIN_i + \beta_8 PSOS_i + \varepsilon_i \end{aligned} \tag{6}$$

where $i = 1, 2, \ldots, n$, n is the total number of sample stocks. *Efficiency* is the market efficiency measure estimated on a firm-by-firm basis over the sample period. The logit transformation to the *Efficiency* variable is applied because the *adjusted* R^2 measure is bounded by zero and one. *Efficiency* is also rescaled by multiplying this variable by −1 so that, for ease of interpretation, higher values of *Efficiency* represent higher degrees of market efficiency. *Cap* is the winsorized average daily total capitalization at the 1% level in logarithm; *Volatility* is the standard deviation of daily returns; *Volume* is the winsorized average daily trading volume at the 1% level in logarithm; *Insholding* is the average previous year-end institutional holdings of each stock expressed as a percentage and is considered the proxy for institutional trading.[7] *Accnum*, *Noise*, *AdjPIN*, and *PSOS* are defined in Section 4.1. *Accnum* is also in logarithm.

Larger companies are usually considered to have a better informational environment and less information asymmetry. Thus, market capitalization is supposed to be positively related to market efficiency. The literature finds that market efficiency is associated with higher trading volumes (Visaltanachoti and Yang, 2010). Ross (1989), however, finds that volatility is directly related to the rate of information flow in the market. Research (Chakravarty, 2001; Sias et al., 2006) shows that, on average, institutional investors are better informed and that their information is incorporated into securities prices when they trade. More

[6] Chordia and Subrahmanyam (2004) argue that "the concept of order imbalance over an interval makes sense only in a paradigm of an intermediated market, wherein market makers accommodate buying and selling pressures from the general public" (p.486). The Chinese stock market is an electronic continuous auction market without market makers. Thus, the order imbalance method may not be applicable to the Chinese stock market; however, they also indicate that "order imbalances can signal excessive investor interest in a stock, and if this interest is autocorrelated, then order imbalances could be related to future returns" (p.486). Thus, the use of the order imbalance method is justified by this statement. Empirical findings verify the correlation between order imbalance and future stock returns (Narayan et al., 2015). The predictability of short-horizon return with order imbalance is also documented in other order-driven market (Yamamoto, 2012).

[7] Some of the sample stocks are for state-owned enterprises (SOE), in which a large proportion of nontradable shares are retained by the enterprises themselves or other SOEs and government institutions. In our sample period, some of these shares became tradable, which entails a sudden increase in the proportion of institutional holdings. However, these shares, which ensure that the majority of holdings are by the state (because these firms are "state owned"), are not actively traded and distort our measure of institutional trading. Chen et al. (2007) balance the costs and benefits of institutional ownership and indicate that long-term investments, such as the corporate holdings of SOEs and government institutions in our case, specialize in monitoring rather than trading. Their holdings enhance the quality of company management, instead of influencing price efficiency by trading actively on information. Therefore, we omit these shares from total institutional trading. *Insholding* represents all institutional holdings—including mutual funds, securities firms, QFII (qualified foreign institutional investors), insurance companies, social security funds, trust companies, banks, and private funds—except general corporate holdings.

Table 1
Summary statistics.

	Efficiency	Cap	Volatility	Volume	Insholding	Accnum
Sample	338	338	338	338	338	338
Mean	2.6731	54.70	0.0442	577.00	6.9543	93,624
Median	2.3112	8.94	0.0449	275.00	3.1057	41,549
SD	0.8664	204.00	0.0064	1020.00	10.7696	161,665
Min	1.4721	2.49	0.0244	74.80	0.0000	4116
1st quantile	1.9324	5.27	0.0404	168.00	1.1160	24,461
3rd quantile	3.3595	24.30	0.0485	529.00	8.2997	86,316
Max	6.0000	1980.00	0.0613	10,100.00	94.4038	1,281,926

Notes: The sample period covers all of 2013, 2014, and 2015. The sample comprises 338 stocks from the Chinese stock market. *Efficiency* is defined in Section 4.2, *Cap* is the average daily total capitalization in billions of RMB, *Volatility* is the standard deviation of daily returns, *Volume* is the average daily trading volume in millions of RMB, *Insholding* is the average previous year-end institutional holdings of each stock expressed as a percentage, *Accnum* is the quarterly average number of active trading accounts.

Table 2
Correlation matrix.

	Efficiency	Cap	Volatility	Volume	Insholding	Accnum	Noise	AdjPIN	PSOS
Efficiency	1	0.2266*	0.0028	0.2381*	0.1699*	0.2335*	0.1707*	−0.0744	−0.1515*
Cap	0.1421*	1	−0.3002*	0.8002*	0.2460*	0.6426*	0.5539*	−0.1765*	−0.6172*
Volatility	0.0519	−0.2322*	1	−0.0469	−0.0353	−0.2522*	−0.2477*	−0.0049	0.4065*
Volume	0.1314*	0.7566*	0.0048	1	0.1279*	0.7968*	0.6225*	−0.1943*	−0.5916*
Insholding	0.1578*	0.3481*	−0.0716*	0.2125*	1	−0.0763*	0.1443*	−0.0688	−0.121
Accnum	0.1349*	0.5614*	−0.2302*	0.7554*	−0.0636*	1	0.5085*	−0.0229	−0.5596*
Noise	0.1601*	0.5044*	−0.2797*	0.5406*	0.1492*	0.4824*	1	−0.4487*	−0.8155*
AdjPIN	−0.1111*	−0.1777*	−0.0035	−0.2275*	−0.0495	−0.0905	−0.4564*	1	0.2436*
PSOS	−0.1264*	−0.5790*	0.4126*	−0.5194*	−0.1921*	−0.5292*	−0.8253*	0.3030*	1

Notes: This table shows the correlation matrix of the regression variables. The sample period covers all of 2013, 2014, and 2015. * Pearson (above diagonal) and Spearman (below diagonal) correlations that are significant at the 1% level.

institutional trading means less noisy trading and greater market efficiency. Based on our analysis, we expect to find that *Cap*, *Volatility*, *Volume*, and *Insholding* are positively related to market efficiency, and so they are included as control variables.

4.3. Data

This study obtains tick data from the China Stock Market and Accounting Research (CSMAR) research database from 2013 to 2015. All A-shares trading in the SHSE and the SZSE is examined. To be included in the sample, stocks have to meet the following criteria:

- They must have been normally traded in each sample year;
- The initial public offering must have been before January 1, 2013; and
- They must have had at least 242 trading days in each sample year.

If there are any stock splits, reverse splits, stock dividends, repurchases, or a secondary offering, the stock is deleted from the sample.

