DO LOCAL OR FOREIGN TRADERS KNOW MORE IN AN EMERGING MARKET? A POSSIBLE SOLUTION OF THE PUZZLE

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ABSTRACT

A branch of the literature in international finance has tried to give a definitive answer to the question, who is better informed in an emerging market, Foreigners or Locals?. We measured the probability of informed trading (PIN) for the Jakarta Stock Exchange for two types of investors, foreigners and locals, developing an extension of the model of Easley, Kiefer and O'Hara (1997). We find that locals do most of the informed trades, but also most of the uninformed trades. On the other hand, given the type of investor, foreigners are more likely to be informed than locals. Besides, the evidence shows that locals tend to be more informed in smaller and more volatile firms, whereas foreigners tend to be more informed in larger an less volatile firms and firms with higher foreign ownership. We also find evidence of market-wide effects on liquidity from the foreign informed trades but not from the local ones.

Introduction

More than 15 years have passed since most emerging markets undertook liberalization processes, allowing a surge of international portfolio flows. The liberalization process itself has been hailed mostly as beneficial, in terms of reduced cost-of-capital, improved information environment and positive economic effects. However, the role of foreign investors in emerging markets is still not well understood. It is not clear if they act most of the time as sophisticated investors keen on selecting undervalued firms or if, on the contrary, they increase the pool of

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noise traders in a market. Assuming that they are informed, it is unclear whether they compete directly with local informed traders or, instead, they bring fresh information to the market.

Whether foreign investors are better or less informed than locals is still a hotly debated issue in the international finance literature. People seem to have strong beliefs about it, hardly surprising since sensible arguments can be offered to support either point. Theoretical models in the 'Home bias' literature including Gehring(1993), Brennan and Cao(1997) and Griffin, Nardari and Stulz(2004) assume that local investors are better informed than foreign investors. The empirical tests of 'Home bias' have been strongly supportive of this claim, (see Edison and Warnock (2004) and Kang and Stulz (1997)). The rationale is that locals have an edge in terms of language, culture and networks that enable them to get better private information than foreigners. This 'Home advantage' effect should be stronger in the emerging markets because of lower standards of corporate governance, public scrutiny and information transparency as suggested by Johnson et al (2000), Klapper and Love(2002), and reduced macro transparency (Gaston-Gelos and Wei(2002)). Moreover, since most emerging countries do not enforce laws against insider trading (Bhattacharya and Daouk (2002)), it is very likely that inside information is actively exploited by local groups with ties to the firms' management.

Others argue exactly the opposite. Foreign flows tend to be driven by experienced and sophisticated institutional investors unlike the typical local investors as shown by Grinblatt and Keloharju(2000) for Finland and Barber et al (2005) for Taiwan. The institutional investor literature, (see Bartov et al(2000), Dennis and Weston (2001)), provides evidence that institutions are better informed than individual investors. Taking together those two facts, the advocates of this position argue that foreign investors are better informed than locals. As the title of Richards (2005) study foreign investors in emerging markets represent 'big fish' in small ponds. Seasholes(2004) and Grinblatt and Keloharju(2000) argue that foreign institutions have the expertise, technology, and resources to make better inferences on expected returns and earnings based on publicly available information, particularly on equities of larger and more publicly

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recognized. Foreign institutions can always set up local offices and hire local personnel to overcome cultural barriers. Huang and Shiu (2005) find that locals are more likely to trade for non-informational reasons than foreigners.

In this paper, we estimate directly the proportion of informed traders from both groups of investors: foreigners and locals in Indonesia, for the period April 2004 - March 2006. We estimate separately the probability of informed trading (PIN) of Easley, O'Hara and Saar (2001) for the two groups locals and foreigners: PIN_L and PIN_F respectively. Both variables are estimated on a stock-month basis from daily summary information on the trades. Our main result is that PIN_L is significantly larger than PIN_F for both the overall market and most of the individual stocks, across the different deciles of size. This means that locals are responsible for most of the informed trades, as the 'Home advantage' side poses. Moreover, locals represent more trades, both informed and uninformed than foreigners. Interestingly, if you compute the probability of being informed given the type of investor, then a foreigner is more likely to be informed than a local. This is consistent with the idea of the average foreign investor being more sophisticated than the average local, as argued by the 'Big fish' supporters. This result holds not only for the overall market but also for each size decile. As a robustness check, we also estimated the PINs base on daily trades computed directly from transaction data for the period April 2005 to July 2005, finding the same results.

Thus, if the research question is which group collectively brings the most informed trades to the market then the answer is the local. However, if the research question is: who is more likely to be informed?, the answer is the foreigner. To our knowledge, no paper has measured directly the probability of informed trading of each group, neither has any paper distinguished between these two research questions, as we do in this paper

The extant empirical literature to the question of who is better informed, foreigners or locals, has been mixed or inconclusive. Overall, the answers vary with the methodology and the particular dataset used. For example, using a database of 44 countries, Froot, O'Connell and

Seasholes (2001) reported that the flows toward emerging markets present positive feedback trading and have positive forecast power for future equity returns. However, the authors recognize that the predictability of future returns can be explained as foreign flows being informed, or alternatively, as caused by price pressure and persistence of foreign flows combined with persistence of flows. Using Korean transaction data, Choe, Kho and Stulz (2005) show that foreign investors trade at a disadvantage when compared with local investors and indeed have a higher price impact[1]. However, they argue that the evidence is consistent with momentum-trading by foreigners rather than with foreign investors being better informed, since the price impact is not permanent.

Several studies have found support for the 'big fish' side. Using daily data on Taiwan, Seasholes (2004) presents three measures suggesting that foreign investors outperform locals, particularly when investing in larger firms and firms with low leverage. His stronger finding is that foreign investors tend to buy more than locals before positive earnings surprises and sell more before negative earning surprises. Thus, the evidence of his paper is suggestive that in Taiwan, the proportion of informed traders in larger in the foreign group of investors than in the local one, but it doesn't rule out that locals can be still doing most of the informed trades of the market as a whole. Other papers that have provided evidence consistent with the 'big fish' argument include: Grinblatt and Keloharju (2000), using a very detailed database in the Finish market; Froot and Ramadorai (2001), showing that cross-border inflows into foreign countries positively forecast changes in the prices of country close-end funds; and Huang and Shiu (2005) and Barber et al (2005), both showing that in Taiwan foreigners have a superior short-term investment performance.

On the contrary, in support of the 'Home advantage' hypothesis, Hau (2001) shows that foreign traders have an inferior performance than local traders in Germany. Kim and Wei (2002) present evidence that foreigners were less informed than locals in Korea in the context of the

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[1] Richards(2005) show the same effect using market wide daily data in 5 emerging markets.

1997 currency crisis. Kaufman, Mehrez and Schmuckler (2005) found that local managers in Russia, Thailand and Korea anticipated the financial crises in their respective countries, but not in Indonesia and Malaysia. Bhattacharya et al (2004) report that returns on Mexican class 'A' shares (restricted to foreigners) predict returns on class 'B' shares (unrestricted).

As in this paper, Dvorak (2005) also investigates the case of Indonesia. His approach consists in separately estimating the returns for the transactions of the two groups, foreigners and locals at different investment periods based on daily buys and sells at firm-level, for the 30 most liquid stocks. He finds that locals have higher profits than foreign investors, suggesting that they might be overall better informed. On the contrary, he finds that clients of global brokerages (which include foreigners) are better at picking long-term winners than clients of local brokerages (which don't include foreigners). As an explanation, the author suggests that global institutions might have better information in picking long-term winners which they pass on to their clients. However, since the identity of the traders are not observed, the study heavily depends on the assumption that all the transactions are done by a representative investor with fixed investment horizon and risk preferences. Moreover, it is unclear why the global brokerage advantage can only be captured by its several clients in the long term, but not in the short-term as implied by a model of competitive informed traders as Holden and Subramanyam (1994).

To estimate the probability of informed trading for the two groups of investors this paper extends the models of Easley, Kiefer and O'Hara (1997) and Easley, O'Hara and Saar (2001)[2]. There are two fundamental assumptions on those models. First, informed traders will actively trade to exploit their information advantage. In those days when informed traders have information, they will increase the number of trades in the direction of the information; however, they will stay away from the market in days without information. The second assumption is that competitive liquidity providers will react to an increasing number of trades in one direction by

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[2] Those models or their extensions have been used, among others, by Easley et al (1998), Gramming, Schiereck, and Theissen, (2001), Heidle and Huang(2002), Cruces and Kawamura (2005), and Vega (2006). However, to our knowledge, they haven't been used to investigate the question of this paper.

increasing the bid-ask spread. The models don't rely on assumptions on the risk-premium model, or the investment horizon of the different group of investors; nor are they restricted to specific information events.

Taking advantage of the estimated PIN numbers for foreigners and locals, we explore the relationship between information and liquidity in our sample data. The microstructural models of Kyle (1985), Glosten and Milgrom (1985) and Easley and O'Hara (1987) explain liquidity, measured either as the bid-ask spread or as the price impact function, as a consequence of the probability of informed anonymous traders in the trading venue. Consequently, the hypothesis that foreign investors are any different than locals in terms of information, can be tested by regressing the liquidity on PIN_F and PIN_L. We find that both PIN_F and PIN_L have positive and significant effects on liquidity, as predicted by the theory. Moreover, we also find that the effect of foreigner informed trades tends to be statistically larger.

Additionally, we investigate the type of firms where foreigners and locals tend to be more informed. By studying the cross sectional distribution of PIN_L and PIN_F, we show that whereas local investors tend to be better informed on smaller and more volatile firms, informed foreigners prefer larger and less volatile, firms and firms with larger foreign ownership. These results provide direct evidence in support of Edison and Warnock (2004) and Kang and Stulz (1997) who suggest that foreigners invest in larger and more actively traded firms in order to maximize their information advantage.

On the other hand, it is expected that the traders in a market be informed not only with respect to firms, but also, to some extent, with respect to market-wide variables. If this is so, we should expect a positive effect on the liquidity not only from the stock PIN numbers but also from the market wide level of information, measured with market-wide averages of each PIN number. We find a positive relationship between the bid-ask spreads and the level of market-wide foreign information, even after controlling for PINs and other firm-specific variables, but not such a relationship with the level of market-wide local information. This foreign market-wide effect is

consistent with foreign investors having an edge in processing macro information, as suggested by Seasholes (2004), as well as with international analysts incorporating macro information in emerging markets as in Chan and Hameed (2005).

The rest of the paper is organized as follows: Section 1 presents and discusses the Hypotheses. Section 2 explains the empirical model used to estimate PIN_L and PIN_F. Section 3 discusses the data, Section 4 presents the results of the model and the subsequent regressions and analysis and Section 5 concludes.

1. Hypothesis

The question of whether foreign investors are better or less informed than locals can be better defined by examining it in three dimensions: First, who makes most of the informed trades in a market; second, given the type of investor, foreign or local, who is more likely to be informed; and third, whose informed trades have a larger impact on the liquidity of stocks. In principle, any combination of answers might be possible. The answers to those questions will guide the first three hypotheses of the paper.

Who's responsible for most of the informed trades in an emerging market such as Indonesia? If we start from the neutral assumption that foreign investors are no different than the average local investor, then locals should do more of the informed trades in the Jakarta stock Exchange, since they do most of the trades [3]. This null Hypothesis is compatible with the literature in Home bias and the models of Brennan and Cao (1997) and Griffin, Nardari and Stulz (2004). We'll test this hypothesis by estimating the probability of informed trading by foreigners (PIN_F) and the probability of informed trading by locals (PIN_L) for each individual stock on a monthly basis.

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[3] Richards(2005) reports that foreigners made 23% of the trading value during 1999-200. Table 2 shows that Locals dominate the trading across the different size quintiles for the studied period.

The Null Hypothesis requires that $PIN_L \geq PIN_F$ for the market as a whole. In contrast, we propose the following alternative hypothesis:

H1: Foreign investors do more informed trades than locals. This will be measured as:

$$PIN_L < PIN_F$$

The question can be posed alternatively as: given the investor type, foreign or local, how likely is she to be informed? This question is important for understanding the relative composition of each group. One possibility is that foreign investors are mostly uninformed investors driven by motives different than information, like herding, portfolio rebalancing, return chasing, as suggested by Sias (2004), Bonser-Neal et al (2002) and Griffin, Nardari and Stulz (2004). Alternatively, foreigners are mostly sophisticated informed investors, namely foreign institutions, that use superior technology to make better predictions of earning surprises and macroeconomic variables, analyze public information, and detect mispriced firms, like in Seasholes (2004) and Barber et al (2005). To the null hypothesis that foreigners are not different than locals as far as information is concerned we oppose the following alternative hypothesis:

H2: Given the type of investor, foreigners are more likely to be informed than locals. This will be measured as:

$$Prob(\text{ informed } | \text{ Foreigner}) > Prob(\text{informed } | \text{ Local})$$

The question can also be presented in terms of the differential effects of informed tradings of the two groups of investors, which is the most common path that the extant literature has taken. If one group, either foreigners or locals, is better informed than the other we should expect that their trades earn higher returns as in Dvorak (2005), Froot and Ramadorai (2001) and Huang and Shiu (2005), cause larger price impacts as in Bonser-Neal et al. (1999) and Choe, Kho and Stulz

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(2005), or better predict earning surprises as in Seasholes (2004). However, we take a different approach. As a direct consequence of the models of Kyle (1985), Glosten and Milgrom (1987) and Easley and O'Hara (1987) we estimate the effects on liquidity of informed trading by each of the two groups. Liquidity should decrease in the event of increased information trading, since liquidity providers increase the bid-ask spread or the slope of the price/volume schedule to compensate for the increased probability of informed traders. Thus, in a regression of the bid-ask spread against PIN_F and or PIN_L the effect of those two variables should be positive. Moreover the model of Easley and O'Hara (1987) will imply that the group with more information will have a higher effect on the proportional spread. Here, the null Hypothesis is that the both effects are the same, and the respective alternative hypothesis is :

H3 : The effect of foreign informed investors on the proportional bid-ask spread is different from the effect of local informed investors. This will be measured in a regression of the spread on PIN_F and PIN_L as :

$$\text{Coefficient of } PIN_F \neq \text{Coefficient of } PIN_L.$$

On the other hand, as to the foreign trading preferences, Edison and Warnock (2004) and Kang and Stulz (1997) argue that foreigners prefer to invest in larger, high volume firms and firms with American Depository receipts (ADR) to minimize their information disadvantage. Huang and Shiu (2005) also provide evidence that foreign investors in Taiwan have an information advantage over locals particularly in those firms with larger foreign ownership. Accordingly, we propose the following alternative hypothesis:

H4. Foreign informed traders are more active in larger firms, higher volume firms, firms with ADRs and firms with higher foreign ownership. This can be tested regressing PIN_F and PIN_L in a set of firm specific characteristics.

