Informed Trade, Uninformed Trade, and Stock Price Delay

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Abstract

This paper examines how the probability of informed trading (PIN), a measure of information-based trading risk developed by Easley et al (1996), affects the speed at which stock prices adjust to market-wide information. We find that in all but the least active stock portfolios, prices of low PIN stocks are faster to impound market-wide news than those of high PIN stocks. PIN's significance in explaining individual stock price delay is robust to the inclusion of size, liquidity and risk controls but is subsumed by the level of uninformed trade. Our results suggest that PIN's role in the delayed response of stock prices is driven by the lack of uninformed or liquidity trading rather than by information asymmetry, and provide new empirical evidence regarding the channel through which trading affects the speed at which stock prices adjust to information. Our findings also suggest that at least part of the "private information" and informed trade captured by PIN relates to the skilled interpretation of public common factor information.

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1. Introduction

Standard asset pricing models assume that investors are rational and that new information is rapidly incorporated into stock prices in a complete and frictionless market. However, a growing body of research suggests that information gradually diffuses across asset markets due to the attention constraints of investors. Since attention is a scarce cognitive resource (Kahneman, 1973; Pashler and Johnston, 1998), attention to one task automatically substitutes the cognitive resources from other tasks. Given the immense amount of information available in financial markets and the inevitability of limited cognitive capacity, investors can only partially process available information and choose to learn about, and trade, a subset of stocks (Merton 1987). Consequently, certain stocks are favoured more than others and information is reflected in stock prices at varying rates, which leads to a price delay effect or a lead-lag pattern in stock returns (Hong and Stein, 1999; Hirshleifer and Teoh, 2003; Peng and Xiong, 2006). Empirical research has documented that the returns of more recognized stocks, such as those stocks of larger firms, with higher volume, higher level of institutional ownership, or more financial analyst coverage, lead the returns of less-recognized stocks (Lo and MacKinlay, 1990; Brennan et al, 1993; Badrinath et al, 1995; Sias and Starks, 1997; Chordia and Swaminathan, 2000). The lead-lag phenomenon has been attributed to variations in the speed of response to common factor information (Brennan et al, 1993; Chordia and Swaminathan, 2000; Hou 2007). Hou and Moskowitz (2005) find that this delay is significantly inversely related to both attention and liquidity proxies.

Ample empirical evidence has supported the notion that the returns of more-recognized stocks lead the returns of less-recognized stocks due to more rapid adjustment of stock prices to common factor information, while trading directly affects liquidity and stock price discovery; surprisingly little empirical research has been devoted to examining the link between the information attributes of trade and the adjustment speed of stock prices. Our research fills this gap by examining how the probability of informed trading (PIN), a measure of private information trading risk developed by Easley et al (1996), affects the speed at which stock prices adjust to common factor (market-wide) information.

Easley et al (1996) describe a microstructure model to estimate PIN based on the abnormal trading of stocks. According to the model, trades for each stock are classified into informed trades and uninformed trades (or liquidity trades). Uninformed trade occurs regardless of there being any new information, such as for portfolio rebalancing and liquidity needs, and is assumed to be constant. Informed traders only transact when they receive a private information signal about the asset's value; a good (bad) news event will trigger buy (sell) orders. Thus informed trade is captured in buy-sell imbalances, and PIN is measured as the ratio of informed trades to total trades. Easley et al (1998) find stocks with more analysts have lower PIN as a result of more informed trade and an even greater level of uninformed trade. They explain such an effect under Merton's (1987) investor recognition framework in which traders transact only in stocks that they are familiar with, and analysts serve to increase volume by showcasing stocks to uninformed traders. Empirical evidence indicates that PIN is related to well-known proxies for investor recognition. For example, PIN is lower for high volume stocks (Easley et al, 1996) and is likely to be higher among less-recognized firms characterized by small size, lower liquidity, fewer shareholders and less analyst coverage (Aslan et al, 2011).

A few papers have suggested the importance of informed trading in stock price response to information. Holden and Subrahmanyam (1992) find that competition among informed traders leads to quicker incorporation of information into prices. In the spirit of Merton (1987), Chordia and Swaminathan (2004) develop a microstructure model to explain the observed cross-autocorrelations in stock returns. They suggest that when informed investors trade only in the sub-set of stocks about which they are informed, stock prices with more informed trading will adjust to common factor information more rapidly than the prices of stocks with less informed trading leading to the observed lead-lag cross-autocorrelations in stock returns.

Motivated by the empirical evidence that low-PIN stocks share the attributes of well-recognized "leader" stock, and the literature that informed trading plays a key role in price discovery efficiency, we investigate whether there is a link between PIN and the speed at which stock prices adjust to market-wide information. More specifically, we examine whether the returns of portfolios comprised of low-PIN stocks adjust more rapidly to market-wide news than high-PIN portfolios after controlling for liquidity, and whether PIN and its component parameters (arrival rate of informed trading, arrival rate of uninformed trading, information event likelihood, and bad news event likelihood) can explain the delayed response of individual stock prices to common factor information.

We address these issues at both portfolio and individual stock levels using data for stocks listed on the Australian Stock Exchange (ASX) over the period from 1996 to 2010. We start by estimating yearly PIN for each stock based on the approach proposed by Easley et al (1996), hereafter referred to as EKOP, using ASX Intraday Trade data provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA). The EKOP methodology is attractive due to its moderate data requirement; the model can be easily estimated by counting the number of buyer-initiated and seller-initiated trades for each stock in each trading day. Unlike the U.S., in the Australian market there is no market maker and on-market trades do not occur inside the spread[1], so trades are signed as buyer or seller initiated in the data we use. Thus we could avoid the estimation error in existing U.S. studies resulting from using Lee and Ready (1991) algorithm to infer trade direction (Odders-White, 2000; Boehmer et al, 2007). Furthermore, the Australian market has a greater relative preponderance of small stocks than the U.S. markets. This provides sharp contrast in the level of uninformed and informed trade among stocks yet sufficient dispersion in the values of PIN for our tests that seek to discern the effect of informed trade and uninformed trade.

For our portfolio level tests, we use Dimson (1979) beta regressions to examine the speed with which the prices of low-PIN and high-PIN portfolios respond to market-wide information. We first form four portfolios ranked by turnover to control for the lead-lag effect of liquidity documented in literature (Chordia and Swaminathan, 2000), and then sort the stocks in each turnover quartile into four portfolios based on PIN. In total we have sixteen portfolios that are rebalanced every year. Using the market return as a proxy for common factor news, we examine the responsiveness of value-weighted daily returns of our extreme (lowest and highest) PIN portfolios, within each turnover quartile, to the

[1] Crossings, that is trades between different clients of the same brokerage firm, do occur but are separately identified in the intraday trade data

contemporaneous market return and to leads and lags of the market return. We also run the regressions using equally-weighted returns to check for robustness.

At the individual stock level, we investigate whether the delayed response of stock prices can be explained by PIN and its component parameters controlling for other factors that may influence price efficiency, such as size (Lo and Mackinlay, 1990), liquidity (Chordia and Swaminathan, 2000) and firm level uncertainty (Peng et al, 2007). Similar to Hou and Moskowitz (2005), we construct a variable to measure a stock's price delay estimated by its price response to contemporaneous and lagged stock market returns, and then regress the price delay variable on PIN, its component parameters and the control variables.

To our knowledge, this paper is the first empirical research to examine the role that PIN and its component parameters play in the delayed response of stock prices to common factor information. Consistent with previous studies on the U.S. markets (Easley et al, 1996; Aslan et al, 2011), our Australian sample shows that lower PIN is associated with more-recognized stocks, such as larger firms, stocks with higher price, more liquid stocks, and stocks with lower firm level risk. Our research sheds light on the link between recognition, price efficiency and informed trade, and contributes to the relevant literature in the following important aspects.