The final sample includes 338 stocks from both exchanges. Every transaction is assigned using the Lee and Ready (1991) trade assignment algorithm to estimate whether it is initiated by the buyer or the seller. Any quote less than 5 s prior to the trade is ignored, and the first quote at least 5 s prior to the trade is retained. A trade is classified as initiated by the buyer (seller) if it is closer to the ask (bid) price of the prevailing quote. If the trade is exactly at the midpoint of the quote, a "tick test" is used in which the trade is classified as initiated by the buyer (seller) if the last price change prior to the trade is positive (negative).

To avoid contamination of the return serial correlations by bid-ask bounce, returns are computed from quote midpoints (Chordia et al., 2005). For each transaction during each day, the prevailing quote before the trade is used to compute a bid-ask midpoint. Returns are then computed from these midpoints.

Trades indicated as either buyer- or seller-initiated are used as indicators to calculate the imbalance measures in three ways. The first is based on the number of the trade (OIBNUM), the second on the share of the trade (OIBSHR), and the third based on the renminbi (RMB) value of the trade (OIBVAL). Following the work of Chung and Hrazdil (2012) and Visaltanachoti and Yang (2010), OIBNUM for each stock is calculated for 1-min intervals.[8]

5. Empirical results

5.1. Summary statistics

Table 1 provides comparable descriptive statistics of the regression variables for the stocks in the entire sample. The data are obtained from the Wind financial database.

The medians of *Cap*, *Volume*, and *Accnum* are much smaller than their means, so these variables are transformed (winsorized and/or taking the logarithm) for a better fit in our regressions.

Table 2 reports the Pearson and Spearman correlations among the tested variables.

Consistent with our expectations, *Efficiency* is significantly and positively correlated with *Cap*, *Volume*, *Insholding*, *Accnum*, and *Noise* and negatively correlated with *AdjPIN* and *PSOS*. Its correlation with *Volatility* is not significant. The trading costs related to asymmetric information (*AdjPIN*) and cluster trading (*PSOS*) slow the speed of information integration. However, the noise trading (*Accnum*, *Noise*) actually accelerates this integration. Certain variables are significantly correlated. Noise trading (*Accnum*, *Noise*) is highly positively correlated with the trading volume (*Volume*), in accordance with the notion that noise trading greatly increases trading volume as well as liquidity in the market (Bloomfield et al., 2009). Moreover, noise trading (*Accnum*, *Noise*) is highly negatively significantly related to the trading cost (*AdjPIN*, *PSOS*),

[8] OIBNUM is the estimated number of buyer-initiated trades minus seller-initiated trades divided by the total number of trades for the time interval.

Table 3
Estimated *AdjPIN*, *PSOS*, and *Noise* in different intervals.

		1 min.	2 min.	3 min.	5 min.	10 min.	15 min.	20 min.	30 min.	40 min.	60 min.
AdjPIN	Min	0.0000	0.0000	0.0000	0.0000	0.0005	0.0003	0.0169	0.0000	0.0001	0.0000
	Mean	0.1231	0.1585	0.1516	0.1389	0.1178	0.1142	0.1044	0.0987	0.0937	0.0871
	Max	0.4485	0.3083	0.2909	0.2535	0.3054	0.2793	0.2777	0.2711	0.2146	0.2029
PSOS	Min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Mean	0.0686	0.1244	0.1369	0.1473	0.1462	0.1432	0.1432	0.1342	0.1307	0.1219
	Max	0.3433	0.3802	0.3935	0.3275	0.3788	0.4113	0.4354	0.4168	0.3996	0.4881
Noise	Min	0.5029	0.5004	0.4920	0.5403	0.4655	0.5298	0.5225	0.5387	0.5680	0.4965
	Mean	0.8083	0.7171	0.7115	0.7138	0.7360	0.7425	0.7524	0.7671	0.7756	0.7910
	Max	1.0000	1.0000	1.0000	1.0000	0.9935	0.9762	0.9699	0.9626	0.9599	0.9678

Notes: This table reports the estimated *AdjPIN*, *PSOS*, and *Noise* with the data in different intervals from one to 60 min. For example, "1 min." reports the minimum, mean, and maximum of *AdjPIN*, *PSOS*, and *Noise* estimated with the data of 1-min intervals.

Table 4
Multivariate regression: Effect of AdjPIN on market efficiency.

N	1 min.	2 min.	3 min.	5 min.	10 min.	15 min.	20 min.	30 min.
	338	338	338	338	338	338	338	338
Intercept	−4.4169***	−4.4603***	−4.7881***	−4.5554***	−4.7806***	−4.4272***	−4.5740***	−4.4988***
	(-3.08)	(-3.14)	(-3.34)	(-3.23)	(-3.34)	(-3.14)	(-3.15)	(-3.20)
Cap	0.2069**	0.2074**	0.1962**	0.2005**	0.1907**	0.2098**	0.2053**	0.2036**
	(2.30)	(2.30)	(2.17)	(2.19)	(2.08)	(2.27)	(2.28)	(2.22)
Volatility	28.50***	28.65***	28.75***	28.71***	28.98***	28.60***	29.00***	28.67***
	(2.95)	(2.94)	(3.00)	(2.99)	(3.02)	(2.98)	(2.99)	(2.99)
Volume	0.0482	0.0491	0.0730	0.0591	0.07780	0.04556	0.05478	0.05434
	(0.48)	(0.48)	(0.70)	(0.56)	(0.73)	(0.43)	(0.53)	(0.52)
Insholding	0.0113***	0.0113***	0.0113***	0.0113***	0.0111**	0.0113***	0.0112***	0.0113***
	(2.63)	(2.63)	(2.62)	(2.63)	(2.59)	(2.64)	(2.61)	(2.62)
AdjPIN	−1.0644***	−1.4723**	−0.0461	−1.4575*	−1.2961	−0.5708	−0.5550	0.5982
	(-3.02)	(-2.23)	(-0.07)	(-1.75)	(-1.34)	(-0.57)	(-0.54)	(0.54)
Adj. R^2	0.0861	0.0861	0.0884	0.0865	0.0883	0.0861	0.0863	0.0862

Notes: This table reports the regression results in Eq. (6) with *AdjPIN* estimated with the data of different time intervals. *Cap* is the winsorized average daily total capitalization at the 1% level in billions of RMB in logarithm, *Volatility* is the standard deviation of daily returns, *Volume* is the winsorized average daily trading volume at the 1% level in millions of RMB in logarithm, *Insholding* is the average previous year-end institutional holdings of each stock expressed as a percentage, *AdjPIN* is defined in Section 4.1. *, **, and *** significance at the 10%, 5%, and 1% levels, respectively. *AdjPIN* estimated with the data of different time intervals are used in the regressions. For example, "1 min." reports the regression results with *AdjPIN* estimated with the data of 1-min intervals.

which is also consistent with Bloomfield et al. (2009), who argue that noise trading significantly lowers the trading cost. Noise trading (*Accnum*, *Noise*) reduces the trading cost related to cluster trading (*PSOS*), as evidenced by their negative correlation. Noise trading (*Noise*) also reduces the trading cost related to asymmetric information (*AdjPIN*). However, the correlation between *Accnum* and *AdjPIN* is not significant.