Kang and Stulz (1997) in Japan, Seasholes (2004) in Taiwan, and Chan and Hameed (2005) in 45 emerging markets provide evidence consistent with foreign institutions having an advantage in terms of market-wide information. This presumed advantage should be manifested in foreign informed traders relatively trading more than informed locals in firms that better incorporate macro-wide information, such as larger firms or firms with high systematic risk. This will be tested along with Hypothesis 4 above. On the other hand, if informed foreign trades contain any relevant market-wide information we should expect that the market-wide average of informed foreign trading has a negative effect on the liquidity of individual stocks, beyond what is explained by firm-specific factors. Thus, to the null hypothesis of foreign informed traders being similar to informed locals we oppose the following alternative hypothesis:

H5. A market-wide average of PIN_F is associated with lower liquidity of individual stocks to a larger extent than a market-wide average of PIN_L. This will be tested in a time series regression of the bid-ask spreads of individual firms, comparing the coefficients of the two market-wide information variables.

2 Trading Model

The model here proposed is an extension of the family of informed trading models of Easley, Kiefer and O'Hara (1997), henceforth EKO, and Easley, O'Hara and Saar (2001), henceforth EOS. In essence these two papers model the arrival of informed and uninformed traders in a market with a designated market-maker, and solve the relation between the probability of informed trading (PIN) and the size of the bid-ask spread. Additionally, they illustrate how the parameters of the model can be estimated from the total numbers of initiated buys and initiated sales (directional trades) in a daily basis. In this section we explain how this framework can be

extended to estimate the PINs of two types of investors, foreigners and locals in a limit order book market. This will be modeled in discrete-time, as in EKO, but allowing uninformed traders to place limit orders as in EOS. Moreover, we illustrate how this model can be estimated from the total number of buys and sells (no directional) for each of the two groups.

<u>2.1. Trade process modeling</u>

There are two types of agents in this market: foreigners and locals, which in turn can be either informed or uninformed. The traded asset has a random value V, which is sampled at the start of each day from a fixed distribution. The information arrival and the distribution of V are modeled using two types of signals about V: Ψ_F, which is known only by the foreign informed traders, and takes either the value L (low) or H(high) with probabilities δ_F and $1- \delta_F$, respectively; and Ψ_L, which is known only by the local informed traders, and takes either the value L (low) or H (high) with probabilities δ_L and $1- \delta_L$, respectively. We assume that the arrival of the two signals is given at the start of each trading day with probabilities α_F and α_L respectively. Whenever foreign (local) information doesn't happen in a given day the respective signal takes the value $\Psi_F = 0$ ($\Psi_L = 0$). Thus, there are nine different types of days, depending on the combinations of foreign and local signals, as illustrated in Figure 1.

We assume that the real value of the asset V is known publicly at the end of the trading day, depending on the arrival of information. The real value of V as a function of the two signals is given as follows:

Foreign signal \ Local signal	$\Psi_L = L$	$\Psi_L = 0$	$\Psi_L = H$
$\Psi_F = L$	$V_{0F} + V_{0L}$	$V_{1F} + V_L{}^*$	$V_{0F} + V_{1L}$
$\Psi_F = 0$	$V_F{}^* + V_{0L}$	$V_F{}^* + V_L{}^*$	$V_F{}^* + V_{1L}$
$\Psi_F = H$	$V_{1F} + V_{0L}$	$V_{0F} + V_L{}^*$	$V_{1F} + V_{1L}$

Where V_{0F}, V_{1F} are parameters that bound the information on V known by informed foreigners, with $V_{0F} < V_{1F}$. Likewise, V_{0L}, V_{1L}, with $V_{0L} < V_{1L}$, bound the information known by informed locals. Besides, V_F^* V_L^*, are the unconditional values of the information on V, known by foreigners and local, respectively, as given by:

$$V_F^* = V_{0F} \times \delta_F + V_{1F} \times (1 - \delta_F) \qquad V_L^* = V_{0L} \times \delta_L + V_{1L} \times (1 - \delta_L) \qquad [1]$$

The liquidity in the market comes from a limit order book, and there is not designated market-maker. We assume that the liquidity providers are uninformed, risk-neutral and competitive, similar to the market maker on EKO and EOS. The competitive bid and ask prices are determined by the perfect competence between the liquidity providers, but taking into account the probability of informed trading so that in expectation the profit of the liquidity provided is zero. Besides, there is a probability φ that the next limit order to be traded, either in the bid or the ask side, has been placed by an uninformed foreigner.

The informed traders, either foreign or local, place buy (sell) market orders during days when their respective signal is high (low), and don't trade in days when there is no signal. Furthermore, we assume they don't use limit orders. As discussed in EOS (p.34), this is a reasonable assumption provided that the information is short-lived and there is competition between the informed traders to exploit it. If the informed trader submits a limit order, the price can move against her position, impeding her to exploit the information advantage. Additionally, we assume that each group of informed traders are risk neutral, and therefore, the potential information of the other group is irrelevant for their decision to trade.

Trade happens in intervals, making this a discrete time model as EKO. The trading day is divided in a fixed number of intervals. In each interval there are only two possibilities: either there is a trade or a no-trade, but there can't be multiple trades in an interval. We'll show that the choice of the total number of intervals doesn't change the relevant results of the model, assuming a sufficient high number of intervals.

The arrival of information before the trading day is illustrated for each one of the nine types of days in Figure 1, at the left of the dashed line. In the first node nature decides if there is an informed signal Ψ_F for foreigners with probability α_F and whether it is low or high, with probabilities δ_F and $1-\delta_F$. Similarly, in the second node, nature decides if there is an informed signal for locals with probability α_L, and whether it is low or high, with probabilities δ_L and $1-\delta_L$. We allow for the two signals to be correlated by means of the parameter ρ. If $\rho = 0$, the two signals are independent, $\rho > 0$ implies a positive correlation between the occurrence of both signals, and $\rho < 0$, a negative correlation[4]. In general, there will be days with both foreign and local information, days with only foreign, days with only local, and days with neither one, with probabilities: $\alpha_F \alpha_L + \rho$, $\alpha_F (1- \alpha_L) - \rho$, $\alpha_L(1-\alpha_F) - \rho$ and $(1-\alpha_F)(1-\alpha_L) + \rho$, respectively.

The arrivals of foreign informed traders, local informed traders and uninformed trades are given by the parameters μ_F, μ_L, and ε, respectively. The different possibilities of trading on the first interval of the day are illustrated in the probability tree of Figure 1, at the right of the dashed line. For example, given that there is a low foreign signal ($\Psi_F = L$) and no local signal ($\Psi_L = 0$), the probability that a sell market order from a foreign informed market order arrives and be executed is given by μ_F, as illustrated in the second branch of Figure 1. With probability $1-\mu_F$ there is no informed trade and then two things might happened: either a market order from an uninformed trader arrives and trades, with probability ε, or there is no trade at all, with probability $1-\varepsilon$, as represented by the module A in Figure 1 [5]. The arriving uninformed trader will be equally likely to place a market buy as to place a market sell. She will be a foreigner with probability φ, or a local with probability $1-\varphi$. Besides, no matter what type of trader placed the market order, the matching limit order is a placed by a foreigner with probability φ or by a local with a probability $1-\varphi$. Thus, the probability of a foreign buy in a trading interval is $\mu_F \varphi + (1- \mu_F)\varepsilon\varphi$, adding the

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[4] By construction ρ is to be restricted in a range : $\max(\alpha_L+\alpha_F-1, 0) - \alpha_L\alpha_F \leq \rho \leq \min(\alpha_L, \alpha_F) - \alpha_L\alpha_F$. The correlation between the two signals is given by $\rho / (\alpha_L (1- \alpha_L) \alpha_F (1- \alpha_F))^{\frac{1}{2}}$
[5] $(1- \varepsilon)$ includes both the cases when no market order arrives and when a market order arrives but is not executed since the limit order book doesn't have a matching limit order.

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foreign buys by market orders with those by limit orders. Likewise, the probabilities of a foreign sell, a local buy, a local sell and a no-trade in a trading interval are given by $\mu_F + (1-\mu_F)\varepsilon\varphi$, $\mu_F(1-\varphi)+(1-\mu_F)\varepsilon(1-\varphi)$, $(1-\mu_F)\varepsilon(1-\varphi)$ and $(1-\mu_F)(1-\varepsilon)$, respectively. The trading processes on the other days with only one signal are analogous to the one just described, and are represented in the fourth, sixth and eight branches of Figure 1.

On the other hand, there are four types of days with both local and foreign signals, represented in the first, third, seventh and ninth branches of Figure 1. In those days there is the possibility that both a foreign and a local informed trader arrive at the same interval. Since there can only be one trade, we break the tie giving each one a 50% chance. Thus, in the trading intervals of those days the probability of having a foreign informed trade is $\mu_F(1-\frac{1}{2}\mu_L)$ and the probability of having a local informed trade is $\mu_L(1-\frac{1}{2}\mu_F)$[6], while the probability of having a trade originated in an uninformed market order trade is $(1-\mu_F)(1-\mu_L)\varepsilon$, and the probability of having a no-trade is $(1-\mu_F)(1-\mu_L)(1-\varepsilon)$.

The remaining type of day to describe is the one when there is no foreign or local signal ($\Psi_F = 0$, $\Psi_L = 0$), presented in the fifth branch of Figure 1. In the trading intervals of those days there are only two possibilities, illustrated in the module A, either a trade among uninformed traders or a no-trade, with probabilities ε and $1-\varepsilon$, respectively. Finally, as in EKO and EOS, we assume that the arrival of investors is independent in each interval. Thus, the probability tree will be extended from the first interval on, with each interval repeating the possibilities of the first, starting from each of the last nodes of the previous interval.

As illustrated above, the probability structure is determined by the parameters $\alpha_F, \alpha_L, \delta_F, \delta_L, \rho, \mu_F, \mu_L, \varepsilon$ and φ, which allows us to calculate the probability of any type of trade. Second, the liquidity providers observe whether a trade was buyer or seller initiated, but also the type, foreigner or local, of the trader that placed the market order. They also know the structure of the

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[6]This assumption is necessary for the restriction of just one trade per interval, required for tractability, but it is unlikely to have any consequences in the estimation when μ_L and μ_F are sufficiently small.

trade process, the parameters, and sequence of past trades on the day. What they don't know is if either of the two information signals has occurred or not, and if so, whether the signal has been high or low. However, based on the information they possess, the liquidity providers can infer the conditional probabilities of each of the nine states of the nature. Accordingly, at the beginning of each trading interval the bid (ask) will be given by the expected value of the asset given that the next transaction is a market sale (buy), taking into account the history of transactions during the day, in a similar manner to equations (2) and (3) of EOS. Intuitively, the more likely the occurrence of any of the 4 information signals ($\Psi_F = L$, $\Psi_F = H$, $\Psi_L = L$, $\Psi_L = H$), the wider will be the bid-ask spread, to compensate for increasing potential losses to informed traders. For example, in a day with a particularly high number of foreign buy market orders the liquidity providers will infer an increased probability of a high foreign signal ($\Psi_F = H$). This will drive up the expected value of the asset, and widen the bid-ask spread.

2.2. Estimating the model from the data

We assume that the econometrician observes the total numbers of foreign buys, foreign sales, local buys, locals sells and no-trades in each trading day, classified regardless of the direction of trade, as given by the vector $\Gamma = [FB, FS, LB, LS, NT]'$ [7]. Unlike in EKO and EOS, he is unable to distinguish between an foreign initiated buy, which is likely to be informed, from a foreign limit order buy, which is necessarily uninformed by assumption. Next, we will show that, in spite of that limitation, the model can still be estimated by maximum likelihood as in those two papers, and used for the purposes of this study.