Firstly, we provide new empirical evidence regarding the channel by which trading affects the speed at which stock prices adjust to information. Distinguished from the previous research focusing on the influence of informed trading (Holden and Subrahmanyam1992; Chordia and Swaminathan 2004), this research investigates the role that PIN, a measure of information-based trading risk, and its parameters play in the speed of stock price response to common factor information. We find that the returns of low-PIN portfolios adjust more rapidly to market news than their high PIN counterparts, controlling for liquidity, however, this relationship is invisible for the least liquid portfolios where both informed trading and uninformed trading are low. Controlling for liquidity, size and firm-specific risk, individual stock price delay is significantly related to higher PIN, a lower probability of information events and lower levels of informed trading. However, the effect of PIN seems to be subsumed by uninformed trading as the PIN variable loses its significance when the variable for uninformed trading enters the regression. The results are consistent with previous empirical evidence that more recognized stocks, such as stocks with high volume or more analysts, have a lower PIN as a result of more informed trading and an even greater level of uninformed trading, and that less recognized stocks have a higher PIN not because they have high level of informed trading but because they have much lower level of uninformed trading (Easley, et al, 1996, 1998). Our results suggest that PIN's role in the delay response of stock prices to common factor information is not driven by the risk of information asymmetry but by the lack of uninformed or liquidity trading. This finding is consistent with recent empirical research that casts doubt on the effect of PIN on asset prices documented by Easley et al. (Easley, Hvidkjaer and O'Hara 2010; Easley, Hvidkjaer and O'Hara 2002). For example, Duarte and Young (2009) find that the price effect of PIN is captured by its illiquidity component rather than the information asymmetry component.

Secondly, this research provides new evidence in support of the view that PIN may have captured private information resulting from skilled interpretation of public common factor information. PIN is designed to measure the probability of private information-based trading estimated from the imbalance of trading orders, which is referred to as information asymmetry risk or private information trading risk. However, it is still an open question as to whether PIN captures exclusively the risk of insider-type trading based on firm-specific private information or also captures informed trade resulting from private interpretation of market wide public information. Easley and O'Hara (2004) demonstrate that, holding other things identical, an asset with more private information and less public information is regarded as more risky and therefore investors (particularly uninformed investors) will require a higher expected return, thus information risk is a determinant of stock returns. Easley et al (2002, 2010) provide empirical evidence in support of the existence of information risk premium in which stocks with higher PIN have higher expected returns. In the above influential studies, PIN seems to identify firm-specific private information. However, a body of growing empirical research questions what PIN has identified. Vega (2006) finds that PIN is contemporaneously positively correlated with the consensus public news surprises and she suggests that private signals might be triggered by public information that is not easily interpreted[2] and therefore PIN may also capture informed trading by investors who are particularly skilled in analysing public news. Akay et al (2012) document a significantly higher average PIN estimate on short-term T-bills than the PIN estimates on equities documented in the literature, which directly questions PIN as a measure of private information-based trading as it is unlikely that the T-bill market has more private information than equity markets. Bardong et al (2009) find strong evidence of a market-wide component in information asymmetry, measured by PIN. On average, almost half of the explained variation in the level of informed trading is attributed to market-wide commonality, and market-wide commonality in information asymmetry is significantly greater for larger firms. Their findings support the existence of a core component in PIN related to private information about systematic factors or sophisticated investors who generate private information from public information. Our price delay measures directly reflect the delayed response of stock prices to public common factor information, and our findings that PIN and its component parameters play a significant role in the adjustment speed of stock prices to common factor information suggest that at least part of the "privately informed" trade captured by PIN comes from the "private interpretation" of common factor information by sophisticated investors.

Moreover, our sample reveals that informed trade has increased dramatically in recent years along with increased market participation. Given the penalties that exist in Australia for insider trading and for failure to promptly disclose value-relevant information, the marked increase in the level of informed trade is unlikely explained by increased access to private firm-specific information. Intuitively, the lower cost associated with trading and technologies that enhance information evaluation and trade execution likely promote interest in pursuing an advantage in analysing *public* information and the advantage may extend to both *firm–specific* and *common factor* news.

The rest of the paper proceeds as follows: Section 2 describes our data and variables measurement. In Section 3 we present our methodology for portfolio-level and individual stock level tests. Our empirical results are contained in Section 4, and Section 5 concludes.

[2] As also described in Kim and Verrecchia (1994).

2. Data and Variables Measurement

Our sample comprises fully paid ordinary shares traded on the ASX between January 1, 1996 and November 26, 2010. All data are sourced from the databases provided by SIRCA. Our PIN and volume-related measures are drawn from an initial 520 million trade observations recorded for the period in the ASX Intraday Trade Data. To reduce the likelihood that delayed price response is a mere function of illiquidity among stocks with large transaction costs, we remove companies whose price, on any day in a year, was below 2 cents[3]. Our final sample comprises 2,810 firms and 11,828 firm-year observations representing between 72% and 93% of total year-end market capitalisation.

We test the robustness of our findings using a 'reduced sample' that excludes firm year observations where a firm's daily closing price was less than $1.00 or where the number of annual trades is less than 1500. This eliminates low value stocks where minimum tick sizes likely impose constraints to trade[4] and observations where PIN estimates are more likely to suffer from too few trades. Our 'Reduced' sample has only 3,196 firm-year observations.

2.1 PIN and its parameters

We estimate PIN based on the model proposed by EKOP that describes a market in which buy orders (B) or sell orders (S) arrive sequentially from two types of traders: the informed trader and the uninformed trader. Uninformed trade is alternatively referred to as liquidity trade or noise trade. It occurs for reasons other than related to the arrival of value-relevant news and is assumed constant. Further, given that the trades are uninformed, they are neither weighted toward buy or sell side so the rate of arrival of uninformed buy orders (ε^B) and uninformed sell orders (ε^S) are assumed equal. Informed trader, on the other hand, only trades when he receives a news signal. News is assumed to arrive in a day with the probability, α. A day can only be associated with a single news event and all such news event days are assumed to be independent of each other. If the news is bad (the probability of which is δ), the informed trader sells and, if the news is good (with probability $1-\delta$), the informed trader buys. The rate of arrival of the informed trades is denoted μ. So, on a bad news day there are

[3] The relative minimum spread on these shares for our sample period is between 5% and 100% given that, in Australia, a minimum tick size of $0.001 applies to trades in shares within the price range $0.001 to $0.10.
[4] Minimum tick on stocks in the price range $0.100 to $0.495 was $0.005 during our sample period and, on stocks $0.505 to less than $2, was $0.010 up to April 1, 2005 and $0.005 after April 1, 2005.

more sell-initiated trades as the sell order flow for the day arrives according to a Poisson distribution with intensity, $\mu+\varepsilon^S$, while the buy order flow (limited to the uninformed buy-side trade) arrives according to the Poisson distribution with intensity ε^B. Conversely, on a good news day there are more buy-initiated trades. On a no-news day, buy and sell trades are roughly equal and total trades are 2ε.

On a day of unknown type the probability of observing a given number of buys (B) and sells (S) is the weighted average of the good news, bad news and no news probabilities. We thus estimate the parameter vector $\theta = (\alpha, \delta, \mu, \varepsilon)$ for each year for each stock using the EKOP maximum likelihood function:

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

The probability of information-based trading is then calculated for each stock for each year as the estimated incidence of informed trade divided by total trades:

$$
PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon^B + \varepsilon^S} \qquad \text{................................(2)}
$$

Consistent with the bulk of existing empirical studies (e.g. Easley et al, 1996; Easley et al, 1997a; Easley et al, 1998; Easley et al, 2002; Vega, 2006), we choose a daily time interval because trade numbers would be insufficient in smaller intervals to estimate PIN parameters for a large proportion of stocks in Australia. The intraday trade data provide historical details of all individual trades placed on the Stock Exchange Automated Trading System (SEATS). Each trade includes details of the price, volume and a flag to identify whether it was buy-initiated (buyer crossed spread), sell-initiated (seller crossed spread), a cross initiated trade (same buyer and seller), or a trade not classified as any of these given the price was determined by the algorithm for opening trade. Unlike the US, the Australian market is order-driven with no market maker and on-market trades do not occur inside the spread. It is possible therefore to identify the direction of the initiated trade without inferring the direction based on tick prices or quotes such as required by the Lee and Ready (1991) algorithm. Trades that are classified as neither buy nor sell (e.g. cross-trades) are excluded but comprise only 5.35% of the total 278.2million trades that were the basis of our PIN calculation. Our count of buy and sell trades is after amalgamating trades that are executed in multiple parts. These are separately denoted in the data so we do not need to adopt techniques to approximate the incidence of part trades, such as suggested by Hasbrouck (1988) and as is common in various US studies.