5.2. Do AdjPIN and PSOS affect market efficiency?

AdjPIN and *PSOS* are estimated with the data of buyer-initiated trades and seller-initiated trades in different time intervals from one to 60 min. The estimated *AdjPIN* and *PSOS* corresponding to different time intervals measure the levels of information asymmetry and illiquidity related to cluster trading in different time intervals respectively. We expect to find that the *AdjPIN* estimated for short time intervals are greater than those estimated for long time intervals because the information asymmetry is reduced as the information is gradually integrated into the price over time. We also expect to find that *PSOS* does not change significantly with different time intervals as the integration of information does not solve the problem of cluster trading. A brief statistical summary of estimated *AdjPIN* and *PSOS* for different time intervals is provided in Table 3.

Consistent with Lai et al. (2014), *AdjPIN* mean is lower than the level in the US stock market, which is caused by the prevalent noise trading. The average of *PSOS* is a little higher than it is in the US stock market. Information asymmetry (*AdjPIN*) is most important at 2-min intervals, and its importance decreases sharply with increasing time intervals. At 60-min intervals, the average *AdjPIN* decreases about 50%. This is consistent with our expectations. Cluster trading (*PSOS*) remain stable across almost all the intervals except 1-min interval, in which *AdjPIN* and *PSOS* are comparatively low and the level of noise trading (*Noise*) is the highest among all the time intervals.

We include the *AdjPIN* and *PSOS* estimated in different time intervals in our regression in Eq. (6). See Tables 4 and 5 for the results.

Tables 4 and 5 show that the coefficients of *Volatility* are positively significant, indicating that the more volatile the price, which reflects a larger amount of incoming information, the more efficient the market. However, trading volume has a marginal effect on market efficiency. This is the opposite of the relationship demonstrated by the correlation coefficient between *Volume* and *Efficiency* in Table 2. Therefore, the driving force of *Volume* with market efficiency is its high correlation with market capitalization. High market capitalization (*Cap*) related with high trading volume increases market efficiency, and high market capitalization mean less information asymmetry in the Chinese stock market. The coefficients of *Insholding* are significant indicating higher market efficiency with more institutional trading.

The most interesting findings relate to the coefficients of *AdjPIN* and *PSOS*. The coefficients of *AdjPIN* are negatively significant for 1- and 2-min intervals and are not significant for 3-min intervals and beyond. This result shows that information asymmetry indeed negatively affects market efficiency, which is consistent with our H1. However, information asymmetry has an impact on market efficiency in a very short period of time. Because information is gradually integrated into prices, the information asymmetry decreases, which reduces its own impact on market efficiency. When the impact of information asymmetry decreases, cluster trading becomes the dominant force that influences market efficiency, which is evidenced by the negatively significant coefficients of *PSOS* for 2-min intervals and beyond. This is consistent with our H2. Over a long period of time, with information gradually integrated into prices and

Table 5
Multivariate regression: Effect of PSOS on market efficiency.

N	1 min.	2 min.	3 min.	5 min.	10 min.	15 min.	20 min.	30 min.
	338	338	338	338	338	338	338	338
Intercept	−4.4037***	−4.1171***	−3.5751**	−4.1098**	−4.4298**	−6.3711***	−4.8561***	−5.8110***
	(-3.11)	(-2.62)	(-2.18)	(-2.33)	(-2.50)	(-3.51)	(-2.87)	(-3.36)
Cap	0.2070**	0.2022**	0.1902**	0.2003**	0.2073**	0.2452***	0.2130**	0.2342**
	(2.31)	(2.24)	(2.09)	(2.16)	(2.26)	(2.66)	(2.35)	(2.56)
Volatility	28.87***	29.25***	29.65***	28.98***	28.63***	26.81***	27.70***	27.30***
	(2.96)	(3.01)	(3.08)	(3.00)	(2.93)	(2.79)	(2.82)	(2.84)
Volume	0.0466	0.0382	0.0264	0.0408	0.0480	0.0975	0.0628	0.0833
	(0.46)	(0.37)	(0.26)	(0.39)	(0.45)	(0.93)	(0.59)	(0.80)
Insholding	0.01134***	0.01136***	0.01137***	0.01131***	0.01132***	0.01125***	0.01144***	0.01164***
	(2.64)	(2.64)	(2.65)	(2.63)	(2.63)	(2.63)	(2.66)	(2.71)
PSOS	-.7914	−1.4633***	−1.8037***	−1.8777***	−1.8184***	−1.1862**	−1.4962***	−1.1557**
	(-1.47)	(-2.98)	(-3.70)	(-3.52)	(-3.33)	(-2.27)	(-2.76)	(-2.20)
Adj. R^2	0.0861	0.0866	0.0888	0.0864	0.0861	0.0933	0.0866	0.0908

Notes: This table reports the regression results in Eq. (6) with *PSOS* estimated with the data of different time intervals. *Cap* is the winsorized average daily total capitalization at the 1% level in billions of RMB in logarithm, *Volatility* is the standard deviation of daily returns, *Volume* is the winsorized average daily trading volume at the 1% level in millions of RMB in logarithm, *Insholding* is the average previous year-end institutional holdings of each stock expressed as a percentage, *AdjPIN* is defined in Section 4.1. *, **, and *** significance at the 10%, 5%, and 1% levels, respectively. *PSOS* estimated with the data of different time intervals are used in the regressions. For example, "1 min." reports the regression results with *PSOS* estimated with the data of 1-min intervals.

trading intensity decreasing, the illiquidity related to cluster trading rises and becomes the dominant force that affects market efficiency.

5.3. Different trading strategies: effects of AdjPIN and PSOS on market efficiency

Based on the adjusted-PIN model, we classify each 1-min trading interval in our sample period into either an informational interval or a non-informational interval and obtain a market efficiency estimate that relates to trading in each of the two types of intervals. We rely on the trading model of Easley et al. (1996) and apply the posterior probability approach in Easley et al. (1998) to classify the trading intervals.[9] After the type of intervals is identified, the regressions in Eq. (5) are run with the data for each type of interval. We also calculate the *adjusted* R^2 as a measure of market efficiency for each stock. Thus, we obtain two measures of market efficiency related to the informational interval and non-informational interval, *Efficiency_news* and *Efficiency_nonews*, respectively. We rerun the regressions in Eq. (6) by replacing the dependent variable with these two new measures of efficiency, and the results are in Table 6.