First, let's consider the probability of a given vector of trades Γ, given that we know the occurrence of the two signals (Ψ_F, Ψ_L). As in EKO, since the occurrence of trades is independent between intervals, the probability of a given vector of trades Γ is proportional to the product of the individual probabilities for each type of trade in a trading interval. To illustrate this, we

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[7] This assumption allows us to use the data provided by Jakarta Stock Exchange to estimate the model.

continue with the example of the low foreign signal day. The probability of a given vector of trades in such a type of day is:

$$\Pr\{\, \Gamma \mid \Psi_F = L, \Psi_L = 0\} =$$

$$C_\Gamma \, [\mu_F \varphi + (1 - \mu_F)\varepsilon\varphi]^{FB} \, [\mu_F + (1 - \mu_F)\varepsilon\varphi]^{FS} \, [\mu_F(1-\varphi) + (1-\mu_F)\varepsilon(1-\varphi)]^{LB} \, [(1-\mu_F)\varepsilon(1-\varphi)]^{LS} \, [(1-\mu_F)(1-\varepsilon)]^{NT} \quad [A1]^{\,8}$$

Similarly, the probabilities of a given vector of trades as a function of the parameters in the remaining 8 types of days are given in Appendix A. The next step is expressing the unconditional probability of the vector trade as function of the probability of each of the 9 types of days and the conditional probabilities ([A1] to [A9]) , using the law of total probabilities:

$$\Pr\{\Gamma \mid \alpha_F, \alpha_L, \delta_F, \delta_L, \mu_L, \mu_F, \varepsilon, \varphi\} = \;\; (\alpha_F(1-\alpha_L)\delta_F \; - \; \rho) \, \Pr\{\Gamma \mid \Psi_F = L, \Psi_L = 0\}$$

$$+ (\alpha_F(1-\alpha_L)(1-\delta_F) - \rho) \; \Pr\{\Gamma \mid \Psi_F = H, \Psi_L = 0\} \; + ((1-\alpha_F)\alpha_L\delta_L - \rho) \; \Pr\{\Gamma \mid \Psi_F = 0, \Psi_L = L\}$$

$$+ ((1-\alpha_F)\alpha_L(1-\delta_L) - \rho) \; \Pr\{\Gamma \mid \Psi_F = 0, \Psi_L = H\} + (\alpha_F\alpha_L\delta_F\delta_L + \rho) \; \Pr\{\Gamma \mid \Psi_F = L, \Psi_L = L\}$$

$$+ (\alpha_F\alpha_L\delta_F(1-\delta_L) + \rho) \; \Pr\{\Gamma \mid \Psi_F = L, \Psi_L = H\} + (\alpha_F\alpha_L(1-\delta_F)\delta_L + \rho) \; \Pr\{\Gamma \mid \Psi_F = H, \Psi_L = L\}$$

$$+ (\alpha_F\alpha_L(1-\delta_F)(1-\delta_L) + \rho) \; \Pr\{\Gamma \mid \Psi_F = H, \Psi_L = H\} + ((1-\alpha_F)(1-\alpha_L) + \rho) \; \Pr\{\Gamma \mid \Psi_F = 0, \Psi_L = 0\}$$

$$[\,2\,]$$

Multiple days will be needed to estimate all the 8 parameters of the model. Clearly the parameters α_F, α_L, δ_F, δ_L and ρ can't be estimated with one day of information since the information signals happen only once a day. Moreover, the vector of observations per day, made up by five elements, has only three degrees of freedom, impeding to estimate the four intraday parameters μ_L, μ_F, ε, and φ from one single day[9]. Thus, as in EKO and EOS, we estimate the

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[8] Where C_Γ is the number of ways of arranging combinations FB foreign buys, FS foreign sales, LB local buys, LS local sells and NT non-trade intervals. As explained in EKO this factor involves data, not parameters, is constant for each trading day, has no effect on the estimated parameters by maximum likelihood, and thus, can be dropped from the equation.
[9] Two degrees of freedom are lost since $FB_d + FS_d + LB_d + LS_d + 2NT_d$ is equal to twice the total number of trading intervals, a constant, and : $FB_d + LB_d = FS_d + LS_d$.

model over a period of consecutive days. The likelihood function over a period of D consecutive days as given by:

$$L\left\{(\Gamma_d)_{d=1}^{'D}\,\alpha_F,\alpha_L,\delta_F,\delta_L,\rho,\ \mu_F,\mu_L,\varepsilon,\varphi\right\} = \prod_{d=1}^{D}\Pr\left\{\Gamma_d\mid\alpha_F,\alpha_L,\delta_F,\delta_L,\rho,\mu_F,\mu_L,\varepsilon,\varphi\right\} \qquad [3]$$

Calculating the likelihood function over D consecutive days assumes, first, that the daily arrival of both types of signals is independent from day to day, and second, that the parameters stay constant over the period of calculation. We can estimate the parameters, maximizing the log of the likelihood function of the model over the D days. As in EOS, the optimization itself is performed, not on the original parameters, but over a logit transformation of them[10]. This transformation is particularly important to obtain meaningful standard errors, especially when the estimated parameters are close to zero or one. Before the optimization itself, we perform a grid search over 512 ($=2^9$) combinations of values of the nine parameters, to obtain different sets of initial values for the optimization. The best five combinations of initial values found in the grid search are used alternatively in the optimization procedure to improve the search for the global maximum of [3]. After the optimization procedure, the optimal transformed parameters are converted back into the original parameters reversing the logit transformation. The asymptotic standard errors of the logit-transformed parameters are obtained using the inverted Hessian at the optimum, and are used to estimate the standard errors of the original parameters by means of the delta method[11].

The Probability of informed trading (PIN) is the most important result of this model. Defined as the probability that a trader in the market be informed, this variable is easily estimated from the

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[10] The original parameters, except ρ, are in [0,1], while the logit-transformed parameters belong to $(-\infty,\infty)$. As noted above, ρ is constrained to be between two values that are functions of α_F and α_L, so it requires an extra transformation.
[11] Greene(2001) compares three possibilities for the estimation of the variance-covariance matrix of errors for the maximum likelihood procedure.

parameters of the model[12]. Moreover, PIN is easily decomposed in two parts, the probability of

foreign informed trading (PIN_F) and the probability of local informed trading (PIN_L) as follows:

$$PIN = \qquad PIN_F \qquad + \qquad PIN_L \qquad [4]$$

$$\frac{\alpha_F\mu_F\,(1-\tfrac{1}{2}\alpha_L\mu_L)-\tfrac{1}{2}\rho\,\mu_F\mu_L}{2(1-(1-\alpha_L\mu_L)(1-\alpha_F\mu_F)(1-\varepsilon)-\rho\,\mu_F\mu_L(1-\varepsilon))} + \frac{\alpha_L\mu_L\,(1-\tfrac{1}{2}\alpha_F\mu_F)-\tfrac{1}{2}\rho\,\mu_F\mu_L}{2(1-(1-\alpha_L\mu_L)(1-\alpha_F\mu_F)(1-\varepsilon)-\rho\,\mu_F\mu_L(1-\varepsilon))}$$

These relations allow us to calculate PIN_F, PIN_L and PIN_L - PIN_F as functions of the

parameters that maximize the likelihood function [3]. Note that the variables δ_F, δ_L and φ don't

play any role in [eq 4], so failing to estimate any of them won't impede to estimate the two PIN

numbers. The standard errors of the PIN numbers and their difference are obtained via the delta

method from the standard errors of the transformed parameters. We are also interested in the

probability of informed trading given the type of investor, which can be easily expressed as a

function of the estimated parameters:

$$\text{Conditional } PIN_F = \text{Prob[informed}\,|\,\text{Foreigner]} = \frac{PIN_F}{\text{Prob(Foreigner)}} = \frac{PIN_F}{(1-PIN)\times\varphi + PIN_F}$$

$$\text{Conditional } PIN_L = \text{Prob[informed}\,|\,\text{Local]} \quad = \frac{PIN_L}{\text{Prob(Local)}} = \frac{PIN_L}{(1-PIN)\times(1-\varphi) + PIN_L}$$

$$[5]$$

While the PIN numbers in [4] estimate the proportion of informed foreigners and locals with

respect to the total population of investors, the conditional probabilities in [5] measure the

proportion of informed traders within each group.

For illustration purposes, we present on Table 1 the results of the estimating model from

simulated daily data. Starting from a vector of known parameters, we simulate a 65 days of

trading, roughly a quarter, with 480 intervals each day, obtaining 65 vectors Γ_d, made up of

foreign buys, foreign sales, local buys, local sales and no-trades.

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[12] Alternatively, PIN_F (PIN_L) can be defined as the probability of the arrival of a foreign (local) informed market order, as defined in the model of EOS, but that simply means to rescale by 2 the adopted definition.

Initially, the number of no-trades is computed assuming that the real value, 480 intervals per day, is known. Optimizing the likelihood function [3], we find the estimated parameters using the 65 days of simulated values. The resulting estimated parameters and the computed PIN numbers, as well as their asymptotic standard errors, are presented in the second row of Table 1. The estimation appears precise, particularly for ε, φ, μ_L, and μ_F. While the estimation for α_F, α_L, PIN_F and PIN_L seems fairly precise, δ_L and δ_F are not so well estimated. Indeed, when we use real market data in section 4, we find that the model is unable to provide small standard errors for δ_F and δ_L in a number of cases. This is simply a consequence of not separating buys (sells) made with market orders from those made with limit orders. However, this limitation is irrelevant for the purpose of this study since those parameters are not needed for the estimation of the PIN numbers. In a series of unreported simulations we tested the ability of model to estimate different combinations of true parameters based on simulated data. In the vast majority of the cases, the maximum likelihood of function [3] is able to identify with good precision the original parameters of the model and the PINs, sometimes with the exception of δ_F and δ_L.

On the other hand, the total number of trading intervals per day is a parameter not observed, but assumed by the econometrician. However, the assumed number of trading interval doesn't affect the estimation of PIN, as long as it is large enough. This is illustrated in Table 1, presenting the results of estimating the model based on the same 65 days of trading but assuming a total of 960 intervals per day. In the two cases, the estimations and standard errors of α_F, α_L, δ_F, δ_L and ρ are the same as in the first estimation, as expected, since the effects of those parameters are observed in a daily basis. On the other hand, the estimators of μ_L, μ_F, and ε tend to decrease proportionally to the assumed number of daily intervals, which is also expected since this parameters measure the frequency of informed and uninformed market order arrivals[13]. However,

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[13] Strictly speaking the inverse proportional relation between μ_L, μ_F, and ε with the number of total intervals is only true in the limit when NT is very large compared with FB+FS+LB+LS and the arrival of market orders becomes a Poisson process, as in EOS. For our purposes it will suffice to choose a NT large

those proportional changes tend to cancel with each other in the estimation of PIN_F and PIN_L in [4] and those variables and their asymptotic standard errors remains about the same. Thus, we expect that the assumed number of trading intervals won't affect the relevant results of the model, and, as a rule, when calculating the model on real data, we assume a number of trading intervals at least double of the maximum number of trades in a single day.

The fourth and fifth rows of Table 1 show the results of estimating the model based on a month of simulated data, 22 trading days, assuming 480 and 960 trading intervals respectively. As expected, the asymptotic errors obtained are larger than for the previous cases. However, the estimation is still reasonably precise for most of the parameters.

Finally, given the finite sample used to estimate the model, the reported asymptotic standard errors are not necessarily good estimators of the true standard errors. To account for that we run a series of Monte Carlo simulations (unreported), finding that, for quarterly estimation the asymptotic standard error for the PINs should be multiplied by 1.5, and for monthly estimation by 2.0, to have a conservative estimation of the true standard error.

3. Market Description and Data

The Jakarta Stock Exchange (henceforth JSE) is the main stock market in Indonesia. It is organized as a continuous limit order book market, without designated market makers. Since May 1995 the orders are processed by means of a computerized system, and since March 2002 a remote trading system is in place. The market comprises four boards, namely the regular, cash, crossing and negotiated boards. The regular board is the market for retail transactions and it is the largest of the four, accounting for about 80% of the trading value of the JSE. In the negotiated board the terms of the transactions are agreed directly between two brokers, while in the crossing board a trade is done by a broker that has two matching buy and sell orders. Trades over 20,000

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enough compared to the daily maximum number of transactions in the firm-quarter to guarantee that the PIN numbers and their asymptotic errors are independent of NT.

shares are usually processed by the crossing or the negotiated boards. Finally, in the cash board the settlement of trades is done the same day, unlike the regular board, where settlements occur on the third trading day after the transaction.

By middle 2006, the JSE is already considered a quite transparent market. At any given time, the investors can know not only the best bid and ask quotes and respective depths, but also the following five quotes and depths on both sides of the limit order book, in screens provided by different data vendors. Changes to the limit order book are updated in real time. After each transaction, agents in the market can observe not only the price and size of the transaction, but also the brokerage firm and the type, whether local of foreigner, of the two parties. This way, the market participants can tell if foreign or local investors are actively trading any given stock, and if they are net buying or selling. This makes the JSE an ideal case-study for the differential information between the two types of investors. Further market description on the JSE can be found in Bonser-Neal et al (1999), (2005) and Dvorak (2005)

From the JSE we obtain four separate datasets for the period April 2004 to March 2006. The first dataset compiles the daily statistics for each individual stock. It includes open, maximum, minimum and close prices, along with closing bid and ask prices and their respective closing depths, the number of transactions, volume and value traded for each stock day. These statistics are based on transactions on trades and quotes on the regular board, not including trades from the other three boards[14].