Following Aslan et al (2011), we exclude firm-years where the trade-day observations are fewer than 60. We use the likelihood function (1) and a grid of initial parameter estimates for $\alpha, \delta, \mu, \varepsilon$ to minimise non convergence issues [5] which primarily related to stocks with too few Buys and Sells, and we exclude these observations.

2.2 Delay

Following Hou and Moskowitz (2005), $DELAY_{i,t}$ is calculated annually for each stock using the R-Squared from the following restricted and unrestricted regressions:

Unrestricted model:

$$r_{i,t} = \alpha_i + \beta_{U,i} Rm_t + \sum_{k=1}^{5} \delta_{i,k} Rm_{t-k} + \varepsilon_{i,t} \quad \text{......................(3)}$$

Restricted model:

$$r_{i,t} = \varphi_i + \beta_{Ri} Rm_t + \nu_t \quad \text{..(4)}$$

where $r_{i,t}$ is the daily return to stock i on day t and Rm_t is the value-weighted market return (VWMR). If the price of a stock adjusts with delay to the market, we expect the explanatory power of equation (3), as measured by its R-Squared, will be higher relative to the R-Squared of equation (4) which includes only the contemporaneous market return. Conversely, if a stock's price responds

[5] We use four different starting values for alpha and five for delta, nine for mu and ten for epsilon: allowing for 1800 permutations. We encounter non-convergence in 36 cases. However, we encounter a further 1859 violations of second-order optimality conditions; 1827 of these produce solutions at the bounds of alpha and/or delta (i.e. corner solutions where the estimate of alpha and/or delta equals one or zero).

without delay to market news then the inclusion of lagged market returns in the unrestricted model (3) will add little explanatory power, and the R-Squared of each equation will be similar. A ratio that reflects the relative explanatory power of each equation will capture the relative importance of lagged market returns to a stock's price and thus provides a measure of the delay in response to market news. DELAY is then calculated annually for each stock as:

$$DELAY_{i,t} = 1 - \frac{R_R^2}{R_U^2} \quad \text{..........(5)}$$

where R_R^2 is the R-squared from the restricted model and R_U^2 is the R-squared from the unrestricted model. We subtract the ratio of the R-Squared from 1 so that our measure is higher where delayed response is greater.

2.3 Daily returns, liquidity and other control variables

2.3.1 Daily returns

We calculate the daily continuously compounded return (Rtn=LN($CPRICE_t$/$CPRICE_{t-1}$), where CPRICEt is the closing price on day *t* adjusted for dividends and capital changes) for each stock using data sourced from ASX Daily Trades. To control for the effect of infrequent trading, we follow Chordia and Swaminathan (2000) and exclude returns for days where there is no closing price for either day *t* or day *t-1*. After removing the most extreme return observations (more than 10 standard deviations from the annual mean), we match 2,355,996 observations to stocks for which we have PIN and liquidity measures. We use this sample to calculate value-weighted market returns ('VWMR'), our proxy for market information: $VWMR_t = \ln\left(1 + \sum_{i=1}^{n} w_{i,t-1} R^*_{i,t}\right)$

where $R^*_{i,t}$ is discrete return for stock *i* on day *t* and, w_{it-1} is the market value of stock *i* on day *t-1* divided the sum of the market value of all stocks on that date .

2.3.2 Liquidity measures

Given the association between PIN and illiquidity (Easley et al, 1996; Duarte and Young, 2009), we include liquidity-related variables in our tests to address the possibility that our results are driven by illiquid stocks rather than by information asymmetry. These liquidity measures include the number of shares traded (VOL), the number of trades (TRANS), and the number of trading days (DAYS TRADE), and turnover (TURN) calculated annually. Turnover is measured as the total number of shares traded in the year divided by the average number of shares outstanding during the year. The average number of shares outstanding is computed based on monthly figures as reported on the Share Price and Price Relative ('SPPR') database.[7] We exclude the top and bottom 0.5% of TURN to control for extremes outliers.

2.3.3 Other variables

Other control variables in our individual stock regressions include firm size (SIZE) measured as the natural log of market value (e.g., a stock's daily closing price multiplied by the number of ordinary shares on issue at the prior month-end as recorded in the SPPR database); firm idiosyncratic volatility (IDIOV) measured as the standard deviation of the residuals from the market model using daily returns; and PRICE using the annual average of the daily closing prices for each stock.

2.4 Summary statistics

Table 1 shows the summary statistics of the variables. The average PIN is 0.251that is substantially higher than the 0.211 reported by Aslan et al (2011) and the 0.208 reported by Easley et al (2010) in their US studies; which indicates that our Australian sample likely includes a greater number of small, less active stocks. The probability of an information event (alpha) on any day averages 0.239 and, given a news event, there is a near equal chance of it being good news and bad news (delta 0.491). Our sample shows a wide range in PIN and in both the uninformed trade and informed trade arrival rates. DELAY averages 0.506 but ranges from an extremely low 0.003 indicative of high

[7] We also check the robustness of our results using annualised turnover with adjustment for stocks that existed for only part of a year, so that their annual turnover is not understated. The results are qualitatively the same.

synchronicity with the market, to the highest possible value 1.0, suggesting, in that case, no immediate response to market news.

Table 2 reports simple cross-correlations between the yearly measures of our key variables. DELAY is negatively related to liquidity variables (TURN, TRANS, VOL and DAYS TRADE) and to firm size (SIZE), which is consistent with evidence that liquidity and firm visibility reduce common factor price response delay (Hou and Moskowitz, 2005). The correlation between DELAY and PIN is significantly positive (0.16), indicating a higher probability of informed trade is associated with delayed response to market-wide news or less synchronicity with the market as Roll (1988) suggests. Uninformed trade (epsilon) and informed trade (mu) are negatively correlated with PIN but are highly positively correlated with each other (0.89).

2.5 Characteristics of PIN portfolios

In order to gauge the firm characteristics associated with PIN, we sort our stocks at the end of each year based on PIN and form five portfolios ranked from lowest PIN, quintile 1, to highest PIN, quintile 5. The portfolios are rebalanced every year. Table 3 reports the mean values of the key variables for each of the five portfolios.

Table 3 indicates that PIN is associated with the price response delay. DELAY is monotonically increasing in PIN with a statistically significant difference between the extreme quintile portfolios (0.144, p-value<0.01). While our extreme PIN portfolios identify significant differences in the attributes of low PIN and high PIN stocks, trends are less discernible in the intermediate quintiles. Unlike the U.S., the Australian market is characterised by very few large firms and an abundance of small firms, so it is conceivable that our portfolio sorts based on PIN, fail to detect noticeable variation in firm characteristics beyond the two extreme quintiles.

The results reported in Table 3 are consistent with existing empirical research. Lower PIN stocks demonstrate the characteristics of great investor recognition: larger firms, higher prices (Easley et al, 2002; Vega, 2006; Aslan et al, 2011) , greater liquidity (Easley et al, 1996; Duarte and Young, 2009), high informed trade and even greater uninformed trade (Easley et al 1998).

Finally, we note that high PIN stocks tend to have slightly more bad news events than lower PIN stocks and, in the highest quintile, bad news (sell-side informed trade) was more likely (delta= 0.577) than good news (buy-side informed trade) in our sample period. We control for delta (bad news) in our regressions to reduce the possibility that any observed delay is related only to a slow response to bad news such as Hong et al (2000) have observed.