To save space, we only present the results of 2-, 5-, 10-, 15-, 20- and 30-min intervals. The results of other intervals are available from the authors upon request. The coefficients of *Cap* are not significant for informational intervals and are marginally positive for non-informational intervals. The coefficient of *Volatility* are significant for informational intervals and are not significant for non-informational intervals, which is consistent with the notion that volatility is directly related to the rate of information flow. The coefficients of *Volume* for informational intervals are significantly negative, indicating that the trading volume is not information-related. This is not consistent with the finding in the US stock market. However, this result may be due to the prevalence of noise trading in the Chinese stock market, which needs further investigation. The coefficients of *Insholding* remain insignificant for both intervals. The significantly positive coefficients of *Accnum* for non-informational intervals provide supportive evidences to our argument on the positive effect of noise trading on market efficiency by reducing the illiquidity related to cluster trading, which we will further discuss in Section 5.4.

For informational intervals in which new information comes into the market, the coefficients of *AdjPIN* are steady and negatively significant across short time intervals, which means that information asymmetry is a key factor affecting market efficiency when there is incoming information. This is consistent with our H3. For non-informational intervals in which no new information comes into the market, the coefficients of *AdjPIN* are insignificant across all time intervals. The results provide supportive evidence on the information-motivation model, in which informed traders compete to exploit their information advantage. Their concentrated trading leads to a high level of trading cost related to information asymmetry.

The results on the relationship of *PSOS* with *Efficiency_news* and *Efficiency_nonews* demonstrate the opposite phenomenon (see Table 7). For informational periods, the coefficients of *PSOS* are positively significant. This is consistent with our analysis that the trading is concentrated and intensive while information is coming into the market, which increases the speed of information integration. The postponement of trading to informational periods when the trading volume is much higher and trading costs are much lower actually further increases information integration in the informational period. Therefore, the more obvious the cluster trading is, the more rapid the information integration is. During non-informational periods in which no new information is coming into the market, the coefficients of *PSOS* are negatively significant across all time intervals, indicating that the illiquidity that results from the less intensive trading is always the main force that slows the speed of information integration, which is consistent with H3. The results also provide supportive evidence for the liquidity-motivation model, in which the traders balance between trading immediately, involving a high price impact and trading costs, and trading postponed to a later time when liquidity is improved.

This investor trading strategy is not unique in the stock market. They always balance gains from trading on information against losses from trading costs. Although the information is still of great value, the investors choose to speed their trading to materialize the gain by increasing trading volume and bearing the corresponding trading cost. As the information is gradually integrated into prices, the investor postpones trading for various reasons (e.g., portfolio rebalancing) to avoid high trading costs.

5.4. Through which channel does noise trading affect market efficiency, AdjPIN or PSOS?

We analyze the relationship between noise trading (*Accnum*, *Noise*) and information asymmetry (*AdjPIN*) and cluster trading (*PSOS*),

[9] In the application of the posterior probability approach, we follow Chung and Hrazdil (2012) and Easley et al. (1998) in setting a cut-off rate of 80% for classifying trading intervals into an "informational interval" or a "non-informational interval." If the 80% cut-off rate is not met for some trading intervals, they are not classified.

Table 6
Multivariate regression: Effect of *AdjPIN* on Efficiency_news and Efficiency_nonews.

N	2 min.	5 min.	10 min.	15 min.	20 min.	30 min.
	338	338	338	338	338	338
Dependent variable: *Efficiency_news*						
Intercept	1.6101	1.7909*	1.6449	1.8510*	1.7189	1.7177*
	(1.52)	(1.72)	(1.56)	(1.79)	(1.62)	(1.66)
Cap	0.0961	0.1022	0.0948	0.1077*	0.0997	0.0968
	(1.54)	(1.62)	(1.50)	(1.69)	(1.61)	(1.53)
Volatility	20.82***	20.37***	20.43***	20.43***	20.53***	20.42***
	(2.99)	(2.94)	(2.95)	(2.95)	(2.94)	(2.95)
Volume	−0.1889*	−0.2048**	−0.1902*	−0.2130**	−0.1996**	−0.1960**
	(-1.94)	(-2.10)	(-1.93)	(-2.18)	(-2.09)	(-2.02)
Insholding	−0.0009	−0.0010	−0.0011	−0.0009	−0.0010	−0.0010
	(-0.30)	(-0.31)	(-0.35)	(-0.31)	(-0.33)	(-0.33)
AdjPIN	−1.0470**	−1.1479**	−1.0592*	−0.0702	−0.2531	0.0137
	(-2.38)	(-2.10)	(-1.68)	(-0.11)	(-0.38)	(0.02)
Accnum	0.0553	0.0616	0.0590	0.0621	0.0611	0.0604
	(0.90)	(1.01)	(0.97)	(1.02)	(1.00)	(0.99)
Adj. R^2	0.0548	0.0539	0.0544	0.0545	0.0539	0.0541
Dependent variable: *Efficiency_nonews*						
Intercept	−1.0493	−1.2599	−1.3728	−1.0709	−1.2988	−1.1994
	(-1.01)	(-1.22)	(-1.31)	(-1.04)	(-1.22)	(-1.17)
Cap	0.1360**	0.1287*	0.1231*	0.1451**	0.1286*	0.1336**
	(2.06)	(1.92)	(1.84)	(2.15)	(1.95)	(1.99)
Volatility	11.88*	12.94*	13.08*	12.97*	13.10*	12.86*
	(1.67)	(1.84)	(1.86)	(1.85)	(1.84)	(1.83)
Volume	−0.0031	0.0097	0.0196	−0.0137	0.0110	0.0027
	(-0.04)	(0.13)	(0.25)	(-0.18)	(0.15)	(0.03)
Insholding	0.0048	0.0050	0.0050	0.0051	0.0050	0.0051
	(1.53)	(1.60)	(1.58)	(1.62)	(1.59)	(1.62)
AdjPIN	−1.0413*	−0.4597	−0.8696	0.3384	−0.2684	0.9887
	(-1.91)	(-0.68)	(-1.11)	(0.42)	(-0.33)	(1.13)
Accnum	0.2859***	0.2696***	0.2677***	0.2711***	0.2685***	0.2695***
	(4.47)	(4.24)	(4.21)	(4.29)	(4.24)	(4.25)
Adj. R^2	0.0954	0.0884	0.0883	0.0917	0.0883	0.0888

Notes: This table reports the regression results in Eq. (6) with *PSOS* estimated with the data of different time intervals. *Efficiency_news* is the efficiency measure obtained based on the data from the information interval, *Efficiency_nonews* is the efficiency measure obtained based on the data from the non-information interval, *Cap* is the winsorized average daily total capitalization at the 1% level in billions of RMB in logarithm, *Volatility* is the standard deviation of daily returns, *Volume* is the winsorized average daily trading volume at the 1% level in millions of RMB in logarithm, *Insholding* is the average previous year-end institutional holdings of each stock expressed as a percentage, *AdjPIN* and *Accnum* are defined in Section 4.1. *Accnum* is also in logarithm. *, **, and *** significance at the 10%, 5%, and 1% levels, respectively.

respectively. We run the following regression:

$$\begin{aligned} Illiquidity_i = \alpha_i + \beta_1 Cap_i + \beta_2 Volatility_i + \beta_3 Volume_i + \beta_4 Insholding_i \\ + \beta_5 Accnum_i + \beta_6 Noise_i + \beta_7 SHSZ_i + \varepsilon_i \end{aligned} \quad (7)$$

Illiquidity is *AdjPIN* or *PSOS* estimated with the data of 1-min intervals. *Noise* is defined in Section 4.1 and is estimated with the data of 1-min intervals. The other explanatory variables are defined in Section 4.2. The results are in Table 8.