The second dataset consists of the volume of shares sold and the volume of shares bought per day and per stock by foreign investors in all four boards. The third database compiles the total daily volume traded by stock in each one of the four boards. To note, none of the three datasets registers the number of buys and sells by foreigners and locals, required by the informed trading model. To estimate the required variables we need to make two assumptions: First, we assume

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[14] This limitation for our analysis also happens in the NYSE, where data on the upstairs market is not usually available. However, as indicated, most of the trading volume takes place in the regular board.

that, in a given stock-month, the average size trade for foreigners in the regular board is about the same as for locals. Thus, we approximate the number of buys and sells in the regular board by foreigners (locals), as proportional to the volume traded by foreigners (locals) in the regular board and the total number of transactions by stock-day, taken from the first database. Second, we assume that the volume bought (sold) by foreigners in a stock in the regular board is proportional to the fraction of the daily volume traded in the regular board relative to the daily volume of the four boards. Using those two assumptions we estimate the number of daily foreign and local buys and sells per stock as follows:

$$\text{Daily Foreign buys: FB} = \frac{\text{Number\_of\_transactions}}{\text{Regular Board}} \times \frac{\text{Volume shares bought by FI All Boards}}{\text{Volume shares traded All Boards}}$$

$$\text{Daily Foreign sells: FS} = \frac{\text{Number\_of\_transactions}}{\text{Regular Board}} \times \frac{\text{Volume shares sold by FI All Boards}}{\text{Volume shares traded All Boards}}$$

$$\text{Daily Local buys: LB} = \frac{\text{Number\_of\_transactions}}{\text{Regular Board}} - \text{FB}$$

$$\text{Daily Local sells: LS} = \frac{\text{Number\_of\_transactions}}{\text{Regular Board}} - \text{FS} \qquad [6]$$

Clearly, in the above procedure the average transaction size per group and board affects the estimation of the number of trades. This is not necessarily undesirable, since models as Easley and O´Hara (1987) imply that informed traders tend to trade in larger sizes. However, it is uncertain how much the transaction size effect might distort the main results of this paper. Consequently, we use a transaction database from JSE for the period April 2005 to July 2005, as an alternative source to estimate the vectors of trades. That database includes every transaction completed, identifying not only the date, stock, price, size and type of buyer and seller (foreigner or local), but also the board where the transaction takes place. Using this database we are able to compute exactly, for each stock-day, the number of buys and sell for each group of investors in the regular board (FB, FS, LB and LS). This alternative database will be used to run robustness checks on the major results of the paper.

Finally, the last dataset reports the number of shares owned by foreign investors per day and per stock, along with the maximum allowed share of ownership for foreigners. Although in the past foreign investors were banned from owning more than 50% in some strategic industries, these limits have been lifted, and since 1999 foreigners can own up to 100% in all type of firms, except banks, where they can still own up to 99%. Thus, we don't expect that foreign ownership limits constitute an important factor in our analysis.

After merging the four datasets by firm and day, we eliminate those pertaining to warrants and rights, ending with 359 stocks. Then, we group the observations by stock-month and by stock-quarters for the purposes of estimating the informed trading model explained in section 2. Furthermore, we eliminate those months or quarters which have no more than 6 trading days in the month or quarter, ending with 5,246 stock-months and 2,148 stock-quarters as the input data of the informed trading model.

The summary statistics for the data are presented in Table 2, for the size deciles and for the total sample. It is apparent that most of the trading value and transactions take place in the top two size deciles, and that foreigners actively trading in those, while they don't trade much on average in medium and small firms. Thus, we'll devote special attention to the results of the informed trading model for large firms. Table 2 also shows that the ownership of foreign investors tends to be quite uniform across the size deciles, at an average of 16%, but, at the same time, there is considerable variation across firms in the same size decile.

4. Results

The summary statistics of the estimated parameters of the informed trading model are presented in Table 3, for the model estimated on stock-quarters, as well as for the model estimated on stock-months. Out of the initial 2,148 stock-quarters and 5,246 stock-months we were able to estimate the model for 2,144 stock-quarters and 5,228 stock-months. Most of the

observations for which the maximum likelihood didn't converge belong to the lower deciles in volume, and were typically small firms[15].

Table 3 reports, as discussed in section 2, that the estimation for the parameters μ_L, μ_F, ε, φ is more precise than for α_F, α_L, δ_F, δ_L, ρ as given by the average standard errors. Besides, as expected, the model is limited on detecting the sign of the information: the estimated errors of δ_F, δ_L are typically very high, as expected from the discussion in section 2. Notwithstanding, the parameters of interest PIN_L and PIN_F were estimated with reasonable precision, with average standard errors below 0.04 for both the stock-quarters and stock-months, respectively.

From Table 3, we don't see a dramatic improvement in the standard errors by estimating the model by stock-quarters instead of stock-months. Moreover, the estimation by stock-months better allows for the intertemporal variation of the parameters of the model and to estimate the time series effects of PIN_L and PIN_F on liquidity. The informed trading model has been usually estimated in the literature using one month of daily data, as in EKO. For those reasons, henceforth, we will only present the results of the analysis using the parameters estimated by stock-months. The main inferences of the paper are also obtained but not reported using the parameters estimated by stock-quarters.

The average estimated PIN_L and PIN_F are respectively 0.218 and 0.057 for the stock-month results, corresponding to an total average PIN of 0.28 which estimates the proportion of informed traders in the market. This value is comparable with, as the average between 0.16 to 0.22 reported by Easley et al (1996) for NYSE, and the averages between 0.17 and 0.29 for Latin American stock markets of Cruces and Kawamura (2005).

We start looking into Hypothesis 1 by plotting the estimated PIN_F vs. PIN_L for each stock-month in Figure 2. Most of the points are concentrated below the 45 degrees line, not only for the overall sample, but also for the top three deciles where most of the foreign trading is

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[15] Easley et al (1996) also reports problems in estimating a similar model based on infrequently traded stocks.

concentrated. This is a strong indication that most of the informed trades are done by locals. This is formally tested conducting a Wald test of the null-hypothesis $PIN_F < PIN_L$. As presented in the panel A of Table 4, this hypothesis is supported for the full sample as well as for each size deciles, at the 1% of significance level.

Another test of this hypothesis is conducted by performing a Wald test on the hypothesis $PIN_L - PIN_F = 0$ for each stock-month, using the estimated difference $PIN_L - PIN_F$ and its estimated error[16]. The results of this test are presented in Panel B of Table 4. For 46% of the entire sample we reject $PIN_L = PIN_F$ in favor of $PIN_L > PIN_F$. For only 1% of the stock-months we reject it in favor of $PIN_L < PIN_F$, and for the remaining 53% the hypothesis is not rejected. The results are robust across the different size deciles and using the stock-quarter estimations of PIN_L and PIN_F and strongly support the 'Home advantage' side.

The informed trading model assumes that only in those days with local (foreign) information the local (foreign) informed traders walk into the market, actively placing market orders. Thus, in this context, we can naturally ask whether the reported $PIN_L > PIN_F$ is due to more frequent days of local information than foreigner information ($\alpha_L > \alpha_F$) or to more aggressive informed trading by locals than by foreigners ($\mu_L > \mu_F$) when information is present.

Figure 3 illustrates the answer by plotting α_F vs α_L and μ_F vs μ_L for each one of the stock-months. In the graph of α_F vs α_L the points seem uniformly scattered, except some points concentrated in $\alpha_F = 0$. On the contrary, in the graph of μ_F vs μ_L the points tend to lay below the 45 degree line. This suggests that PIN_L is larger than PIN_F mostly because of more intensive trading by informed locals than more frequent arrivals of local information. A formal test is presented in Panel E of Table 4. On average, the mean of α_L is significantly higher than the mean of α_F, and that the same is true for μ_L with respect to μ_F. This result holds in all but the top decile. We conclude that PIN_L is larger than PIN_F in general, due to both more intense informed trading

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[16] To reject $PIN_L = PIN_F$ at the 5% level we required that the estimated difference $PIN_L - PIN_F$ be larger than four standard errors larger. This takes into account our findings regarding to the finite sample behavior of the asymptotic standard errors.

from locals than from foreigners, and to more frequent local informed days than foreign informed days.

So far, the results indicate that locals execute most of the informed trades in the JSE, supporting the 'Home advantage' position. This finding is not too surprising, since local investors carry on 89 % of the average trading value by firm, while foreigners only contribute the remaining 11%, as indicated in Table 2. A different perspective results from asking what is the probability of informed trading given the type of investor, measured as Conditional PIN_F and Conditional PIN_L [5]. The answer will tell us whether foreign investors are as likely to be informed as locals, or more likely, as proposed by Hypothesis 2, and the relative proportion of informed and uninformed traders in each group.

Figure 4 plots the probability of informed trading given that the investor is a foreigner (Conditional PIN_F) against the probability of informed trading given that the investor is local (Conditional PIN_L). The result goes completely opposite to the one on Figure 2: most of the points lay above the 45 degree line, indicating that the proportion of informed traders in the foreign group is higher than for the local group for most stock-months. This finding is confirmed by testing the null hypothesis that Conditional PIN_F = Conditional PIN_L as indicated in Panel D of Table 4. This hypothesis is rejected at the 1 % level both for the full sample and for all the size deciles. For the full sample the average probability of informed trading given that a foreigner arrives to the market is 47%, while when the market order comes from a local is 26%.

An alternative way to present those results is estimating the average composition of informed locals, uninformed locals, informed foreigners and uninformed foreigners in the JSE. The shares of informed traders, both foreigners and locals, are given directly by PIN_F and PIN_L. On the other hand, the share of uninformed traders in the market is presented in panel D of Table 4[17]. Summarizing, the informed trading model estimates that, on average, 29% of the market

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[17] Calculated at stock-month level as follows: Share of uninformed foreigners = $(1-PIN_L-PIN_F)\varphi$; Share of uninformed locals = $(1-PIN_L-PIN_F)(1-\varphi)$.

participants are informed traders posting market orders, and 71% are uninformed, whether posting market orders or providing liquidity by means of limited orders. Foreigners constitute a small part of either group, accounting for 21 % of the informed traders and 9% of the uninformed. The ratio of informed to uninformed for foreigners is 1 to 1.13 , whereas for locals is 1:2.8. In summary, foreigners are more likely to be informed traders than locals, and conversely, less likely to be uninformed or liquidity providers, as argued by the 'Big fish' proponents[18].

Taken together, the results conciliate the 'Home advantage' and 'Big Fish' positions: Domestic investors are by far the source of most of the informed trading, but at the same time, they are an even larger proportion of the uninformed traders. Table 4 and Figure 5 show that this assertion is valid for all the size deciles of the JSE: Locals consistently make up most of the informed traders across the size deciles, although for the top deciles the gap between the two groups is largely reduced. On the other hand, foreigners are more likely to be informed than locals for all the deciles.

As a robustness check, we run the informed trading model using the vector of trades computed from the JSE transaction database from April 2005 to July 2005. Although this sample represents just four months of trading activity, this database allow us to compute exactly the foreign buys, foreign sales, local buys and local sales in the regular board of JSE, without the assumptions implicit in [6]. The summary results are presented in panel C of Table 3, and panels F, G and H of Table 4 present the basic tests of the respective PIN numbers, as we did before. Apparently, these new results are in agreement with those already presented: Locals do most of the informed trades, while foreigners are more likely to be informed, both for the whole sample and for each one of the size deciles. Moreover, this also indicates that differential in the average size of trades between the two groups of investors don't seem to be driving the results

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[18] In a former version of this paper, the informed trading model was run for the period March 2004 to July 2005, assuming independence between the two signals, which is just a particular case of the present model with $\rho = 0$. The results were qualitatively the same.

Next, we explore the differential effects of foreign and locals on the liquidity of the stocks. A direct implication of the theoretical models of Glosten and Milgrom (1985) and EOS is that higher PINs should lead to higher bid-ask spreads. Liquidity providers increase the bid-ask spread to compensate themselves because they expect to suffer higher losses to informed traders. Furthermore, the model of EOS implies that for a fixed PIN, the higher the potential information of the informed trader, the higher the expected losses for the liquidity provider, and the higher the spread[19].

Table 5 presents the results of regressing bid-ask spreads against PIN_F and PIN_L. The regressand is the log of the average proportional spread in the stock-month, as in Grullon, Kanatas and Weston (2004). Panel A presents a time-series regression of the spread on the firm specific variables traditionally associated with time-series changes in liquidity: value traded, return and volatility as in Chordia, Sarkar and Subrahmanyam (2005). The model also includes firm-fixed effects to filter out cross-sectional effects, and a lag of the left-hand variable to control for its persistence and avoid autocorrelation in the residuals. The firm specific variables show up significant with the expected sign: negative for value traded and return and positive for volatility. Panel B includes PIN_F and PIN_L, yielding positive and significant effects from both variables, as implied by the theoretical models of Glosten and Milgrom (1985) and EOS. The effect of PIN_F is larger and more significant than the one of PIN_L. A Wald test confirms that the null hypothesis of equal effects of PIN_F and PIN_L is rejected at the 5% level. As mentioned before the PIN measures are estimated with a sampling error that might induce an errors-in-variable problem. To mitigate this, we remove from the model any stock-month with standard errors larger than 0.05 for PIN_F or 0.10 for PIN_L. Panel C reports the resulting model. The coefficients of PIN_F and PIN_L remain significant and positive, while the coefficients of the control variables show up with the expected

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[19] In our model the potential information of foreigners is given in [1] as $V_{1F} - V_{0F}$ while for locals is $V_{1L} - V_{0L}$

sign. Supporting Hypothesis 3, there is still significant difference between the effects of the two groups of informed traders, as given by a Wald-test on the respective coefficients.