3. Empirical Framework

3.1 Portfolio-level tests

We follow Brennan et al (1993) and Chordia and Swaminathan (2000) to test for the price response delay at portfolio level and use two-way portfolio sorts to reduce firm-level noise in the return series. First, we sort stocks at the end of each calendar year into quartiles based on annual turnover (TURN) and then, within each quartile, into four portfolios based on their PIN. Our first level sort controls for the illiquidity effect on price delay (Chordia and Swaminathan, 2000).

We then use the Dimson (1979) beta regressions to test the relevance of PIN to the speed of price response controlling for illiquidity. Specifically, we form portfolio that is long in the lowest PIN stocks and short in the highest PIN stocks within each turnover quartile, which lead to four portfolios that are reformed annually. We calculate the daily value-weighted returns (and alternatively, for robustness, equal-weighted returns) for each of these portfolios, denoted as $r_{0,t}$, over the year following portfolio formation. Using value-weighted market return, Rm, as the proxy for market-wide news, we regress $r_{0,t}$ on the contemporaneous, five leads and lags of daily market portfolio returns, expressed by the following equation:

$$r_{0,t} = \alpha_0 + \beta_0 Rm_t + \sum_{k=-1}^{-5} \lambda_{0,k} Rm_{t-k} + \sum_{k=+1}^{5} \delta_{0,k} Rm_{t-k} + \mu_t \text{ ....(6)}$$

Our lag length of five (5) days is consistent with Chordia and Swaminathan (2000), and we use daily returns rather than weekly to better control for the possible influence of non-synchronous trading without suffering a severe reduction in our sample.

We predict that the returns of low PIN portfolios will adjust more rapidly to market news than those of high PIN portfolios. The slope coefficients indicate the speed of adjustment to market news. Given that $\delta_0=\delta_{(Low\ PIN)}-\delta_{(High\ PIN)}$, if high PIN stocks respond to market news with more delay, we expect $\delta_{(High\ PIN)}$ to be greater than $\delta_{(Low\ PIN)}$, and $\sum \delta_{0,k}$, the coefficients of the lagged market returns, to be significant and negative. Additionally, if low PIN stocks respond more rapidly to the market, then, given $\beta_0 = \beta_{LowPIN} - \beta_{HighPIN}$, we expect the coefficient of the contemporaneous market return, β_0 , to be significant and positive.

The *F test* statistic tests the unrestricted model (Equation 6) against the restricted model, being Equation 6 but imposing the restriction, $\delta_{0,k} = 0$, and tests the null hypothesis that lags of the market return do not influence portfolio returns. The asymptotically equivalent *Chi Square test* statistic is also provided.

3.2 Individual stock tests

Using DELAY as the dependant variable, we run the cross-sectional regressions, expressed in equation (7), to test the influence of PIN and its component parameters on individual stock price delay controlling for liquidity, size and firm specific risk:

$$DELAY_{i,t} = \alpha_t + \sum_{k=1}^{K} b_{k,t}\Gamma_{k,i,t} + \sum_{s=1}^{S} \lambda_{s,t} X_{s,i,t} + e_{i,t} \qquad \text{...(7)}$$

where $DELAY_{it}$ is the individual stock annual DELAY, Γ_k is a set of K information-related variables (from among PIN, mu, epsilon , alpha and delta) and X_s is a set of control variables including liquidity, size and risk. The trade based measures of liquidity including in the analyses are turnover (TURN), number of trading days (DAYS TRADE) the natural log of VOL (lnVOL). We exclude the number of trades (TRANS) to avoid multicollinearity as its correlation with mu and epsilon is 0.901 and 0.995 respectively. We include SIZE because it has been shown to influence the lead-lag price response (Lo and MacKinlay, 1990; Chang et al, 1999; Haque, 2011) and, as a measure of a stock's visibility, may be attributed to the investor recognition explanation (Hou and Moskowitz

2005). We control for firm specific risk (IDIOV) given that uncertainty in a firm's information environment may be an alternative explanation for delayed price response such as in evidence where there is greater dispersion in analyst forecasts (Chan and Hameed, 2006; Hou, 2007).

4. Empirical Results

4.1 PIN and the delayed response of portfolio returns to market information

4.1.1 Turnover-PIN portfolio characteristics

Table 4 describes the ex-ante characteristics of our 16 Turnover-PIN portfolios for the year of formation. The Kruskal-Wallis test shows that the sample provides considerable variation in PIN within each turnover quartile, as is desired. Our sort procedure appears to adequately control for turnover as evidenced in the insignificant difference in turnover among PIN-rankings within each turnover quartile, yet a significantly greater turnover as we move from the first turnover quartile to the fourth one.

As a general observation, in the first two turnover quartiles (lower turnover) our sub sorts by PIN do not significantly distinguish portfolios in terms DELAY, size, risk, and trade volume. However, among the top 50% of stocks by turnover, we detect significant differences in firm characteristics between our PIN portfolios. While the effect may be a result of PIN measurement errors in thinly traded stocks, if portfolio tests show delay is evident among high PIN portfolios in the two lower turnover quartiles, the effects may be difficult to ascribe to illiquidity, or indeed to firm size given the second turnover quartile shows firm size in increasing (not decreasing) in PIN. We note that uninformed trade (epsilon) and informed trade (mu) have greater influence on PIN among the more actively traded stocks whereas alpha plays a relatively greater role in determining PIN among the two lower turnover quartiles. This motivates our later tests to examine whether the component parameters of PIN (alpha, delta, mu, epsilon) are responsible for any price delay among high PIN stocks.

4.1.2 Dimson beta regressions

Table 5 presents the regression results of equation (6) for the full sample (Panels A and B) and the reduced sample (Panels C and D) using value-weighted and equal-weighted portfolio returns respectively. Panel A reports the results using value-weighted portfolio returns. The summed coefficients on our lagged market returns, $\sum \delta_0$, are negative and significant at the 1% level for all portfolios except the smallest turnover portfolio which is significant at the 10% level. The results suggest that prices of high PIN stocks are indeed slower to adjust to common factor news compared to low PIN stocks. The result is unlikely to be attributable to lead-lag effect of size given, as we have noted in Table 4, our second quartile portfolio has, on average, significantly larger stocks in its highest PIN portfolio than in its lowest PIN portfolio. The coefficient of contemporaneous market returns, β_0, is significantly positive for the second and third turnover quartiles, and negative but insignificant for the lowest turnover quartile. An exception to our predictions is observed in the highest turnover portfolio, where β_0 is significant but negative. We find this is due to the contemporaneous beta for high-PIN portfolio (P44) being significantly higher than that of low-PIN portfolio (P41) in the years corresponding to the Asian Financial crisis, the 2000-01 economic downturn, the global financial crisis and post financial crisis years. It appears that the contemporaneous beta on well traded high PIN stocks may be responsive to shifts in market-level uncertainty.

When we use equal-weighted portfolio returns (Panel B) we in effect give greater weight to small stocks in constructing portfolio returns. If the portfolio's lead or lag response in Panel A relates to the largest stocks within the portfolio then the effect will be less likely to exist using equal-weighted returns. We find similar results to that shown in Panel A except that the summed coefficients on our lagged market returns, $\sum \delta_0$, for the lowest turnover quartile shows no evidence of price response delay. The results tend to indicate that the probability of informed trade affects common factor price efficiency except among the least actively traded stocks.