Table 8 shows that the relationship between noise trading and information asymmetry is not stable.[10] When the dependent variable is *AdjPIN*, the coefficients of noise trading (*Accnum*) are not stably significant, depending on whether we control for trading volume. Therefore, the effect of noise trading on *AdjPIN* is through trading volume, which is the driving force in this case. However, the coefficients of noise trading (*Accnum*) when the dependent variable is *PSOS* are all negatively significant. It clearly shows a stable negative relation between noise trading and the illiquidity related to cluster trading. Therefore, noise trading increases market efficiency by reducing the illiquidity related to cluster trading. Noise trading provides the market with additional liquidity when it is low and liquidity providers are scarce, which facilitates information integration. This result is consistent with the evidence of correlation matrix. The correlation between noise trading (*Accnum*) and information asymmetry (*AdjPIN*) is not significant, while noise trading (*Accnum*, *Noise*) and cluster trading (*PSOS*) are highly negatively correlated.

Our conclusions are further corroborated in the multivariate regressions in Eq. (6).

Unlike in the multivariate regressions in Section 5.2., here we add noise trading (*Accnum*, *Noise*) to control for its effect on information asymmetry (*AdjPIN*) and cluster trading (*PSOS*).[11] Table 9 shows that when we control for noise trading, the coefficients of *AdjPIN* are the almost the same as they are without noise trading. This is clearly evidence that noise trading does not influence market efficiency because it alleviates information asymmetry.

In contrast to the results in Table 9, when we replace *AdjPIN* with *PSOS*, the results in Table 10 clearly show that the coefficients of *PSOS* are affected by *Accnum*. When we control for noise trading in the regressions, the coefficients of *PSOS* all become insignificant. This is strong evidence that noise trading affects market efficiency by reducing the illiquidity related to cluster trading, which is consistent with our H5.

Bloomfield et al. (2009) argue that noise trading has a positive effect on market efficiency by enhancing market liquidity and reducing trading costs. Our empirical results are consistent with their arguments and provide further evidence on the specific channel through which noise trading affects market efficiency. The additional liquidity provided by noise traders greatly alleviates the problem of illiquidity related to cluster trading when informed trading and liquidity trading are both less

[10] We present only the results of regressions with *Accnum*. The results of regressions with *Noise* are almost the same and are available from the author upon request.

[11] We present only the results of regressions with *Accnum*. The results of regressions with *Noise* are almost the same and are available from the author upon request.

Table 7
Multivariate regression: Effect of *PSOS* on Efficiency_news and Efficiency_nonews.

N	2 min.	5 min.	10 min.	15 min.	20 min.	30 min.
	338	338	338	338	338	338
Dependent variable: *Efficiency_news*						
Intercept	0.5495	−0.09756	0.1548	−0.2264	0.1660	−0.2942
	(0.51)	(-0.08)	(0.13)	(-0.18)	(0.14)	(-0.25)
Cap	0.1089*	0.1274**	0.1171*	0.1266**	0.1110*	0.1278**
	(1.76)	(2.02)	(1.87)	(2.01)	(1.80)	(2.05)
Volatility	16.57**	16.54**	16.19**	16.72**	15.50**	16.61**
	(2.50)	(2.51)	(2.43)	(2.54)	(2.31)	(2.53)
Volume	−0.1115	−0.1035	−0.1023	−0.0963	−0.0945	−0.0945
	(-1.57)	(-1.46)	(-1.41)	(-1.34)	(-1.30)	(-1.33)
Insholding	−0.0019	−0.0017	−0.0016	−0.0018	−0.0014	−0.0014
	(-0.64)	(-0.60)	(-0.56)	(-0.63)	(-0.49)	(-0.48)
PSOS	0.6545*	0.9731**	0.8304	0.9814**	0.8860*	1.0987**
	(1.67)	(2.02)	(1.65)	(2.01)	(1.86)	(2.39)
Adj. R^2	0.0320	0.0357	0.0318	0.0356	0.0340	0.0403
Dependent variable: *Efficiency_nonews*						
Intercept	−1.0661	−1.0934	−1.2401	−2.7078**	−1.5435	−1.5145
	(-0.93)	(-0.85)	(-0.96)	(-2.04)	(-1.25)	(-1.19)
Cap	0.1266*	0.1263*	0.1295*	0.1581**	0.1335**	0.1348**
	(1.91)	(1.86)	(1.93)	(2.35)	(2.02)	(2.01)
Volatility	13.28*	13.10*	12.94*	11.57	12.27*	12.67*
	(1.87)	(1.85)	(1.81)	(1.64)	(1.71)	(1.79)
Volume	0.0028	0.0049	0.0082	0.0457	0.0188	0.0152
	(0.04)	(0.064)	(0.11)	(0.59)	(0.24)	(0.20)
Insholding	0.0051	0.0050	0.0050	0.0050	0.0051	0.0051
	(1.61)	(1.60)	(1.60)	(1.60)	(1.63)	(1.62)
PSOS	−0.7953**	−1.0153***	−0.9888**	−0.5213	−0.7790**	−0.8065**
	(-2.23)	(-2.62)	(-2.50)	(-1.38)	(-1.98)	(-2.13)
Adj. R^2	0.0562	0.0560	0.0559	0.0639	0.0564	0.0562

Notes: *Efficiency_news* is the efficiency measure obtained based on the data from the information interval, *Efficiency_nonews* is the efficiency measure obtained based on the data from the non-information interval, *Cap* is the winsorized average daily total capitalization at the 1% level in billions of RMB in logarithm, *Volatility* is the standard deviation of daily returns, *Volume* is the winsorized average daily trading volume at the 1% level in millions of RMB in logarithm, *Insholding* is the average previous year-end institutional holdings of each stock expressed as a percentage, *PSOS* and *Accnum* are defined in Section 4.1. *Accnum* is also in logarithm. *, **, and *** significance at the 10%, 5%, and 1% levels, respectively.