Panels D to G explore the robustness of those findings. The model of Panel D uses the first half of the sample: stock-months until March 2005 inclusive, whereas Panel E uses the second half of the sample, from April 2005 on. The model reported in Panel F works with the firms in the deciles 1 to 5 (smaller), while the one of Panel G uses the firms in the deciles 6 to 10 (larger). The results confirm that the positive effect of the PINs on liquidity are robust, and that the effect of PIN_F is larger and more significant than the effect of PIN_L

Summarizing, the results of Table 5 reveal that both PIN variables have the effect on liquidity predicted by the theoretical models and, that PIN_F have a larger effect than PIN_L, not rejecting Hypothesis 3. We propose two possible interpretations for this. On the one hand, in the theoretical framework of Glosten and Milgrom (1985) and EOS this implies that the potential information of foreigners is higher on average than for locals. On the other hand, it might be just a consequence of foreigners posting more aggressive orders compared to locals, as suggested by Bonser-Neal et al (2005).

Before proceeding, it is important to discuss two alternative explanations of the results reported in Tables 4 and 5: one based on transaction size and the other based on inventory effects. First, it might be the case that part of what we detect as informed trades are simply larger trades. Anecdotal evidence indicates that foreign institutional investors engage periodically in large portfolio rebalancing trades, which are not necessarily information-based, and might impact the bid-ask spreads as in Koski and Michaely (2000). However, there are at least three reasons to think that this 'size effect' is not driving our results. First, it is expected that most non-information based larger trades (over 20,000 shares) be processed on the negotiated and crossing boards. Second, while this confounding size effect might take place on the top size deciles, where institutional investors trade the most, this would be hardly the case for the medium and lower size deciles where our main results still hold. And, third, while the estimation of the vector of trades in

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[6] might be affected by the 'size effect', as noted before, when computing the vector of trades from the JSE transaction data each trade is counted independent of its size, so the results derived from this database won't be subjected to this criticism.

The second alternative explanation of our results is that the effect of the PINs on the spread might be reflecting inventory costs from the liquidity provider rather than information asymmetry, as in Grossman and Miller (1988) and Ho and Stoll (1983). Although it is clear that the informed trading model here presented, as well as those of EOK and EOS, doesn't account for inventory effects on spreads, the inventory cost explanation creates more problems than it solves. In a limit market order such as the JSE without designated liquidity providers, one is left to guess who carry the inventory in the first place. One possible answer is that there are 'ad-hoc' liquidity providers simultaneously placing sell and limit orders and maintaining an inventory of the stock. However, two additional arguments further weaken the inventory cost explanation: First, Ahn et al (2002) provides evidence that inventory costs are less relevant in a limit-order market as the Tokyo Stock Exchange, compared with a hybrid market as the NYSE. Second, those 'ad-hoc' liquidity providers are unlikely to appear in the medium and small firms of the JSE characterized by low turnovers and frequent no-trade days, where our main results hold.

Next, we test whether both types of informed traders trade in the same type of firms. Hypothesis 4 poses that informed foreign investors trade in larger, higher volume firms, and firms with higher foreign ownership, where foreigners have less of a informational disadvantage. Figure 5 and panel A of Table 4 suggest that this might be the case: Informed foreign traders seem to prefer larger firms, while local informed traders slightly prefer smaller ones. To formally test this hypothesis we set-up Tobit models that explain the cross-sectional distributions of PIN_F and PIN_L as functions of several firm characteristics, as presented in Table 6. Panel A presents the results of the Tobit models that regress PIN_F and PIN_L on size, volume and volatility. Panel B adds in the share of foreign ownership in the firm. Panel C includes two measures of the internationalization of the firm: the ratio export to sales and a dummy variable equal to one if the firm has an ADR,

and the R^2 of the regression of the firm returns against the market index return. As a robustness test, Panel D includes industry-fixed effects and, to control for the potential endogeneity of PIN_F and PIN_L, a one-month lag of PIN_F in the regression of PIN_L and vice versa [20]. Finally, Panel E and Panel F check for the robustness of the findings in the first and second half of the sample, respectively.

The results of Table 6 shows unambiguously that PIN_L is higher the smaller and more volatile the firm, whereas PIN_F is higher for larger and less volatile firms. These results for PIN_L and PIN_F are robust in each of the alternative specifications presented in Table 6, even after controlling for industry effects and for the potential endogeneity of the two PIN variables, and in both the first and the second half of the sample (panels D to F) Additionally, Panels D to F show that informed locals and foreigners tend to trade in different types of firms, beyond the stated relations with size and volume: higher PIN_Fs are associated with lower PIN_Ls and the other way around, after controlling for firm-specific variables and industry-fixed-effects, reflecting that the two types of informed trading are substitute of each other.

Taking the results of Panel D we confirm that these results are economically significant: moving from the percentile 25% to the percentile 75% in size is associated with a reduction of 7.5% on PIN_L and a rise of 12% on PIN_F. Additionally, an increase of 10% in the PIN_F (PIN_L) is associated with a reduction of about 1% (0.8%) on PIN_L (PIN_F), holding constant size and trading volume.

Panels B to F show that an increase of 10% in the share of ownership by foreigners is associated with a 1% increase in PIN_F, statistically significant in all the models, and a 0.5% reduction in PIN_L, significant in all but in F. This is evidence that, in the JSE, foreign ownership is associated to information advantage to some extent, as Huang and Shiu (2005) shows in Taiwan. On the other hand, two other factors that have been related to improved information for

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[20]. Besides, it is likely that informed trading by locals hinders potential informed foreign traders and the other way around, creating a potential omitted-variable bias if those variables are not included.

foreigners, the ratio exports to sales and the ADR dummy variable, don't appear related to higher

PIN_Fs once controlling for all the other firm specific variables.

Finally, the results of Panels C to E show that both informed locals and foreigners tend to prefer firms with higher idiosyncratic risk, as given by the R^2. While this might due to reversal causality—The more informed trading, the larger the idiosyncratic risk—this is also consistent with the claims of Morck et al. (2000) in the sense that analysts prefer more transparent firms, which in turn tend to have higher idiosyncratic risk,..

Taken together these results are consistent with locals having an informational advantage in smaller and more volatile firms, while facing more competence from foreign investors in large, less volatile and higher foreign ownership firms. Thus, we provide direct evidence supporting some of the claims of Edison and Warnock (2004) and Kang and Stulz (1997) who conjectured that foreign investors reduce their information disadvantage by trading in the upper deciles of size.

Alternatively, the results are also consistent with foreign investors being better at processing macro information as suggested by the results of Seasholes (2004) in Taiwan and the study of Chan and Hameed (2005) on the effect of foreign analysts in emerging markets. If a group of investors is better at gathering and processing information that concerns the entire market, it is expected that they trade in the largest and most traded stocks, since those can provide an approximation to the market portfolio with reduced transaction costs. In fact, for the sample period, the 33 firms of the top size decile represented 83% of the market capitalization of the JSE. Thus, we have two different, but not incompatible, explanations for the increased information of foreigners in the largest firms: they might be better in processing firm-specific information for that group of firms or they might be better at obtaining market-wide information, which they exploit by trading in the largest firms[21].

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[21] Institutional factors might be playing a role. Freeman and Bartels (2000) reports that 55% of the institutional investors surveyed won't invest in Indonesian firms under US$ 50 M. However, as presented in

According with Hypothesis 5, if foreigner trades contain some market-wide information, a rise in the activity of foreign investors in the market should be taken as a signal of increased asymmetric information by the liquidity providers, triggering an overall increase on the bid-ask spreads. We test this implication in Table 8, which presents the results of a time-series regression of the proportional bid-ask spread on market-wide averages of the PIN variables, controlling for the firm-specific PIN_F and PIN_L and the usual control variables.

As a starting point, panel A of Table 7 reproduces the basic time-series regression of the proportional bid-ask spread on firm variables and firm-fixed effects, from panel B of Table 5. Panels B and C include, respectively, the value-weighted averages of PIN_F, PIN_L for the market, that measure the overall level of foreign and local information on the JSE. Interestingly, the effect of the market PIN_F is positive and significant, while the effect of the market PIN_L is smaller and not significantly different from zero. Those results are still present when we use both variables in the model presented in panel D. Moreover, The PIN_F effect appears both in the first and in the second part of the sample (panels E and F) and turns up significantly higher than the effect of the PIN_L at the usual confidence levels, using a Wald test (unreported). Overall, the results of the models B to F indicate that the level of informed foreign activity in the market is associated with a reduction on liquidity, even after controlling for the individual PIN_F and PIN_L of each stock-month and the usual confounding effects[22].

We are interested in understanding whether this macro-wide effect of PIN_F is incorporated in the market-wide level of liquidity of the market[23]. For this purpose, we incorporate a value-weighted average of the proportional bid-ask spread in the model, presented in panel G, that

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Table 2, the average share of foreigner ownership tends to be similar in every size decile of the JSE, so this can not be a complete explanation of the distribution of PIN_F

[22] The results are robust at using equally weighted averages of PINs and spread, instead of value weighted averages (unreported). Besides, the effect of PIN_F is also economically significant. Going from the minimum to the maximum of the monthly value-weighted averaged PIN_F in the sample (+10% change) is associated with an average growth of 16% in the proportional bid-ask spreads, according to the results in panel D.

[23] Also called systematic liquidity' by a strand of the literature that starts with Chordia, Roll and Subhramanyam (2000).

leaves the effect of market PIN_F reduced but still significant. This suggests that the market-wide effect of PIN_F is only partially incorporated in the market-wide liquidity of JSE

Thus, the evidence points to foreign informed traders having not only firm-specific but also market-specific information, unlike informed locals, providing support for Hypothesis 5. This is consistent with foreigners being better at processing macro information as suggested by Seasholes (2004) for Taiwan, and the results of Chan and Hameed (2005).

5. Conclusion

Studying the case of the Jakarta Stock Exchange, this paper addresses the question of who is better informed, foreigners or locals in emerging markets. We discuss three alternative ways to define this question: first, who is responsible for most of the informed trades in the market; second, given the type of investor, who is more likely to be informed; and third, whose trades have a larger negative impact on the bid-ask spreads.

The empirical strategy adopted starts by extending the model of Easley, Kiefer and O'Hara (1996), and Easley, O'Hara and Saar (2001) to a market where the liquidity is provided by a limit order book, and with two types of investors, which in turn can be informed or uninformed. We show how the parameters of the model can be estimated from observing the total buys and sells of both groups on a daily basis. Then, we show how to estimate the probability of informed trading (PIN) for both foreigners and locals separately.

We estimate the extended model with data from the Jakarta Stock Exchange, obtaining the PIN numbers for foreigners and locals on a stock-month basis. The analysis of those results provides direct answers to the three questions: First, locals do most of the informed trades, both at an aggregate market level as well as for most of the stock-months. Second, given the type of investors, foreigners are more likely to be informed than locals, both at an aggregate market level,

as well as for most of the stock-months. Third, both types of informed trading have a negative effect on the proportional bid-ask spreads, having the foreigners a larger negative impact.

In conclusion, locals are more informed in Indonesia, agreeing with Dvorak (2005) and the literature on 'Home bias'. But, at the same time, the overall result is consistent with foreigners being more sophisticated investors, more likely to trade on information than the average local, and with larger firm and market wide effects on liquidity, in agreement with the results of Seasholes (2005) and Huang and Shui(2005) for Taiwan and the literature on institutional investors.

Future research can take advantage of the methodology presented here to study differentials of information across groups of investors and their effects on liquidity. On the other hand, we consider that additional research be done concerning the differences between the local and foreigner information in emerging markets. Seasholes (2004), Chan and Hameed (2005) and this paper provide results consistent with the common intuition that foreigners have an edge in terms of macro information, but more direct evidence needs to be provided.