The results using the 'Reduced' sample stocks reported in Table 5 Panels C and D confirm our findings. Given fewer firm year observations, we use only nine Turnover-PIN portfolios (3 TURN x 3 PIN). We find that Low PIN portfolios, across all turnover terciles are more responsive to current market returns (at 1% significance). The contemporaneous beta on the high turnover portfolio that was observed as significantly negative in the full sample (Panel A and B) is positive and significant in the reduced sample suggesting low priced stocks were responsible for the negative beta. The sum of the coefficients on lags of market return, $\sum \delta_0$, is positive and significant at the 1% level for all portfolios, except the lowest turnover tercile which is significant at the 5% level. This result applies to both equal-weighted portfolio returns and value-weighted portfolio returns. The regressions provide substantial evidence that low PIN stocks are faster to respond to market news than high PIN stocks.

4.2 Price delay of individual stocks, PIN and its component parameters

Our results at portfolio-level are consistent with the notion that PIN may relate to common factor price efficiency. In this section we test the effect of PIN and its component parameters on the price-response delay to common factor news among individual stocks.

Table 6 reports the average parameter estimates and White heteroskedasticity-corrected *t-test* statistics for regressions of equation (7). Model 1 in Panel A shows that PIN, as the sole explanatory variable, is highly significant (at 1% level) in explaining variations in individual stock DELAY. Including delta and alpha in the regression (Model 2) adds significant explanatory power to the model (R-Squared=0.215), and greater news events tend to reduce DELAY. The significant positive slope coefficient on delta suggests an asymmetry in the speed of response between firms that face more abnormal sell-side activity than buy-side activity, and may relate to short-selling constraints among small, less active stocks.

PIN, alpha and delta remain significant when we include liquidity variables (Model 4) and idiosyncratic risk (Model 5). Liquidity, especially as captured by lnVOL and DAYS TRADE, reduces delay as expected (Model 3) while firm-level uncertainty (IDIOV) tends to increase the price-response delay (Model 5). It seems logical that greater firm-level uncertainty is associated with greater risk of privately informed trade and that both would contribute to noisy signals of the value-effect of common factor news.

SIZE has significantly negative link with DELAY in our full sample controlling for liquidity and risk (Model 7). This fits with evidence that higher visibility/recognition is associated with greater common factor price efficiency (Hou and Moskowitz, 2005). However, while SIZE subsumes part of the effect of information asymmetry on DELAY, PIN remains significant (at 5% level). We conclude that PIN appears to play a separate and significant role in explaining DELAY.

Although the positive relationship between PIN and DELAY suggests that the risk of privately-informed trade will more likely be associated with common factor price inefficiency, the *level* of competition among informed traders rather than the *risk*, may be pivotal to the observed effect (Holden and Subrahmanyam, 1992; Chordia and Subrahmanyam, 2004). Recalling that low PIN stocks are associated with both greater informed trade and uninformed trade, we introduce the mu and epsilon components of the PIN algorithm as proxies for informed trade and uninformed trade, respectively. [9] We use the natural log of both (lnMU and lnEPSILON) to lessen the skewed nature of the variables. If PIN captures something more than its component parameters, it is expected to remain significant in the presence of alternative lnMU and lnEPSILON.

Panel B of Table 6 shows that both the informed trade and uninformed trade variables are significantly and negatively related to DELAY and, individually, the R-Squared of the respective models, 0.259 (Model 1) and 0.371 (Model 2), suggest both have far greater influence on price efficiency than PIN alone (R-Squared 0.035 in Panel A Model 1). Notably, considered individually, lnEPSILON explains more of DELAY than does SIZE (Panel A Model 6).

If PIN's role in price delay is a result of its association with a cost (adverse selection) that deters informed traders, in segmented markets (Chordia and Swaminathan, 2004), then we would expect that a proxy for informed trade would severely detract from PIN's significance. This is not the case as reported inModels 5 and 7. However, while PIN remains reliably significant in explaining individual stock DELAY in the presence of informed trade, it does not in the presence of the uninformed trade. This relationship exists in the model variants that include idiosyncratic firm risk (Model 6) as well as

[9] Moderate multicollinearity concerns exist with lnMU and lnEPSILON so we do not tabulate results that include them in the same regressions, although they support our conclusion that lnEPSILON is most significant and subsumes the effect of PIN, SIZE, alpha and lnMU when all are present together.

firm size (Model 8). The SIZE also loses its significance in the presence of lnEPSILON. SIZE (market capitalisation) has been shown to be highly associated with a stock's propensity to trade (Foerster and Keim, 1993; Clare et al, 2002) but our proxy for uninformed trade is drawn directly from market trade data and, as such, it is likely to be highly associated with stocks that are more visible, that are more often in the news and that are better represented among investor portfolios. Alpha also loses some significance when lnEPSILON enters the regression suggesting the arrival rate of liquidity trade captures, in part at least, the importance the propensity of news has on price response efficiency. Noise trade may well be greater for stocks more often in the news (Vega 2006).

Consistent with the notion that information diffuses from well-recognised stocks to less recognised stocks, we find strong evidence that PIN's significance in explaining price delay relates to its association with the level of liquidity trade rather than to information asymmetry.

We repeat the regressions using the 'Reduced' sample which excludes firm year observations with fewer than 1500 trades and with closing price (on any day) of less than $1. The sample is reduced dramatically to only 719 of the higher priced, more active firms. The results (untabulated for the sake of brevity) are qualitatively the same as Table 6. Notably, PIN alone shows an R-Squared of 0.165 in the reduced sample highlighting its greater relevance to DELAY among more actively-traded, higher priced stocks. SIZE is less significant in explaining delay among these stocks when included with PIN or lnMU or lnEPSILON. We conclude that our results are not driven by minimum price variation effects nor the effect infrequent trade may have on PIN estimation.

We check the robustness of our results by replacing our proxy for market returns, VWMR, with the ASX All Ordinaries index return (AOI). Our results are near identical to the above as we would expect given the correlation between the AOI and our VWMR is over 0.98.

We also employ a split-sample test to address the concern that the results are sample-specific. The results are not reported here but are available upon request. We identify that from 2007, transaction numbers and trading volumes in our data increase dramatically. This is consistent with the increased turnover which Chordia and Subrahmanyam (2011) observe for NYSE-listed stocks and which they attribute to a dramatic increase in small trades by institutional investors. We therefore split our sample into two: the first subsample being for the period 1996 to 2006 and the second, 2007 to 2010. Coincidentally, the second period captures the effect of the global financial crisis and post financial crisis. We perform the individual stock regressions separately for each period and find the results are qualitatively the same as those for our full sample.

5. Conclusion

Predicated on empirical evidence that common factor information gradually diffuses across markets from well recognised stocks to those stocks more likely be neglected in investor portfolios (Hou and Moskowitz, 2005), and on other studies that identify lower private information risk among better-recognised stocks (eg Aslan et al, 2011), we examine the relationship between Easley et al's (1996) PIN and the speed with which stock prices adjust to market-wide news. Our study is the first, to our knowledge, that makes use of the PIN market microstructure measure and its component parameters (the likelihood of a private news event, the likelihood of bad news and the arrival rate of informed and uninformed trade) to test the relevance of these information attributes to common factor price efficiency. We use Australian listed stocks over the period from 1996 to 2010, and benefit from a data set that, unlike comparable US data, identifies buyer or seller initiated trade direction (as required for PIN estimation) and therefore avoids potential bias resulting from PIN estimation errors.

We find that, controlling for liquidity, size and firm-specific risk, the delay response of individual stock prices to common factor news is significantly related to higher PIN, a low probability of information event and lower levels of informed trading. Similarly, the returns of low-PIN portfolios adjust faster to market news than their high PIN counterparts. Our findings that PIN and its component parameters play a significant role in delayed response of stock prices to common factor news provide new empirical evidence in support of the view that at least part of the "private information" and informed trade captured by PIN comes from the skilled interpretation of public common factor information by sophisticated investors.

We also find that PIN loses its significance in explaining individual stock price delay at the presence of uninformed or liquidity trading. And for the least liquid portfolios where both informed and uninformed trading are low, we do not observe a lead-lag relationship between low- and high-PIN stock returns. These results suggest that PIN's role in stock price delay is driven by the lack of uninformed or liquidity trading rather than by the risk of information asymmetry, and provide new empirical evidence concerning the channel by which trading affects the adjustment speed of stock prices to information.