Table 8
Multivariate regression: Effect of noise trading on AdjPIN and PSOS.

N	Dependent variable: *AdjPIN*				Dependent variable: *PSOS*			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	338	338	338	338	338	338	338	338
Intercept	0.5374***	0.4024***	0.6440***	0.3198***	0.4268***	0.4202***	0.3631***	0.2308***
	(5.07)	(3.83)	(6.63)	(5.89)	(2.86)	(2.94)	(2.68)	(3.11)
Cap	0.0155**	−0.0045			−0.0093	−0.0103		
	(2.42)	(-0.92)			(-1.03)	(-1.55)		
Volatility	−1.5268**	−3.1233***	−2.5902***	−2.8602***	2.4501**	2.3723***	3.0854***	2.9752***
	(-2.12)	(-4.81)	(-4.51)	(-4.91)	(2.42)	(2.68)	(3.85)	(3.73)
Volume	−0.0451***		−0.0290***		−0.0022		−0.0118	
	(-4.59)		(-3.98)		(-0.16)		(-1.16)	
Insholding	−0.0002	−0.0005	−0.0002	−0.0005*	−0.0001	−0.0007	−0.0008	−0.0002
	(-0.69)	(-1.48)	(-0.57)	(-1.75)	(-0.13)	(-0.16)	(-0.18)	(-0.53)
Accnum	0.0198***	0.0001	0.0184***	−0.0029	−0.0192**	−0.0202***	−0.0184**	−0.0271***
	(3.13)	(0.02)	(2.90)	(-0.82)	(-2.16)	(-3.08)	(-2.07)	(-5.64)
Adj. R^2	0.1178	0.0647	0.1049	0.0651	0.1958	0.1957	0.1932	0.1899

Notes: This table reports the regression results in Eq. (7) when the dependent variable is *AdjPIN* and *PSOS*, respectively. *Cap* is the winsorized average daily total capitalization at the 1% level in billions of RMB in logarithm, *Volatility* is the standard deviation of daily returns, *Volume* is the winsorized average daily trading volume at the 1% level in millions of RMB in logarithm, *Insholding* is the average previous year-end institutional holdings of each stock expressed as a percentage, *Accnum* and *Noise* are defined in Section 4.1. *Accnum* is also in logarithm. *, **, and *** significance at the 10%, 5%, and 1% levels, respectively.

intensive, which accelerates information integration.

However, noise trading does not seem to help reduce trading costs associated with information asymmetry. The possible explanations are as follows. First, based on our results in Table 3, the noise trading level is lowest at 3-min intervals and increases as the time interval becomes longer. We do not have direct evidence that informed trading deters the participation of noise traders. However, the noise trading level is effectively low while informed trading is concentrated and information asymmetry is prevalent. Deterred by the uncertainty related to informed trading, noise traders do not actively participate in trading immediately after new information first comes into the market. While the new information is gradually integrated into the price, noise traders begin to trade more actively. Second, informed trading is concentrated in informational periods, during which discretionary liquidity trading is also intensive (Admati and Pfleiderer, 1988). Therefore, as indicated by Collin-Dufresne and Fos (2015), the traditional measures of information asymmetry are distorted by the additional liquidity, and the effect of noise trading on market liquidity is also overwhelmed by the intensive trading

Table 9
Multivariate regression: Effect of noise trading on AdjPIN.

N	1 min.	2 min.	3 min.	5 min.	10 min.	15 min.	20 min.	30 min.
	338	338	338	338	338	338	338	338
Intercept	−2.5572	−2.7953*	−3.1997**	−3.0345**	−3.2591**	−2.9239*	−3.1078**	−3.0048**
	(-1.64)	(-1.83)	(-2.08)	(-2.02)	(-2.14)	(-1.95)	(-2.03)	(-2.02)
Cap	0.2255**	0.2357***	0.2236**	0.2269**	0.2169**	0.2349**	0.2279**	0.2283**
	(2.53)	(2.62)	(2.48)	(2.49)	(2.38)	(2.56)	(2.55)	(2.51)
Volatility	36.91***	36.67***	37.02***	37.20***	37.31***	37.22***	37.62***	37.21***
	(3.70)	(3.65)	(3.70)	(3.72)	(3.74)	(3.72)	(3.73)	(3.72)
Volume	−0.2312*	−0.2236	−0.1878	−0.2020	−0.1809	−0.2152	−0.2018	−0.2049
	(-1.66)	(-1.59)	(-1.32)	(-1.44)	(-1.27)	(-1.53)	(-1.46)	(-1.47)
Insholding	0.0147***	0.0145***	0.0145***	0.0146***	0.0144***	0.0146***	0.0145***	0.0146***
	(3.33)	(3.29)	(3.27)	(3.30)	(3.25)	(3.31)	(3.28)	(3.29)
AdjPIN	−1.0187***	−1.3420**	0.4167	0.2050	0.8887	−0.2642	0.4043	0.1375
	(-2.75)	(-1.96)	(0.49)	(0.18)	(0.69)	(-0.20)	(0.30)	(0.11)
Accnum	0.2628***	0.2507***	0.2369***	0.2428***	0.2392***	0.2446***	0.2441***	0.2436***
	(2.90)	(2.81)	(2.66)	(2.76)	(2.72)	(2.78)	(2.78)	(2.77)
Adj. R^2	0.1060	0.1047	0.1048	0.1043	0.1055	0.1043	0.1044	0.1042

Notes: This table reports the regression results in Eq. (6) with *AdjPIN* estimated with the data of different time intervals. *Cap* is the winsorized average daily total capitalization at the 1% level in billions of RMB in logarithm, *Volatility* is the standard deviation of daily returns, *Volume* is the winsorized average daily trading volume at the 1% level in millions of RMB in logarithm, *Insholding* is the average previous year-end institutional holdings of each stock expressed as a percentage, *AdjPIN* and *Accnum* are defined in Section 4.1. *Accnum* is also in logarithm. *, **, and *** significance at the 10%, 5%, and 1% levels, respectively.

Table 10
Multivariate regression: Effect of noise trading on PSOS.