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Figure 1. Informed Trading Model

Before the trading day   First trading interval

$\Psi_F =L$
$\alpha_F \delta_F$

$\Psi_L =L$ $\alpha_L \delta_L$ $+ \rho$

$\mu_F(1- \tfrac{1}{2} \mu_L)$ — Uninformed Buy / Foreign Sell (Informed)
$\mu_L(1- \tfrac{1}{2} \mu_F)$ — Uninformed Buy / Local Sell (Informed)
$(1- \mu_F)(1-\mu_L)$ — A

$\Psi_L =0$ $(1-\alpha_L)$ $- \rho$

μ_F — Uninformed Buy / Foreign Sell (Informed)
$1- \mu_F$ — A

$\Psi_L =H$ $\alpha_L(1-\delta_L)$ $+\rho$

$\mu_F(1- \tfrac{1}{2} \mu_L)$ — Uninformed Buy / Foreign Sell (Informed)
$\mu_L(1- \tfrac{1}{2} \mu_F)$ — Uninformed Buy / Local Buy (Informed)
$(1- \mu_F)(1-\mu_L)$ — A

$\Psi_F = 0$
$(1-\alpha_F)$

$\Psi_L =L$ $\alpha_L \delta_L$ $- \rho$

μ_L — Uninformed Buy / Local Sell (Informed)
$1- \mu_L$ — A

$\Psi_L =0$ $(1-\alpha_L)$ $+ \rho$

— A

$\Psi_L =H$ $\alpha_L(1-\delta_L)$ $- \rho$

μ_L — Uninformed Buy / Local Buy (Informed)
$1- \mu_L$ — A

$\Psi_F =H$
$\alpha_F (1- \delta_F)$

$\Psi_L =L$ $\alpha_L \delta_L$ $+ \rho$

$\mu_F(1- \tfrac{1}{2} \mu_L)$ — Uninformed Buy / Foreign Buy (Informed)
$\mu_L(1- \tfrac{1}{2} \mu_F)$ — Uninformed Buy / Local Sell (Informed)
$(1- \mu_F)(1-\mu_L)$ — A

$\Psi_L =0$ $(1-\alpha_L)$ $- \rho$

μ_F — Uninformed Buy / Foreign Buy (Informed)
$1- \mu_F$ — A

$\Psi_L =H$ $\alpha_L(1-\delta_L)$ $+\rho$

$\mu_F(1- \tfrac{1}{2} \mu_L)$ — Uninformed Buy / Foreign Buy (Informed)
$\mu_L(1- \tfrac{1}{2} \mu_F)$ — Uninformed Buy / Local Buy (Informed)
$(1- \mu_F)(1-\mu_L)$ — A

Uninformed Buy (Sell) :
φ Foreign Buy (Sell)
$1- \varphi$ Local Buy (Sell)

A :
ε — Uninformed Buy / Uninformed Sell
$1- \varepsilon$ — No-trade

Figure 2. PIN$_F$ vs PIN$_L$

PIN$_L$: Probability of informed local trading. PIN$_F$: Probability of informed foreign trading. Parameters estimated by maximum likelihood, with the informed trading model described in section 2, using data from Jakarta Stock Exchange from April 2004 to March 2006. Model estimated each stock-month from daily data, stock-months with less than 6 trading days are not used in the model. Size deciles by average market capitalization in 2005.

▫ : Size deciles 1-7. ▪ : Size deciles 8-10 (the largest)
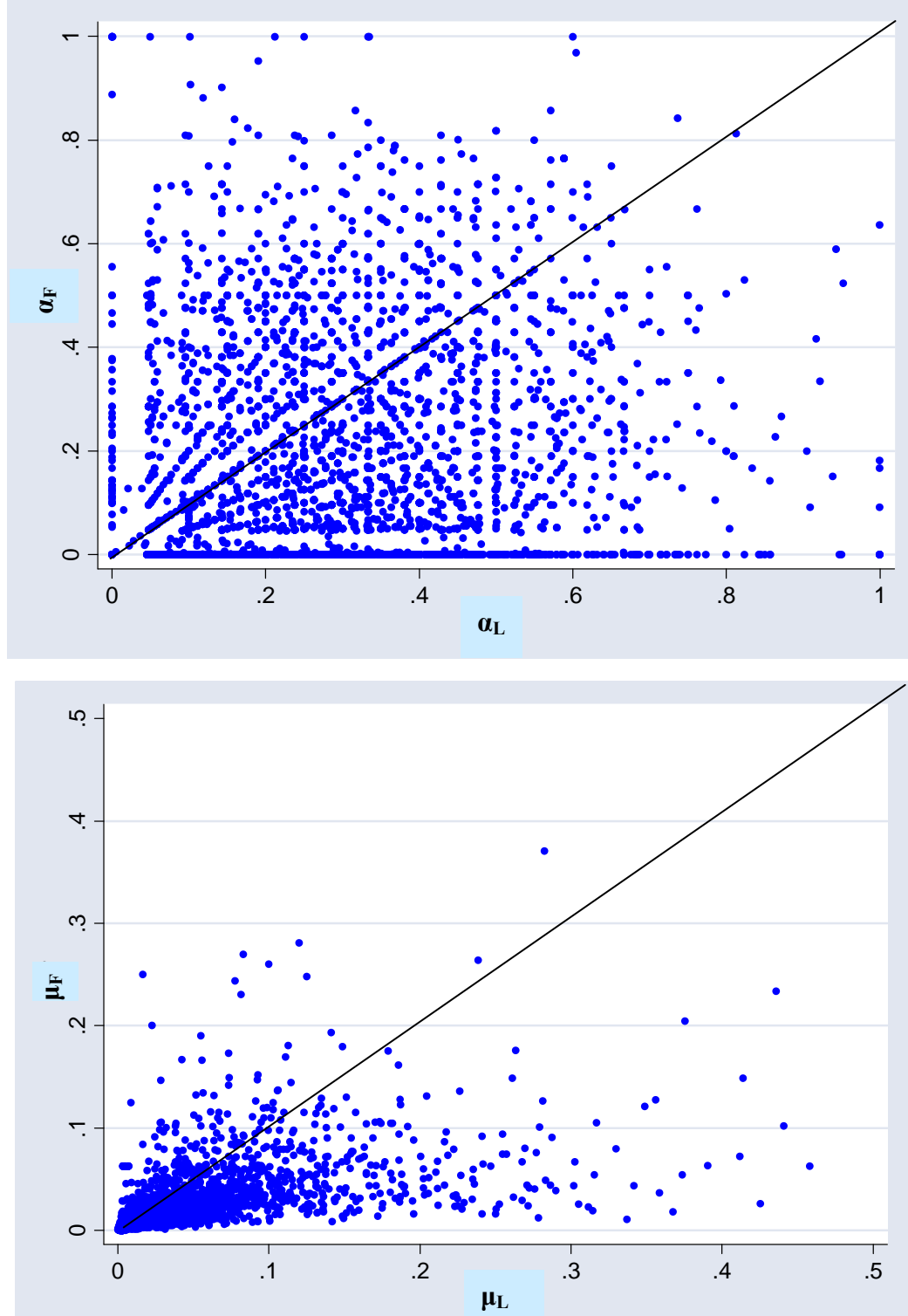
Figure 3. α_F vs α_L , μ_F vs μ_L

α_L : Probability of a local informed day. α_F: Probability of a foreign informed day. μ_L: Probability of local informed trade in an interval, conditional on a local informed day. μ_F: Probability of foreign informed trade in an interval, conditional on a foreign informed day. μ_L, μ_F expressed based on a day with 3,600 intervals. Parameters estimated by maximum likelihood, with the informed trading model described in section 2, using data from Jakarta Stock Exchange from April 2004 to March 2006. Model estimated each stock-month from daily data, stock-months with less than 6 trading days are not used in the model. Stock-months with either μ_L, μ_F larger than 0.5 are not presented (less than 2% of the total data).
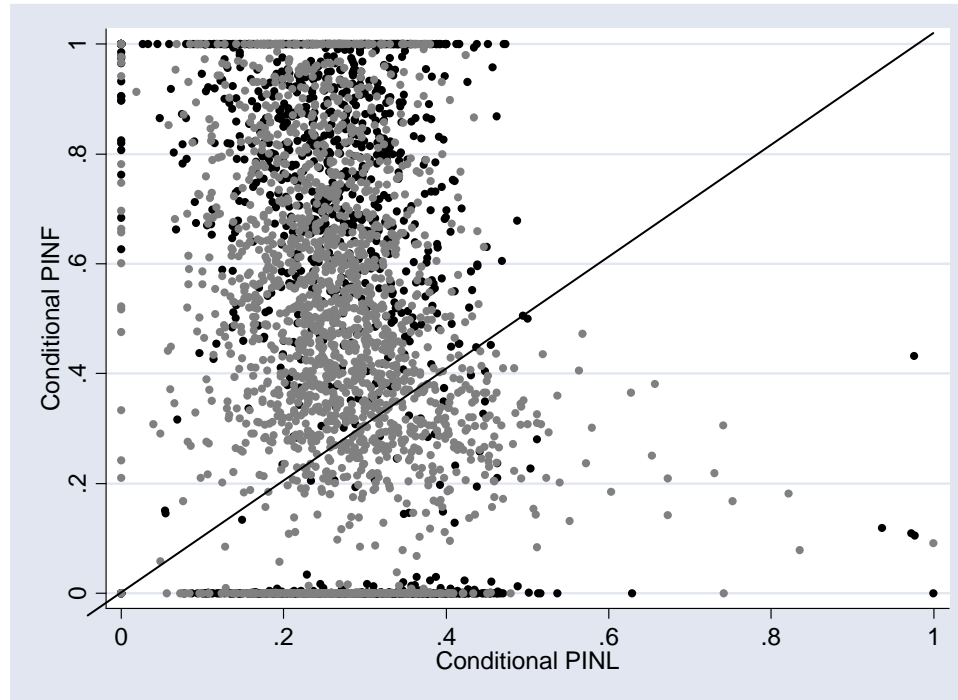
Figure 4. Conditional PIN$_F$ vs Conditional PIN$_L$

Conditional PIN$_L$ (PIN$_F$): Probability of informed trading given that the trader is local (foreigner). Computed from parameters of the informed trading model described in section 2, estimated by maximum likelihood, using data from Jakarta Stock Exchange from April 2006 to March 2005. Model estimated each stock-month from daily data, stock-months with less than 6 trading days are not used in the model.

■ : Size deciles 1-7. ■ : Size deciles 8-10 (the largest)
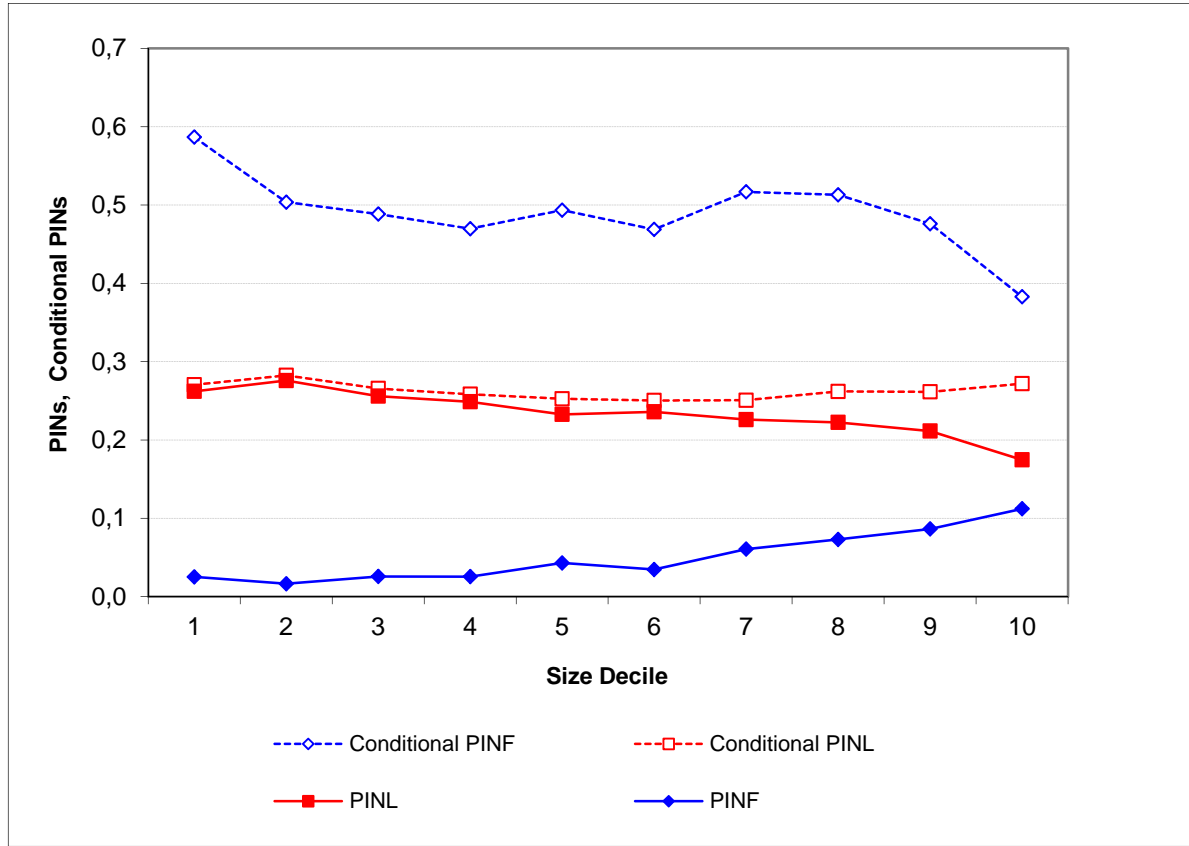
Figure 5. Probability of Informed trading by size deciles

PIN_L: Probability of informed local trading. PIN_F: Probability of informed foreign trading. Conditional PIN_L (PIN_F): Probability of informed trading given that the trader is local (foreigner) computed from the estimated parameters. Parameters estimated by maximum likelihood, with the informed trading model described in section 2, using data from Jakarta Stock Exchange from April 2004 to March 2006. Model estimated each stock-month from daily data, stock-months with less than 6 trading days are not used in the model.

Table 1. Example of estimation of the informed trading model

Results of estimating the parameters of the informed trading model using simulated data. The model described in section 2 is simulated using the parameters in the 'True values' row, with 480 intervals per day. A sample of 65 simulated days is used to estimate back the parameters, indicated in the two rows 'Quarter' .Likewise, a sample of 22 simulated days is used to estimate back the parameters, by maximum likelihood, as indicated in the Row 'Month'..