While substantial literature suggests that informed trade plays an important role in price discovery (eg Holden and Subrahmanyam, 1992; Chordia and Subramanyam, 2004), our findings provide unique insight into the nexus between investor recognition and common factor price efficiency by highlighting the crucial role of *uninformed* trade as a PIN component in stock price delay. Our study opens up fruitful avenue for future empirical research that explores the channels by which PIN affects stock prices.

Table 1 - Summary Statistics

The table below shows the mean, median, standard deviation, minimum and maximum values for each of our key variables for the sample period: 1 January 1996 to 26 November, 2010. PIN represents the probability of informed trade per equation (2) calculated for each stock annually. Alpha, delta mu and epsilon are the component parameters of PIN per equation (1) and represent the probability of an information event, the probability of bad news, the arrival rate of informed trade and the arrival rate of uninformed trade, respectively. TURN, is the annual turnover of shares. TRANS, VOL and DAYS_TRADE are annual measures of, respectively, total number of trades, total number of shares traded (millions) and total number of days that trade occurred in a stock. Returns (RtN) represents the average of the non-missing daily returns expressed in continuously compounding form and as a percentage. IDIOV is idiosyncratic volatility calculated annually as the standard deviation of the residuals from a market model which regresses daily stock returns on value-weighted market return. SIZE is based on annual average of the daily log (Market Value). PRICE is the average daily closing price. DELAY represents the speed of response to common factor news and is calculated using equation (7). The total number of daily observations relevant to our RtN variable is 2,355,996 and, for all other variables is 11,828 firm-year observations. Annual variables are calculated for each calendar year except for 2010 which is for the period January1, 2010 to November, 26, 2010.

	Mean	Median	Std Dev	Min.	Max.
DELAY	0.506	0.480	0.318	0.003	1.000
PIN and PIN Parameters					
PIN	0.251	0.241	0.084	0.000	0.887
alpha	0.239	0.196	0.166	0.000	1.000
delta	0.491	0.475	0.215	0.000	1.000
mu	50.132	16.763	97.522	0.290	1,730.588
epsilon	36.311	3.770	137.698	0.100	3,226.226
Liquidity Variables					
TURN, Turnover (annual)	0.561	0.420	0.469	0.003	3.809
TRANS (annual)	22,556	2,499	80,441	165	1,851,587
VOL (annual mill.)	172.936	46.415	496.136	0.190	17,351.429
DAYS TRADE	214.015	231.000	46.249	60.000	255.000
Return, Risk					
RtN (Daily %)	0.016	0.000	4.605	-72.705	71.562
IDIOV	0.043	0.039	0.023	0.004	0.171
Other Variables					
SIZE	18.182	17.879	1.963	13.951	25.636
PRICE $	2.330	0.622	5.688	0.025	114.722

Table 2 – Cross Correlation Matrix for Key Variables

The table reports Pearson correlations for annual measures of our key variables. The last column shows p-values for the test of the null hypothesis, H0: ρ=0 for the correlation each variable has to DELAY based on Fisher's Z transformation. PIN represents the probability of informed trade per equation (2) calculated for each stock annually. Alpha, delta mu and epsilon are the component parameters of PIN per equation (1) and represent the probability of an information event, the probability of bad news, the arrival rate of informed trade and the arrival rate of uninformed trade, respectively.. TURN, is the annual turnover of shares, TRANS, VOL and DAYS_TRADE are annual measures of, respectively, total number of trades, total number of shares traded (millions) and total number of days that trade occurred in a stock. Returns (RtN) represents the average of the non-missing daily returns in the year expressed in continuously compounding form. IDIOV is idiosyncratic volatility calculated annually as the standard deviation of the residuals from a market model which regresses daily stock returns on value-weighted market return. SIZE is the average of the daily log value of a firm's Market value. PRICE is the average of the daily closing prices. DELAY represents the speed of response to common factor news and is calculated using equation (7) Each variable is calculated annually to 31st December except for 2010 where our sample ends at 26th November, 2010. The number of firm year observations is 11828.

	DELAY	PIN	alpha	delta	mu	epsilon	TURN	TRANS	VOL	DAYS TRADE	RtN	IDIOV	SIZE	p-value Fisher's Z (with DELAY)
PIN	0.159													<.001
alpha	-0.237	0.414												<.001
delta	0.159	0.267	0.301											<.001
mu	-0.376	-0.185	0.227	-0.086										<.001
epsilon	-0.294	-0.256	0.229	-0.031	0.892									<.001
TURN	-0.287	-0.115	0.014	-0.255	0.429	0.291								<.001
TRANS	-0.308	-0.253	0.243	-0.035	0.901	0.995	0.307							<.001
VOL	-0.252	-0.149	0.169	-0.049	0.560	0.489	0.426	0.514						<.001
DAYS TRADE	-0.404	-0.125	0.155	-0.217	0.194	0.144	0.279	0.171	0.169					<.001
RtN	0.068	0.003	-0.059	-0.244	-0.005	-0.008	0.029	-0.007	-0.009	-0.075				<.001
IDIOV	0.326	0.132	-0.342	0.079	-0.225	-0.215	0.082	-0.226	-0.144	-0.416	-0.082			<.001
SIZE	-0.522	-0.200	0.424	-0.113	0.556	0.490	0.095	0.510	0.383	0.460	0.028	-0.733		<.001
PRICE	-0.281	-0.206	0.218	-0.081	0.476	0.529	0.076	0.534	0.129	0.178	0.036	-0.360	0.565	<.001

Table 3 – Exante Characteristics of PIN Portfolios

Equal-weighted portfolio averages are reported for our key variables for the whole sample period, 1 January, 1996 to 26 November, 2010, for each of five (5) portfolios formed, annually, by sorting stocks, from lowest to highest (Portfolio 1 being the lowest) based on the individual stock probability of informed trade (PIN). PIN is calculated at the end of each calendar year (or at November in the case of the year 2010) using trade data for the period from the preceding January 1. Statistics for portfolios formed at the end of year *t* relate to year *t*. Alpha, delta mu and epsilon are the component parameters of PIN per equation (1) and represent the probability of an information event, the probability of bad news, the arrival rate of informed trade and the arrival rate of uninformed trade, respectively. TURN, is the annual turnover of shares. TRANS, VOL and DAYSTRADE are annual measures of, respectively, total number of trades, total number of shares traded (millions) and total number of days that trade occurred in a stock. Returns (RtN) represents the average of the non-missing daily returns in the year expressed in continuously compounding form and as a percentage. IDIOV is idiosyncratic volatility calculated annually as the standard deviation of the residuals from a market model which regresses daily stock returns on value-weighted market return. SIZE is the average of the daily log value of a firm's Market value. PRICE is the average of the daily closing prices. DELAY represents the speed of response to common factor news and is calculated using equation (7). 'NOBS' represents the number of firm-year observations for each portfolio. .'Diff 5-1' represents the difference in means between the Highest PIN portfolio (5) and Lowest PIN portfolio (1).We use the Mann-Whitney statistic to test the null hypothesis that the difference in means is equal to zero and report the two-tailed p-value from the Z distribution, 'Pr>|Z|'.