N	1 min.	2 min.	3 min.	5 min.	10 min.	15 min.	20 min.	30 min.
	338	338	338	338	338	338	338	338
Intercept	−3.0162**	−2.8077*	−2.2823	−2.6942	−3.0078	−4.8479**	−3.3171*	−4.3130**
	(-2.03)	(-1.72)	(-1.35)	(-1.48)	(-1.65)	(-2.58)	(-1.88)	(-2.40)
Cap	0.2312***	0.2273**	0.2155**	0.2241**	0.2309**	0.2663***	0.2347***	0.2561***
	(2.59)	(2.53)	(2.37)	(2.43)	(2.53)	(2.91)	(2.61)	(2.81)
Volatility	36.97***	37.48***	37.89***	37.50***	37.14***	35.36***	36.42***	35.87***
	(3.67)	(3.72)	(3.78)	(3.73)	(3.66)	(3.53)	(3.56)	(3.58)
Volume	−0.2080	−0.2121	−0.2217	−0.2143	−0.2074	−0.1579	−0.1956	−0.1730
	(-1.53)	(-1.54)	(-1.62)	(-1.55)	(-1.49)	(-1.13)	(-1.39)	(-1.25)
Insholding	0.0146***	0.0146***	0.0146***	0.0146***	0.0146***	0.0145***	0.0147***	0.0149***
	(3.31)	(3.30)	(3.30)	(3.30)	(3.30)	(3.29)	(3.32)	(3.37)
PSOS	0.0896	−0.1392	−0.4888	−0.1865	0.0201	1.1201	0.2406	0.8624
	(0.17)	(-0.24)	(-0.82)	(-0.27)	(0.028)	(1.59)	(0.35)	(1.29)
Accnum	0.2457***	0.2423***	0.2394***	0.2435***	0.2440***	0.2410***	0.2431***	0.2427***
	(2.78)	(2.75)	(2.72)	(2.77)	(2.78)	(2.75)	(2.77)	(2.77)
Adj. R^2	0.1043	0.1044	0.1060	0.1044	0.1042	0.1109	0.1045	0.1087

Notes: This table reports the regression results in Eq. (6) with *PSOS* estimated with the data of different time intervals. *Cap* is the winsorized average daily total capitalization at the 1% level in billions of RMB in logarithm, *Volatility* is the standard deviation of daily returns, *Volume* is the winsorized average daily trading volume at the 1% level in millions of RMB in logarithm, *Insholding* is the average previous year-end institutional holdings of each stock expressed as a percentage, *PSOS* and *Accnum* are defined in Section 4.1. *Accnum* is also in logarithm. *, **, and *** significance at the 10%, 5%, and 1% levels, respectively.

of liquidity traders and even becomes negligible.

6. Summary and conclusions

Based on the measure of short-horizon market efficiency proposed by Chordia et al. (2008), this study represents the first comprehensive investigation of the relationship between two types of trading costs—information asymmetry and illiquidity related to cluster trading—and market efficiency in the Chinese stock market, which is characterized by prevalent speculative trading.

This study finds that the information asymmetry and illiquidity related to cluster trading both negatively affect market efficiency in the Chinese stock market. While the effect of information asymmetry on market efficiency is dominant over short horizons, illiquidity related to cluster trading becomes major force negatively affecting market efficiency over long horizons as information asymmetry dissipates with time. Moreover, they affect market efficiency at different points in the trading process. When information comes into the market, information asymmetry is most prevalent. The trading costs from the adverse selection problem are most obvious at this stage of the trading process, which negatively affects market efficiency. At the same time, trading volume is magnified, and illiquidity related to cluster trading is not significant. On the contrary, the elevated trading intensity that results from cluster trading marginally enhances information integration. Because information is gradually integrated into the price and trading intensity decreases, trading costs resulting from information asymmetry also gradually shrink and lose this effect on market efficiency. At this stage of the trading process, illiquidity related to cluster trading becomes the dominant force that negatively affects market efficiency. However, our empirical results suggest that asymmetric information still has a negative effect on market efficiency. The speculative noise trading in the Chinese stock market actually increases market efficiency by greatly alleviating the illiquidity related to cluster trading. However, speculative noise trading does not address information asymmetry.

Our results provide supporting evidence for both the information-motive model and the liquidity-motive model. This investor trading strategy is not unique and adjusts according to the situation. When new information comes into the market, investor trading is motivated primarily by the exploitation of informational advantage as long as the information is not totally integrated into prices. When the informational advantage is not obvious in other periods, the primary concern of investors is trading costs related to illiquidity.

This study has important implications for investors, listed companies, regulators, and stock exchanges. It answers questions concerning trading costs and prevalent speculative noise trading, which affect stock market efficiency in China. This is significant for portfolio construction by investors and arbitrageurs. The findings are also significant for regulators. This study provides insight into the Chinese stock market and provides regulators with a solid basis from which to develop market policies and evaluate their effect.

One limitation of the study, however, is that our analysis considers only two kinds of trading costs, information asymmetry and illiquidity related to cluster trading. Although Bloomfield et al. (2009) indicate that noise trading has a positive effect on market efficiency by providing the market with additional liquidity, they do not specify the channel through which noise trading reduces trading costs. In this paper, we investigate two possible channels, information asymmetry and illiquidity related to cluster trading; however, other channels may exist through which noise trading affects market efficiency. Future research could usefully analyze other channels. Additionally, this study could be generalized to other stock markets.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.econmod.2018.04.001.