Interval: The sum of the total number of trades and no-trades in a day. α_L : Probability of a local informed day. α_F: Probability of a foreign informed day. δ_L: Probability of a low information given that is a local informed day δ_F: Probability of a low information given that is a foreign informed day. μ_L: Probability of local informed trade in an interval, conditional on a local informed day. μ_F: Probability of foreign informed trade in an interval, conditional on a foreign informed day. ε: Probability of arrival of an uninformed trader. φ: probability of a foreign uninformed, placing either a market or a limit order. PIN$_F$: Probability of informed foreign trading. ρ: parameter of correlation of the two signals. PIN$_L$: Probability of informed local trading. PIN$_L$ - PIN$_F$: difference between the two probabilities of informed trading. Standard errors in parenthesis, estimated by the inverse of the Hessian Matrix.

	No. intervals	α_L	α_F	δ_L	δ_F	μ_L	μ_F	ε	φ	ρ	PIN$_F$	PIN$_L$	PIN$_L$-PIN$_F$
True values	480	0.25	0.15	0.70	0.30	0.30	0.20	0.20	0.30	0.10	0.10	0.27	0.17
Simulated period													
Quarter 65 days	480	0.23	0.14	0.77	0.39	0.31	0.20	0.20	0.30	0.09	0.09	0.25	0.16
		(0.034)	(0.028)	(0.076)	(0.115)	(0.004)	(0.005)	(0.001)	(0.003)	(0.018)	(0.015)	(0.028)	(0.027)
Quarter 65 days	960	0.23	0.14	0.77	0.39	0.13	0.08	0.10	0.30	0.09	0.08	0.22	0.14
		(0.034)	(0.028)	(0.076)	(0.115)	(0.002)	(0.002)	(0.001)	(0.003)	(0.018)	(0.014)	(0.025)	(0.023)
Month 22 days	480	0.41	0.27	0.89	0.50	0.31	0.21	0.19	0.29	0.12	0.15	0.37	0.22
		(0.069)	(0.062)	(0.069)	(0.135)	(0.005)	(0.006)	(0.002)	(0.005)	(0.029)	(0.027)	(0.041)	(0.05)
Month 22 days	960	0.41	0.27	0.89	0.50	0.14	0.09	0.10	0.29	0.12	0.14	0.33	0.19
		(0.069)	(0.062)	(0.069)	(0.135)	(0.003)	(0.003)	(0.001)	(0.005)	(0.029)	(0.025)	(0.036)	(0.043)

Table 2. Summary Statistics

Size decile	Traded value (Billion Rupiah)	Number of Trades	%Foreign Investor Trade		Proportional bid-ask spread	Market Capitalization (Million Rupiah)	% Foreign Investor ownership		
			Mean	p95			Mean	p5	p95
1	89.9	23.0	1.9%	10.4%	12.1%	14,913	17.6%	0.1%	50.6%
2	115.0	22.2	1.4%	7.4%	9.9%	29,394	10.4%	0.0%	48.6%
3	65.2	14.3	2.8%	20.0%	9.3%	60,977	16.5%	0.4%	55.9%
4	162.4	21.3	3.4%	30.2%	8.3%	117,493	13.5%	0.0%	42.1%
5	247.6	25.7	5.8%	50.0%	5.1%	151,112	15.3%	0.0%	38.8%
6	573.9	42.2	3.8%	30.3%	5.2%	290,692	21.2%	0.7%	63.0%
7	669.0	39.2	9.4%	50.0%	4.5%	523,349	13.5%	0.9%	39.9%
8	1965.1	52.0	11.6%	50.0%	3.4%	1,008,397	16.4%	0.3%	46.1%
9	4751.7	102.0	15.5%	55.2%	3.1%	2,391,294	18.3%	2.0%	50.9%
10	23261.8	216.7	34.3%	77.1%	1.5%	19,900,000	20.3%	1.6%	57.3%
Total	4496.1	68.8	11.2%	53.9%	5.4%	2,687,820	16.3%	0.0%	50.9%

The deciles of market capitalization are given by the average market capitalization during 2005. Traded value and number of trades are averages of the daily values for the entire period, including non-trading days. % Foreign investor Trade is an average of the daily values of (Foreign sales + Foreign buys)/2/ volume. Proportional bid-ask spread is the average whenever quotes are available. Market capitalization and % of Foreign Investor ownership are averages for the first quarter of 2006. % Foreign Investor Ownership is the proportion of listed shares owned by investors. Exclude stock-months with less than 5 trading days. Total sample: 359 firms. Period: April 2004 to March 2006. Source: Jakarta Stock Exchange.

Table 3. Summary of results of estimating the Informed trading model

From JSE daily databases

	Panel A				Panel B			
	Based on stock-quarters				Based on stock-months			
Parameter	Number of estimations	Mean	Standard Deviation	Mean standard error	Number of estimations	Mean	Standard Deviation	Mean standard error
α_L	2144	0.213	0.147	0.149	5228	0.267	0.172	0.186
α_F	2144	0.131	0.172	0.164	5228	0.146	0.199	0.212
δ_L	2144	0.555	0.363	0.320	5228	0.569	0.384	0.362
δ_F	2144	0.476	0.372	0.306	5228	0.456	0.392	0.355
μ_L	2144	0.038	0.078	0.006	5228	0.034	0.064	0.007
μ_F	2144	0.024	0.088	0.014	5228	0.018	0.068	0.054
ϵ	2144	0.018	0.015	0.068	5228	0.025	0.018	0.080
φ	2144	0.081	0.144	0.126	5228	0.092	0.159	0.144
ρ	2144	0.016	0.034	0.039	5228	0.015	0.045	0.039
PIN_L	2144	0.212	0.094	0.037	5228	0.218	0.096	0.042
PIN_F	2144	0.057	0.067	0.021	5228	0.057	0.074	0.021
Conditional PIN_L	2144	0.242	0.106		5228	0.251	0.108	
Conditional PIN_F	1680	0.553	0.345		3814	0.473	0.365	

Panel C: Based on stock months, from JSE transaction databases

Parameter	Number of estimations	Mean	Standard Deviation	Mean standard error
α_L	912	0.258	0.174	0.184
α_F	912	0.124	0.198	0.224
δ_L	912	0.567	0.387	0.368
δ_F	912	0.489	0.394	0.382
μ_L	912	0.032	0.056	0.006
μ_F	912	0.008	0.021	0.001
ϵ	912	0.026	0.017	0.075
φ	912	0.065	0.112	0.143
ρ	912	0.015	0.040	0.037
PIN_L	912	0.215	0.102	0.044
PIN_F	912	0.041	0.066	0.019
Conditional PIN_L	912	0.237	0.110	
Conditional PIN_F	613	0.423	0.369	

Parameters resulting of the estimation of the informed trading model described in section 2, estimated by maximum likelihood, using daily data from Jakarta Stock Exchange from April 2004 to March 2006 (Panels A and B) and transaction data from April 2005 to July 2005 (Panel C). α_L: Probability of a local informed day. α_F: Probability of a foreign informed day. δ_L: Probability of a low information given that is a local informed day δ_F: Probability of a low information given that is a foreign informed day. μ_L: Probability of local informed trade in an interval, conditional on a local informed day. μ_F: Probability of foreign informed trade in an interval, conditional on a foreign informed day. ϵ: Probability of arrival of an uninformed trader. φ: probability of a foreign uninformed, placing either a market or a limit order. ρ: parameter of correlation of the two signals. PIN_F: Probability of informed foreign trading. PIN_L: Probability of informed local trading. Conditional PIN_L (PIN_F): Probability of informed trading given that the trader is local (foreigner) computed from the estimated parameters. The parameters μ_L, μ_F and ϵ are expressed based on a day with 3600 intervals. Number of estimations: the number of stock-quarters (stock-month) where the parameter could be estimated, 'Mean' and 'Standard deviation' are the average and standard deviation of the parameter across the estimations, respectively. 'Mean standard error' is the average standard error for the parameter, estimated using the Hessian Matrix.

Table 4 Comparing probability of informed trading for locals and foreigners

Size decile	A			B		C		
	PIN_L	PIN_F		$PIN_L > PIN_F$	$PIN_L < PIN_F$	PIN_L conditional	PIN_F conditional	
1	0.26	0.03	**	56%	0%	0.27	0.59	**
2	0.28	0.02	**	66%	1%	0.28	0.50	**
3	0.26	0.03	**	57%	1%	0.27	0.49	**
4	0.25	0.03	**	55%	3%	0.26	0.47	**
5	0.23	0.04	**	54%	0%	0.25	0.49	**
6	0.24	0.03	**	56%	2%	0.25	0.47	**
7	0.23	0.06	**	48%	2%	0.25	0.52	**
8	0.22	0.07	**	42%	1%	0.26	0.51	**
9	0.21	0.09	**	39%	1%	0.26	0.48	**
10	0.17	0.11	**	18%	0%	0.27	0.38	**
Total	0.23	0.06	**	46%	1%	0.26	0.47	**

Size decile	D			E					
	Market Share uninformed								
	Locals	Foreigners		α_L	α_F		μ_L	μ_F	
1	70.5%	0.8%	**	0.25	0.04	**	0.041	0.020	*
2	70.0%	0.8%	**	0.26	0.04	**	0.043	0.018	**
3	70.4%	1.4%	**	0.23	0.05	**	0.023	0.011	**
4	71.4%	1.2%	**	0.24	0.05	**	0.020	0.014	
5	69.9%	2.5%	**	0.26	0.08	**	0.019	0.009	**
6	70.6%	2.4%	**	0.26	0.09	**	0.035	0.014	**
7	67.4%	3.9%	**	0.28	0.14	**	0.022	0.010	**
8	64.1%	6.3%	**	0.28	0.17	**	0.033	0.015	**
9	61.1%	9.1%	**	0.30	0.22	**	0.054	0.029	**
10	49.6%	21.7%	**	0.34 *	0.36		0.073	0.042	**
Total	64.7%	6.7%	**	0.28	0.15	**	0.045	0.024	**

Size decile	F			G		H		
	PIN_L	PIN_F		$PIN_L > PIN_F$	$PIN_L < PIN_F$	PIN_L conditional	PIN_F conditional	
1	0.279	0.008	**	71%	0%	0.282	0.400	
2	0.295	0.009	**	79%	0%	0.298	0.433	
3	0.250	0.018	**	65%	0%	0.257	0.480	*
4	0.263	0.019	**	65%	0%	0.270	0.355	
5	0.217	0.031	**	56%	1%	0.226	0.375	*
6	0.243	0.023	**	64%	0%	0.255	0.385	*
7	0.226	0.040	**	60%	0%	0.242	0.427	**
8	0.223	0.053	**	51%	1%	0.246	0.485	**
9	0.220	0.059	**	51%	1%	0.253	0.445	**
10	0.174	0.093	**	28%	0%	0.232	0.413	**
Total	0.230	0.043	**	55%	2%	0.252	0.429	**

Averages of the parameters estimated with the informed trading model detailed in section 2 for each decile of market capitalization and for the Total sample. Parameters of the informed trading model described in section 2, estimated by maximum likelihood, using daily data from Jakarta Stock Exchange from April 2004 to March 2006 (Panels A to E) and transaction data from April 2005 to July 2005 (Panels F to H). The Model is estimated for each stock-month from daily data, stock-months with less than 6 trading days are not used in the model. PIN_L: Probability of informed local trading. PIN_F: Probability of informed foreign trading. $PIN_L > PIN_F$ and $PIN_L < PIN_F$: stock-months for which this different is significant at the 5% level. α_L: Probability of a local informed day. α_F: Probability of a foreign informed day. μ_L: Probability of local informed trade in an interval, conditional on a local informed day. μ_F: Probability of foreign informed trade in an interval. μ_L, μ_F expressed based on a day with 3600 intervals (maximum number of trades) and conditional on $\alpha_F > 0$ and $\alpha_L > 0$. Conditional PIN_L (PIN_F): Probability of informed trading given that the trader is local (foreigner). Local (Foreign) Uninformed: % of the traders that correspond to the local (foreign) uninformed group either by posting market orders or providing liquidity with limit orders. **, *: lower than the average for the local (foreigner) group at 1% and 5% level, respectively.

Table 5. Time series regressions of liquidity against PIN_F and PIN_L

	A		B		C		D		E		F		G	
LAG_SPREAD	0.469	**	0.462	**	0.505	**	0.456	**	0.298	**	0.415	**	0.541	**
VALUE	-0.110	**	-0.112	**	-0.108	**	-0.123	**	-0.121	**	-0.106	**	-0.109	**
RETURN	-3.345	**	-3.274	**	-4.525	**	-3.942	**	-3.294	**	-3.285	**	-5.874	**
VOLAT	4.769	**	4.759	**	4.422	**	3.932	**	4.888	**	3.909	**	5.484	**
PIN_F			0.186	**	0.271	**	0.329	**	0.228	*	0.447	*	0.195	**
PIN_L			0.065	*	0.138	**	0.207	**	0.126	**	0.16	*	0.106	*
N	4334		4334		2726		1339		1387		858		1868	
R2	0.91328		0.91376		0.93156		0.9294		0.95582		0.89446		0.90152	
PIN_F =PIN_L effect p-value			0.014		0.067									

Results of regressing of liquidity (log of average proportional bid-ask spread) against PIN_F, PIN_L and firm characteristics for stock-months. Data from the Jakarta stock Exchange, from April 2004 to March 2006. Excludes stock-months with less than 6 trading days, or less than 21 transactions. All models include firm-specific effects and a constant (omitted). Panel A and B include the whole sample, while Panels C to G are restricted to those stock-months with standard errors below 0.10 for PIN_L, and 0.05 for PIN_F . Panel D are stock-months before April 2005, whereas Panel E is after March 2005. Panel F is for stocks in deciles 1 to 5, while Panel G is for deciles 6 to 10. LAG SPREAD is the log of average proportional bid-ask spread for the previous month. VALUE is the log of the average value traded by stock month in million Rupiah. RETURN is the return in the stock month. VOLAT is the average of the absolute value of the daily return in the stock month. PIN_L: Probability of informed local trading. PIN_F: Probability of informed foreign trading. PIN_F, PIN_L estimated with the informed trading model detailed in section 2, by maximum likelihood. PIN_F effect ≠PIN_L effect is the p-value of a Wald-test on the difference of the coefficients of PIN_F and PIN_L.. Heteroskedastic Robust standard errors: *: Significant at the 5% level, ** significant at the 1% level.