PIN rank	NOBS	PIN	alpha	delta	mu	epsilon	DELAY	TURN	TRANS	VOL (Mills)	DAYS TRADE	RTN%	IDIOV	SIZE	PRICE
Lowest 1	2360	0.156	0.210	0.452	105.426	124.421	0.425	0.612	74,119	348	217	0.005	0.036	19.218	5.459
2	2368	0.209	0.194	0.470	40.284	23.220	0.503	0.539	14,914	159	215	0.011	0.043	18.051	1.734
3	2369	0.242	0.205	0.472	35.343	14.843	0.512	0.568	9,767	141	216	0.028	0.045	17.861	1.391
4	2368	0.278	0.230	0.486	33.596	10.774	0.520	0.590	7,549	118	216	0.045	0.046	17.847	1.348
Highest 5	2363	0.371	0.354	0.577	36.174	8.546	0.570	0.499	6,578	99	206	0.035	0.044	17.939	1.729
Diff 5-1		0.215	0.145	0.124	-69.252	-115.875	0.144	-0.112	-67540	-249	-11	0.030	0.009	-1.279	-3.729
Pr > |Z|		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.000	<.0001	<.0001	<.0001

Table 4- Exante TO-PIN Portfolio Characteristics

Average characteristics for the year of portfolio formation are shown for each Turnover-PIN portfolio. P*ij* refers to the *i*th ranked turnover portfolio (from lowest turnover to highest) and the *j*th ranked PIN portfolio from lowest to highest. Eg P11 is the lowest turnover, lowest PIN portfolio. Portfolio averages are across the 15 years of our sample. 'Av .Annual firms' represents the average number of observations each year for each portfolio. PIN represents the probability of informed trade per equation (2) calculated for each stock annually. Alpha, delta mu and epsilon are the component parameters of PIN per equation (1) and represent the probability of an information event, the probability of bad news, the arrival rate of informed trade and the arrival rate of uninformed trade, respectively. TURN, is the annual turnover of shares. TRANS, VOL and DAYS_TRADE are annual measures of, respectively, total number of trades, total number of shares traded (millions) and total number of days that trade occurred in a stock. Returns (RtN) represents the average of the non-missing daily returns in the year expressed in continuously compounding form and as a percentage IDIOV is idiosyncratic volatility calculated annually as the standard deviation of the residuals from a market model which regresses daily stock returns on value-weighted market return. SIZE is the natural log of firm Market Value; PRICE is the average daily closing price. DELAY represents the speed of response to common factor news and is calculated using equation (7). We use the Kruskal-Wallis test to test the null that PIN portfolios 1 to 4, within each turnover quartile, have the same mean ranks of the variable for which the test is conducted and report the p-value from the Chi-distribution.

Portfolio	Av. Annual firms	TURN	PIN	DELAY	alpha	delta	mu	epsilon	TRANS	VOL (Mill)	DAYS TRADE	Rtn %(daily)	IDIOV	SIZE	PRICE
P11	48.73	0.145	0.165	0.623	0.122	0.469	12.330	4.241	2,306	22.649	187	0.038	0.040	18.022	1.960
P12	49.40	0.148	0.220	0.600	0.180	0.526	12.087	4.216	2,446	25.152	193	0.019	0.040	18.168	2.231
P13	49.60	0.153	0.270	0.600	0.240	0.546	11.996	3.539	2,113	25.499	197	0.037	0.039	18.316	2.189
P14	49.07	0.137	0.405	0.635	0.468	0.687	16.226	3.467	2,535	23.486	189	-0.020	0.038	18.315	2.868
p-value		0.389	<.001	0.900	<.001	<.001	0.924	0.166	0.894	0.416	0.034	0.366	0.572	0.110	0.248
P21	48.87	0.318	0.174	0.598	0.135	0.468	18.961	8.534	4,870	52.807	202	0.004	0.047	17.438	1.267
P22	49.53	0.325	0.224	0.551	0.201	0.487	17.965	7.216	4,606	53.234	212	0.035	0.042	17.827	1.388
P23	49.67	0.323	0.263	0.554	0.232	0.513	20.814	7.260	4,853	55.789	214	0.051	0.042	17.946	1.429
P24	49.20	0.316	0.361	0.573	0.372	0.605	25.759	6.142	4,751	52.518	211	0.011	0.041	17.916	1.571
p-value		0.927	<.001	0.560	<.001	<.001	0.981	0.133	0.688	0.959	0.009	0.811	0.244	0.005	0.464
P31	48.93	0.565	0.166	0.376	0.212	0.438	76.161	74.916	45,490	230.591	228	-0.014	0.037	19.100	5.455
P32	49.53	0.552	0.221	0.459	0.210	0.451	33.170	15.649	10,415	109.832	227	0.020	0.042	18.016	1.779
P33	49.67	0.559	0.258	0.502	0.217	0.459	30.238	10.230	7,129	96.973	222	0.021	0.047	17.671	1.169
P34	49.33	0.556	0.327	0.518	0.293	0.513	40.652	12.828	9,655	105.639	213	0.054	0.045	17.911	1.506
p-value		0.974	<.001	0.002	<.001	0.016	<.001	<.001	<.001	<.001	<.001	0.521	0.013	<.001	<.001
P41	48.80	1.105	0.153	0.233	0.294	0.416	191.143	239.842	143,698	719.236	241	-0.003	0.028	20.724	8.607
P42	49.40	1.173	0.211	0.380	0.245	0.411	99.477	74.661	47,450	452.645	234	-0.002	0.042	18.516	1.916
P43	49.67	1.169	0.253	0.434	0.206	0.402	61.586	24.929	16,939	320.720	229	0.017	0.052	17.505	0.823
P44	49.13	1.205	0.314	0.477	0.216	0.405	58.544	14.655	10,947	238.098	220	0.144	0.056	17.276	0.700
p-value		0.805	<.001	<.001	0.008	0.969	0.012	<.001	<.001	<.001	<.001	0.311	<.001	<.001	<.001

Table 5 – Portfolio Regressions

This table reports the results of regressing daily returns of zero net investment portfolios, $r_{0,t}$, on k leads and lags of the market using the equation:

$$r_{0,t} = \alpha_0 + \beta_0 Rm_t + \sum_{k=-1}^{-n} \lambda_{0,k} Rm_{t-k} + \sum_{k=+1}^{n} \delta_{0,k} Rm_{t-k} + \mu_t$$

where K=5 and R_m is the value-weighted market return (VWMR). Each zero investment portfolio, return, $r_{0,t}$ is calculated daily by subtracting the returns of the highest-ranked PIN portfolio from the returns of the lowest PIN-ranked portfolio, within each turnover quantile. Eg Portfolio P11-P14 represents the return on the lowest turnover lowest PIN portfolio minus the return on the lowest turnover highest PIN portfolio. Panel A and B show results for the 'Full Sample' for the period 1997 to 2010 using value-weighted portfolio returns and equal-weighted portfolio returns, respectively. Panels C and D show the results, using value-weighted and equal-weighted portfolio returns, respectively, for the 'Reduced Sample' which excludes stocks with price below $1 and with fewer than 1500 annual transactions. The slope coefficient of contemporaneous beta, β, is given as is the p-value showing the probability of obtaining a t statistic at least as extreme as the one observed assuming the null H0: β=0 is true (***, ** and * denote significance at the 1% level, 5% level, and 10% level, respectively). We also report the sum of lead betas, $\sum\lambda_{0,k}$, and the sum of the lagged betas, $\sum\delta_{0,k}$. The significance of each lag coefficient estimate (ordered from 1 to 5) is depicted for 5% significance levels and denoted with a '+' or '-' to show the sign of the significant coefficient. The F test statistic (with related p-value) is provided and tests the unrestricted model (above) against the restricted version where the constraint imposed is $\sum\delta_{0,k}$ .The null is H0: that lags of the market, $\sum\delta_{0,k}$, do not influence portfolio returns. The asymptotically equivalent Chi Square test statistic (with related p-value) is also provided. All regression standard errors are White-heteroskedasticity corrected. The adjusted R-Squared (Adj R2) for the unrestricted regression is given. The number of observations for each regression is 3010.