References

Admati, A.R., Pfleiderer, P., 1988. A theory of intraday patterns: volume and price variability. Rev. Finance Stud. 1, 3–40.
Ahn, H.-J., Cai, J., Hamao, Y., Melvin, M., 2014. Little guys, liquidity, and the informational efficiency of price: evidence from the Tokyo Stock Exchange on the effects of small investor participation. Pac. Basin Finance J. 29, 163–181.
Amihud, Y., 2002. Illiquidity and stock returns cross-section and time-series effects. J. Finance Market. 5, 31–56.
Back, K., Baruch, S., 2007. Working orders in limit order markets and floor exchanges. J. Finance 62, 1589–1621.
Back, K., Cao, H.H., Willard, G.A., 2000. Imperfect competition among informed traders. J. Finance 55, 2117–2155.
Beltratti, A., Bortolotti, B., Caccavaio, M., 2016. Stock market efficiency in China: evidence from the split-share reform. Q. Rev. Econ. Finance 60, 125–137.
Bernhardt, D., Hughson, E., 1997. Splitting orders. Rev. Finance Stud. 10, 69–101.
Bernhardt, D., Miao, J., 2004. Informed trading when information becomes stale. J. Finance 59, 339–390.
Biais, B., Martimort, D., Rochet, J.-C., 2000. Competing mechanisms in a common value environment. Econometrica 68, 799–837.
Bloomfield, R., O'Hara, M., Saar, G., 2009. How noise trading affects markets: an experimental analysis. Rev. Financ. Stud. 22, 2275–2302.
Chakravarty, S., 2001. Stealth-trading: which traders' trades move stock prices? J. Finance Econ. 61, 289–307.
Chang, S.S., Wang, F.A., 2015. Adverse selection and the presence of informed trading. J. Empir. Finance 33, 19–33.
Chen, T., Cai, J., Ho, R.Y.K., 2009. Intraday information efficiency on the Chinese equity market. China Econ. Rev. 20, 527–541.
Chen, X., Harford, J., Li, K., 2007. Monitoring: which institutions matter? J. Finance Econ. 86, 279–305.
Chordia, T., Roll, R., Subrahmanyam, A., 2005. Evidence on the speed of convergence to market efficiency. J. Finance Econ. 76, 271–292.
Chordia, T., Roll, R., Subrahmanyam, A., 2008. Liquidity and market efficiency. J. Finance Econ. 87, 249–268.
Chordia, T., Subrahmanyam, A., 2004. Order imbalance and individual stock returns: theory and evidence. J. Finance Econ. 72, 485–518.
Chung, D.Y., Hrazdil, K., 2010a. Liquidity and market efficiency: a large sample study. J. Bank. Finance 34, 2346–2357.
Chung, D.Y., Hrazdil, K., 2010b. Liquidity and market efficiency: analysis of NASDAQ firms. Global Finance J. 21, 262–274.
Chung, D.Y., Hrazdil, K., 2012. Speed of convergence to market efficiency: the role of ECNs. J. Empir. Finance 19, 702–720.
Collin-Dufresne, P., Fos, V., 2015. Do prices reveal the presence of informed trading? J. Finance 70, 1555–1582.
Copeland, L., Wong, W.K., Zeng, Y., 2009. Information-based trade in the Shanghai stock market. Global Finance J. 20, 180–190.
Copeland, T.E., Galai, D., 1983. Information effects on the bid-ask spread. J. Finance 38, 1457–1469.
Cullen, G., Gasbarro, D., Monroe, G.S., 2010. Mutual fund trades and the value of contradictory private information. J. Bank. Finance 34, 378–387.
Ding, R., Cheng, P., 2011. Speculative trading, price pressure and overvaluation. . Int. Finance Market. Institut. Money 21, 419–442.
Duarte, J., Young, L., 2009. Why is PIN priced? J. Finance Econ. 91, 119–138.
Easley, D., Kiefer, N.M., O'Hara, M., Paperman, J.B., 1996. Liquidity, information, and infrequently traded stocks. J. Finance 51, 1405–1436.
Easley, D., O'Hara, M., 1987. Price, trade size, and information in securities markets. J. Finance Econ. 19, 69–90.
Easley, D., O'Hara, M., Paperman, J.B., 1998. Financial analysts and information-based trade. J. Finance Market. 1, 175–201.
Fama, E.F., 1970. Efficient capital markets: a review of theory and empirical work. J. Finance 25, 383–417.
Fong, W.M., 2009. Speculative trading and stock returns: a stochastic dominance analysis of the Chinese A-share market. J. Int. Finance Market. Instit. Money 19, 712–727.
Foster, F.D., Viswanathan, S., 1990. A theory of interday variations in volumes, variances, and trading costs in securities markets. Rev. Finance Stud. 3, 593–624.
Foster, F.D., Viswanathan, S., 1994. Strategic trading with asymmetrically informed traders and long-lived information. J. Finance Quant. Anal. 29, 499–518.
Foster, F.D., Viswanathan, S., 1996. Strategic trading when agents forecast the forecasts of others. J. Finance 51, 1437–1478.
Gençay, R., Gradojevic, N., 2013. Private information and its origins in an electronic foreign exchange market. Econ. Modell. 33, 86–93.
Glosten, L.R., 1994. Is the electronic open limit order book inevitable? J. Finance 49, 1127–1161.
Glosten, L.R., Milgrom, P., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. J. Finance Econ. 14, 71–100.
Griffin, J.M., Kelly, P.J., Nardari, F., 2010. Do market efficiency measures yield correct inferences? A comparison of developed and emerging markets. Rev. Finance Stud. 23, 3225–3277.
Grossman, S.J., Stiglitz, J.E., 1980. On the impossibility of informationally efficiency markets. Am. Econ. Rev. 70, 393–408.
Holden, C.W., Subrahmanyam, A., 1992. Long-lived private information and imperfect competition. J. Finance 47, 247–270.
Huddart, S., Hughes, J.S., Levine, C.B., 2001. Public disclosure and dissimulation of insider trades. Econometrica 69, 665–681.
Hung, J.-C., 2009. Deregulation and liberalization of the Chinese stock market and the improvement of market efficiency. Q. Rev. Econ. Finance 49, 843–857.
Kaniel, R., Liu, H., 2006. So what orders do informed traders use? J. Bus. 79, 1867–1913.
Klein, O., Maug, E., Schneider, C., 2017. Trading strategies of corporate insiders. J. Financ. Market. 34, 48–68.
Kubota, K., Takehara, H., 2009. Information based trade, the PIN variable, and portfolio style differences: evidence from Tokyo stock exchange firms. Pac. Basin Finance J. 17, 319–337.
Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica 53, 1315–1336.
Lai, S., Ng, L., Zhang, B., 2014. Does PIN affect equity prices around the world? J. Finance Econ. 114, 178–195.
Lee, B.S., Li, W., Wang, S.S., 2010. The dynamics of individual and institutional trading on the Shanghai Stock Exchange. Pac. Basin Finance J. 18, 116–137.
Lee, C.M.C., Ready, M.J., 1991. Inferring trade direction from intraday data. J. Finance 46, 733–746.
Mei, J., Scheinkman, J.A., Xiong, W., 2009. Speculative trading and stock prices: evidence from Chinese A-B share premia. Ann. Econ. Finance 10, 225–255.
Narayan, P.K., Narayan, S., Westerlund, J., 2015. Do order imbalances predict Chinese stock returns? New evidence from intraday data. Pac. Basin Finance J. 34, 136–151.
Ross, S.A., 1989. Information and volatility: the no-arbitrage martingale approach to timing and resolution irrelevancy. J. Finance 44, 1–17.
Sias, R.W., Starks, L.T., Titman, S., 2006. Changes in institutional ownership and stock returns: assessment and methodology. J. Bus. 79, 2869–2910.
Sukpitak, J., Hengpunya, V., 2016. The influence of trading volume on market efficiency: the DCCA approach. Phys. A: Stat. Mech. Appl. 458, 259–265.
Vayanos, D., 1999. Strategic trading and welfare in a dynamic market. Rev. Econ. Stud. 66, 219–254.
Vayanos, D., 2001. Strategic trading in a dynamic noisy market. J. Finance 56, 131–171.
Visaltanachoti, N., Yang, T., 2010. Speed of convergence to market efficiency for NYSE-listed foreign stocks. J. Bank. Finance 34, 594–605.
Wang, A.F., 2010. Informed arbitrage with speculative noise trading. J. Bank. Finance 34, 304–313.
Wang, X.L., Shi, K., Fan, H.X., 2006. Psychological mechanisms of investors in Chinese stock markets. J. Econ. Psychol. 27, 762–780.
Yamamoto, R., 2012. Intraday technical analysis of individual stocks on the Tokyo Stock Exchange. J. Bank. Finance 36, 3033–3047.