Table 6 . Cross-sectional Tobit regression of PIN_F and PIN_L on firm variables

Variable	A PIN_L		A PIN_F		B PIN_L		B PIN_F		C PIN_L		C PIN_F		D PIN_L		D PIN_F		E PIN_L		E PIN_F		F PIN_L		F PIN_F	
SIZE	-0.029	**	0.045	**	-0.030	**	0.046	**	-0.028	**	0.045	**	-0.030	**	0.046	**	-0.041	**	0.039	**	-0.018	**	0.051	**
VOLAT	0.636	**	-0.890	**	0.640	**	-0.887	**	0.689	**	-0.901	**	0.576	**	-0.743	**	0.422	*	-0.734	**	0.852	**	-0.879	**
VALUE	0.005	**	0.001		0.006	**	-0.001		0.009	**	0.006	*	0.012	**	0.008	**	0.019	**	0.013	**	0.005		0.004	
FOREIGN OWN.					-0.044	**	0.109	**	-0.038	**	0.114	**	-0.044	**	0.114	**	-0.052	*	0.139	**	-0.034		0.116	**
EXPORT									0.025	**	-0.064	**	0.008		-0.036	*	-0.005		-0.051	*	0.020		-0.025	
ADR									-0.020		-0.001		-0.016		0.031		-0.018		0.032		-0.012		0.021	
R2									-0.113	**	-0.192	**	-0.120	**	-0.243	**	-0.158	**	-0.281	**	-0.082		-0.212	**
LAG PIN_F													-0.113	**			-0.079	**			-0.138	**		
LAG PIN_L															-0.085	**			-0.053	*			-0.114	**
N	4870		4870		4870		4870		4866		4866		4152		4152		1976		1976		2176		2176	
Industry effects?	No		No		No		No		No		No		Yes		Yes		Yes		Yes		Yes		Yes	

Results of a Tobit model of PIN_F, PIN_L by stock month against firm characteristics. Data from the Jakarta stock Exchange, from April 2004 to March 2006, unless noticed otherwise. Excludes stock-months with less than 6 trading days, or less than 21 transactions. All models include month specific effects and a constant (omitted). Models D to F include industry specific effects. PIN_L: Probability of informed local trading. PIN_F: Probability of informed foreign trading. PIN_F, PIN_L estimated with the informed trading model detailed in section 2, by maximum likelihood. SIZE is the log of the average market capitalization of the stock month in million Rupiah. VOLAT is average of the absolute value of the daily return in the period. VALUE is the log of the average value traded in million Rupiah by the stock in the period. FOREIGN OWN. Is the average foreign share of ownership. EXPORT: Is the ratio of total export sales on total sales for 2005 (from Bloomberg). R2 is the r^2 on the regression the daily returns of the stock against the JSE market index for days with transactions for the entire period. ADR is a dummy variable, =1 if the stock has an ADR (from Bank of NewYork ADR database). LAG PIN_F(LAG PIN_L) is the last month PIN_F (PIN_L). Standard errors: *: Significant at the 5% level, ** significant at the 1% level.

Table 7 Market-wide effects of PIN_L and PIN_F on liquidity

Variable	A		B		C		D		E		F		G	
LAG_SPREAD	0.462	**	0.455	**	0.462	**	0.454	**	0.399	**	0.275	**	0.432	**
PINL	0.186	**	0.146	**	0.186	**	0.143	**	0.161	*	0.129		0.128	**
PINF	0.065	*	0.069	*	0.066	*	0.065	*	0.080		0.017		0.052	
VALUE	-0.11	**	-0.11	**	-0.11	**	-0.114	**	-0.12	**	-0.13	**	-0.113	**
RETURN	-3.274	**	-2.67	**	-3.23	**	-2.73	**	-2.45	**	-2.68	*	-2.628	**
VOLAT	4.759	**	4.519	**	4.746	**	4.538	**	4.287	**	4.887	**	4.467	**
MKT_PIN$_F$			1.542	**			1.610	**	2.114	**	0.618	*	0.608	**
MKT_PIN$_L$					-0.123		0.279		1.165	**	-0.03		-0.233	
MKT_SPREAD													16.345	**
N	4334		4334		4334		4334		2170		2164		4334	
adj R2	0.907		0.909		0.907		0.909		0.904		0.925		0.911	

Results of a time-series model of liquidity for stock-months (log of average proportional bid-ask spread). Data from the Jakarta stock Exchange, from April 2004 to March 2006. Excludes stock-months with less than 6 trading days, or less than 21 transactions. All models include firm specific effects and a constant (omitted). PIN$_L$: Probability of informed local trading. PIN$_F$: Probability of informed foreign trading. PIN$_F$, PIN$_L$ Parameters estimated by maximum likelihood, with the informed trading model described in section 2. VALUE is the log of the average value traded by stock-month in million Rupiah. RETURN is the return in the stock month. VOLAT is the average of the absolute value of the daily return in the stock month. MKT_PIN$_F$ (MKT_PIN$_L$): Value weighted average across stocks of PIN$_F$ (PIN$_L$) for a given month with standard errors lower than 0.05 (0.10). MKT_SPREAD. Log of the Value weighted average across stocks of proportional bid-ask spread.

Robust standard errors: * significant at the 5% level. ** significant at the 1% level

Appendix

The probability of a given vector of foreign buys, foreign sells, local buys and local sells, $\Gamma = $ [FB, FS, LB, LS, NT]' is a function of the signals Ψ_F, Ψ_L and the parameters of the model described in section 2, as follows.

$$\Pr\{\Gamma \mid \Psi_F = L, \Psi_L = 0\} = C_\Gamma \; [\mu_F \varphi + (1 - \mu_F)\varepsilon\varphi]^{FB} \; [\mu_F + (1 - \mu_F)\varepsilon\varphi]^{FS}$$
$$\cdot \; [\mu_F(1-\varphi) + (1-\mu_F)\varepsilon(1-\varphi)]^{LB} \; [(1-\mu_F)\varepsilon(1-\varphi)]^{LS} \; [(1-\mu_F)(1-\varepsilon)]^{NT} \qquad [A.1]$$

$$\Pr\{\Gamma \mid \Psi_F = H, \Psi_L = 0\} = C_\Gamma \; [\mu_F + (1 - \mu_F)\varepsilon\varphi]^{FB} \; [\mu_F \varphi + (1 - \mu_F)\varepsilon\varphi]^{FS} \; [(1-\mu_F)\varepsilon(1-\varphi)]^{LB}$$
$$\cdot \; [\mu_F(1-\varphi) + (1-\mu_F)\varepsilon(1-\varphi)]^{LS} \; [(1-\mu_F)(1-\varepsilon)]^{NT} \qquad [A.2]$$

$$\Pr\{\Gamma \mid \Psi_F = 0, \Psi_L = L\} = C_\Gamma \; [\mu_L \varphi + (1 - \mu_L)\varepsilon\,\varphi]^{FB} \; [(1 - \mu_L)\varepsilon\,\varphi]^{FS} \; [\mu_L(1-\varphi) + (1-\mu_L)\varepsilon(1-\varphi)]^{LB}$$
$$\cdot \; [\mu_L + (1-\mu_L)\varepsilon(1-\varphi)]^{LS} \; [(1-\mu_L)(1-\varepsilon)]^{NT} \qquad [A.3]$$

$$\Pr\{\Gamma \mid \Psi_F = 0, \Psi_L = H\} = C_\Gamma \; [(1 - \mu_L)\varepsilon\,\varphi]^{FB} \; [\mu_L \varphi + (1 - \mu_L)\varepsilon\,\varphi]^{FS} \; [\mu_L + (1-\mu_L)\varepsilon(1-\varphi)]^{LB}$$
$$\cdot \; [\mu_L(1-\varphi) + (1-\mu_L)\varepsilon(1-\varphi)]^{LS} \; [(1-\mu_L)(1-\varepsilon)]^{NT} \qquad [A.4]$$

$$\Pr\{\Gamma \mid \Psi_F = L, \Psi_L = L\} = C_\Gamma \; [(\mu_F + \mu_L - \mu_F \mu_L)\varphi + (1-\mu_F)(1-\mu_L)\varepsilon\varphi]^{FB}$$
$$\cdot \; [\mu_F(1 - \tfrac{1}{2}\mu_L) + (1-\mu_F)(1-\mu_L)\varepsilon\varphi]^{FS} \; [(\mu_F + \mu_L - \mu_F \mu_L)(1-\varphi) + (1-\mu_F)(1-\mu_L)\varepsilon\varphi]^{LB}$$
$$\cdot \; [\mu_L(1 - \tfrac{1}{2}\mu_F) + (1-\mu_F)(1-\mu_L)\varepsilon(1-\varphi)]^{LS} [(1-\mu_F)(1-\mu_L)(1-\varepsilon)]^{NT} \qquad [A.5]$$

$$\Pr\{\Gamma \mid \Psi_F = H, \Psi_L = H\} = [\mu_F(1 - \tfrac{1}{2}\mu_L) + (1-\mu_F)(1-\mu_L)\varepsilon\varphi]^{FB}$$
$$\cdot \; [(\mu_F + \mu_L - \mu_F \mu_L)\varphi + (1-\mu_F)(1-\mu_L)\varepsilon\varphi]^{FS} \; [\mu_L(1 - \tfrac{1}{2}\mu_F) + (1-\mu_F)(1-\mu_L)\varepsilon(1-\varphi)]^{LB}$$
$$\cdot \; [(\mu_F + \mu_L - \mu_F \mu_L)(1-\varphi) + (1-\mu_F)(1-\mu_L)\varepsilon\varphi]^{LS} [(1-\mu_F)(1-\mu_L)(1-\varepsilon)]^{NT} \qquad [A.6]$$

$$\Pr\{\Gamma \mid \Psi_F = H, \Psi_L = L\} = C_\Gamma \; [\mu_F(1 - \tfrac{1}{2}\mu_L) + \mu_L(1 - \tfrac{1}{2}\mu_F)\varphi + (1-\mu_F)(1-\mu_L)\varepsilon\varphi]^{FB}$$
$$\cdot \; [\mu_F(1 - \tfrac{1}{2}\mu_L)\varphi + (1-\mu_F)(1-\mu_L)\varepsilon\varphi]^{FS} \; [\mu_L(1 - \tfrac{1}{2}\mu_F)(1-\varphi) + (1-\mu_F)(1-\mu_L)\varepsilon(1-\varphi)]^{LB}$$
$$\cdot \; [\mu_L(1 - \tfrac{1}{2}\mu_F) + \mu_F(1 - \tfrac{1}{2}\mu_L)(1-\varphi) + (1-\mu_F)(1-\mu_L)\varepsilon(1-\varphi)]^{LS} [(1-\mu_F)(1-\mu_L)(1-\varepsilon)]^{NT} \qquad [A.7]$$

$$\Pr\{\Gamma \mid \Psi_F = L, \Psi_L = H\} = C_\Gamma \; [\mu_F(1 - \tfrac{1}{2}\mu_L)\varphi + (1-\mu_F)(1-\mu_L)\varepsilon\varphi]^{FB}$$
$$\cdot \; [\mu_F(1 - \tfrac{1}{2}\mu_L) + \mu_L(1 - \tfrac{1}{2}\mu_F)\varphi + (1-\mu_F)(1-\mu_L)\varepsilon\varphi]^{FS}$$
$$\cdot \; [\mu_L(1 - \tfrac{1}{2}\mu_F) + \mu_F(1 - \tfrac{1}{2}\mu_L)(1-\varphi) + (1-\mu_F)(1-\mu_L)\varepsilon(1-\varphi)]^{LB}$$
$$\cdot \; [\mu_L(1 - \tfrac{1}{2}\mu_F)(1-\varphi) + (1-\mu_F)(1-\mu_L)\varepsilon(1-\varphi)]^{LS} [(1-\mu_F)(1-\mu_L)(1-\varepsilon)]^{NT} \qquad [A.8]$$

$$\Pr\{\Gamma \mid \Psi_F = 0, \Psi_L = 0\} = C_\Gamma \; [\varepsilon\varphi]^{FB+FS} \; [\varepsilon(1-\varphi)]^{LB+LS} \; [1-\varepsilon]^{NT} \qquad [A.9]$$

Where C_Γ is the number of ways of arranging combinations FB foreign buys, FS foreign sales, LB local buys, LS local sells and NT non-trade intervals