PANEL A: Full Sample Value-Weighted Portfolio Returns: 1996-2010

Portfolio	Rm_t		Leads Rm	Lags Rm				Adj R2
	β		$\sum\lambda_{0,k}$	$\sum\delta_{0,k}$	Sig. at 5%	F Test	Chi Squ Test	
P11-P14	-0.011		0.076	-0.189	_ _ - _ _	2.149	10.777	0.001
p value	0.707					0.057	0.056	
P21-P24	0.487	***	0.082	-0.278	- - - - _	6.990	35.059	0.094
p value	<.001					<.001	<.001	
P31-P34	0.102	***	0.014	-0.212	- - _ - _	6.099	30.589	0.016
p value	<.001					<.001	<.001	
P41-P44	-0.348	***	-0.140	-0.352	_ - _ _ _	3.928	19.699	0.021
p value	<.001					0.001	0.001	

PANEL B: Full Sample Equal-Weighted Portfolio Returns: 1996-2010

Portfolio	Rm_t		Leads Rm	Lags Rm				Adj R2
	β		$\sum\lambda_{0,k}$	$\sum\delta_{0,k}$	Sig. at 5%	F Test	Chi Squ Test	
P11-P14	0.021		0.021	0.012	_ _ _ _ _	1.369	6.868	0.001
p value	0.315					0.233	0.231	
P21-P24	0.106	***	-0.010	-0.158	_ - _ _ _	2.791	13.998	0.010
p value	<.001					0.016	0.016	
P31-P34	0.039	*	-0.040	-0.194	- _ _ _ -	4.398	22.060	0.006
p value	0.063					0.001	0.001	
P41-P44	-0.067	***	-0.100	-0.304	- - _ - _	8.673	43.502	0.013
p value	0.004					<.001	<.001	

PANEL C: Reduced Sample Value-Weighted Portfolio Returns: 1996-2010

Portfolio	Rm_t		Leads Rm	Lags Rm				Adj R2
	β		$\sum\lambda_{0,k}$	$\sum\delta_{0,k}$	Sig. at 5%	F Test	Chi Squ Test	
P11-P13	0.401	***	0.024	-0.094	_ _ - _ _	2.562	12.849	0.115
p value	<.001					0.025	0.025	
P21-P23	0.111	***	-0.013	-0.122	- _ _ _ _	3.795	19.035	0.016
p value	<.001					0.002	0.002	
P31-P33	0.279	***	0.021	-0.114	- - _ _ _	5.210	26.134	0.077
p value	<.001					<.001	<.001	

PANEL D: Reduced Sample Equal-Weighted Portfolio Returns: 1996-2010

Portfolio	Rm_t		Leads Rm	Lags Rm				Adj R2
	β		$\sum\lambda_{0,k}$	$\sum\delta_{0,k}$	Sig. at 5%	F Test	Chi Squ Test	
P11-P13	0.173	***	-0.014	-0.011	_ _ - _ _	2.615	13.116	0.044
p value	<.001					0.023	0.022	
P21-P23	0.148	***	-0.041	-0.151	- _ _ _ -	8.685	43.563	0.041
p value	<.001					<.001	<.001	
P31-P33	0.037	***	-0.041	-0.200	- - _ _ _	14.857	74.519	0.023
p value	0.009					<.001	<.001	

Table 6 – Individual Stock Regressions: DELAY and the Parameters of Informed Trade

The table provides the average slope coefficient estimates for annual cross sectional regressions where our regressand is individual stock $DELAY_t$ calculated as described in Section 2 equation (7). The first column indicates the explanatory variables and the header row indicates different regression models. Our explanatory variables are determined for year *t* and are from among PIN (the probability of informed trade) and its components parameters (alpha, being the probability of an information event day; delta, being the likelihood of a bad news event among information days; LnMU being the natural log of mu, the arrival rate of informed trade; LnEPSILON, being the natural log of epsilon, the arrival rate of uninformed trade) as well as liquidity measures TURN (annual turnover), DAYS TRADE (the number of days in the year that the stock traded), lnVOL (the natural log of annual volume of shares (millions) traded), SIZE (the natural log of firm Market Value) and IDIOV (idiosyncratic volatility). PANEL A shows the results of base regressions for our whole sample period 1996 to 2010. PANEL B includes, separately, LnMU and LnEPSILON as regressors. Average *t statistics* are shown in parenthesis and are based on White heteroskedasticity-corrected standard errors. Significance is denoted with asterisks (***, ** and * denote significance at the 1% level, 5% level, and 10% level, respectively). The average Adjusted R Squared (Adj. R-Squared) for each model is also given. Our whole sample includes 11828 firm-years across 15 years.

PANEL A

Model	1		2		3		4		5		6		7	
Intercept	0.337	***	0.250	***	1.182	***	0.895	***	0.688	***	2.036	***	1.607	***
	(9.464)		*(6.118)*		*(26.671)*		*(13.544)*		*(9.549)*		*(28.125)*		*(8.499)*	
PIN	0.686	***	1.196	***			0.744	***	0.541	***			0.332	**
	(5.286)		*(8.138)*				*(5.531)*		*(4.064)*				*(2.464)*	
alpha			-0.815	***			-0.514	***	-0.331	***			-0.186	**
			-(9.915)				*-(6.943)*		*-(4.302)*				*-(2.509)*	
delta			0.320	***			0.157	***	0.118	***			0.092	**
			(6.490)				*(3.335)*		*(2.559)*				*(2.036)*	
TURN					0.018		-0.001		-0.048	**			-0.089	***
					-(0.123)		*-(0.725)*		*-(2.194)*				*-(3.324)*	
lnVOL					-0.066	***	-0.048	***	-0.046	***			-0.020	**
					-(7.314)		*-(5.181)*		*-(5.257)*				*-(2.167)*	
DAYS TRADE					-0.002	***	-0.002	***	-0.001	***			-0.001	***
					-(8.274)		*-(6.389)*		*-(3.986)*				*-(3.881)*	
IDIOV									3.185	***			0.765	
									(5.951)				*(1.119)*	
SIZE											-0.084	***	-0.048	***
											-(21.670)		*-(5.285)*	
Adj R-Squared	0.035		0.215		0.289		0.354		0.390		0.307		0.416	

Table 6 – Individual Stock Regressions: DELAY and the Parameters of Informed Trade (continued)

PANEL B

	1		2		3		4		5		6		7		8	
Intercept	0.888	***	0.723	***	0.721	***	0.647	***	0.862	***	0.793	***	1.455	***	1.131	***
	(37.546)		*(55.429)*		*(14.933)*		*(15.315)*		*(11.408)*		*(11.073)*		*(9.703)*		*(6.245)*	
PIN					0.866	***	0.213		0.614	***	0.139		0.510	***	0.155	
					(6.823)		*(1.378)*		*(4.746)*		*(1.107)*		*(3.546)*		*(1.187)*	
alpha					-0.652	***	-0.196	**	-0.438	***	-0.114		-0.357	***	-0.124	*
					-(9.768)		*-(2.487)*		*-(5.960)*		*-(1.589)*		*-(4.180)*		*-(1.726)*	
delta					0.121	**	0.105	**	0.065		0.063		0.068		0.066	
					(2.553)		*(2.275)*		*(1.422)*		*(1.383)*		*(1.484)*		*(1.443)*	
lnMU	-0.132	***			-0.115	***			-0.089	***			-0.066	***		
	-(18.399)				*-(13.908)*				*-(6.700)*				*-(4.024)*			
lnEPSILON			-0.130	***			-0.116	***			-0.098	***			-0.090	***
			-(26.509)				*-(15.643)*				*-(7.789)*				*-(5.047)*	
TURN									-0.003		0.003		-0.035		-0.008	
									-(0.503)		*-(0.257)*		*-(1.220)*		*-(0.386)*	
lnVOL									-0.004		0.003		0.002		0.007	
									-(0.579)		*(0.017)*		*-(0.051)*		*(0.440)*	
DAYS TRADE									-0.001	***	-0.001	***	-0.001	***	-0.001	***
									-(4.539)		*-(4.349)*		*-(4.775)*		*-(4.797)*	
IDIOV									1.910	***	1.361	**				
									(3.402)		*(2.378)*					
SIZE													-0.031	***	-0.016	
													-(3.290)		*-(1.395)*	
Adj R-Squared	0.259		0.371		0.366		0.389		0.427		0.436		0.425		0.431	

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