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Information attributes, information asymmetry and industry sector returns

Narelle Gordon [a,*], Edward Watts [a], Qiongbing Wu [b]

[a] Faculty of Business and Economics, Building E4A, Macquarie University, North Ryde, NSW 2109, Australia
[b] School of Business, University of Western Sydney, Locked Bag 1797, Penrith, NSW 2751, Australia

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ABSTRACT

We examine whether the probability of informed trading ('PIN') is a determinant of stock returns in Australia, an alternative market with considerably different information attributes to the U.S. Uniquely, we contrast PIN's price effect for the country's historically dichotomous sectors, resources and industrials. Using data for the period from 1996 to 2010, we find a significantly positive relationship between PIN and expected returns among industrials sector stocks, providing evidence in support of Easley and O'Hara (2004). We observe no PIN premium among resources sector stocks and among those with no record of operating revenues, both notable for their speculative nature and uncertainty about true asset values. Our results are consistent with previous empirical evidence that documents strong investor behavioural biases in valuing extremely uncertain stocks or hard-to-value stocks (Kumar, 2009). Our findings shed light on the existing mixed evidence that a strong PIN premium exists in NYSE and AMEX but not in NASDAQ where high-tech stocks are prevalent, and suggest that caution is needed when applying PIN in the pricing of highly speculative stocks.

1. Introduction

The probability of informed trading ('PIN'), a microstructure measure of information asymmetry developed by Easley et al. (1996), has ignited great interest among researchers, and has opened up extensive avenues for empirical studies in asset pricing, corporate finance and market microstructure. One of the most topical issues is whether PIN is a determinant of asset returns.

Easley and O'Hara (2004) propose that, holding other things identical, an asset with more private information and less public information is regarded as more risky and therefore investors (particularly

* Corresponding author.
E-mail addresses: narelle.gordon@mq.edu.au (N. Gordon), edward.watts@mq.edu.au (E. Watts), q.wu@uws.edu.au (Q. Wu)

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uninformed investors) will require a higher expected return. Thus PIN, as a proxy for the risk of privately informed trade, is a determinant of stock returns. Easley et al. (2002) ('EHO') document the existence of a premium for this risk among stocks listed in New York Stock Exchange (NYSE), observing that those stocks with higher PIN have higher expected returns. Extending EHO's sample by including the stocks listed on American Stock Exchange (AMEX), Easley et al. (2010) provide further empirical evidence that PIN is an important determinant of asset returns controlling for the effects of the Fama-French (1992) three risk factors as well as momentum and liquidity factors. On the other hand, Mohanram and Rajgopal (2009) find that the PIN premium only exists for one 5-year period within the EHO sample, and Duarte and Young (2009) show that PIN is priced because of its illiquidity component rather than its information asymmetry component. Fuller et al. (2010) find little evidence that excess returns are increasing in PIN for the stocks listed on the NASDAQ, a stock exchange noted for its predominant high-tech sector. They suggest that the weak PIN-price effect may be the result of differences between the NYSE and NASDAQ in market structure or in the characteristics of their component stocks. The mixed evidence of PIN's influence on asset returns in U.S. markets calls for further empirical studies using alternative markets and motivates us to examine the price effect of PIN in Australia, a market distinguished by its sizeable resources sector, by different trading mechanisms and by different information attributes from the U.S. markets. Furthermore, we benefit from using Australian data to conduct this kind of empirical study because, in Australia, there is no market maker and no on-market trades occur inside the spread. Therefore trade direction (buyer-initiated versus seller-initiated), which is required for the PIN estimate, is identified without introducing estimation biases that generally exist in the empirical studies for the U.S. markets (Odders-White, 2000; Boehmer et al., 2007).

The Australian Stock Exchange (ASX) has more listed stocks from the extractive industries, Metals & Mining and Oil & Gas, than any other major exchange in the world including those in the U.S.[1] Some 45% of listed stocks, comprising approximately 25% of the total market by value, relate to firms in these industries and together form the resources sector. The remainder of the listed firms comprise the industrials sector and are on average larger, more liquid and less risky, than resources sector stocks.

The sector distinction extends to attributes of the information environment relevant to our study. Notably, mining, exploration and gold stocks are identified by market players as being among those where insider trading is most likely (Tomasic and Pentonoy, 1988). Insider trading is the typical example of the 'informed trade' which PIN is intended to capture. Despite regulations that prohibit insider trading and compel the disclosure of value-relevant news, the high sensitivity of prices to news of 'discovery' among exploration firms, likened to an out-of-money option (Brown and Burdekin, 2000), provides greater incentive for privately informed traders, and recent evidence suggests that privately informed trade is more prevalent in this sector. For example, mining stock prices almost fully anticipate the value effect of public announcements (Bird et al., 2013), and directors of resources stocks gain from selling down their own-firm share holdings ahead of price declines (Brown et al., 2003).[2]

In addition, the resources sector comprises many junior (exploration stage) miners, and there is considerable evidence that asset values and the value-effect of information disclosures among these firms are more uncertain. For example, relative to financial disclosures, regulatory disclosures pertaining to mining project progress are full of technical jargon, are less scrutinised by analysts and researchers (Ferguson et al., 2011b) and, across very lengthy exploration time lines, have more uncertain bearing on longer term value. The concern that disclosure rules pertaining to Mining, Oil and Gas companies are somewhat open to interpretation, has prompted a recent review of listing rules with the aim of improving consistency and transparency (ASX, 2011). The Easley and O'Hara (2004) theory predicts that the expected return is not only increasing in the proportion of information that is private, but also decreasing in the precision of prior beliefs about firm value referred to as '*prior precision*'. Those authors explain that greater prior precision exists where investors are more familiar with a firm. Thus the greater the

[1] "Revenue Watch's research included the 31 largest non-U.S. stock exchanges by market capitalization, as ranked by the World Federation of Exchanges, as well as the Oslo Børs of Norway and the NYSE, AMEX and NASDAQ exchanges of the United States."(Voorhees, 2011).

[2] Note also that a study that examines the '*Please Explain*' notices issued by the Australian Stock Exchange ('ASX') in response to significant price changes that appear unrelated to any public disclosure, find that 222 of 911 notices relate to mining firms that were at exploration stage (Neagle and Tsykin, 2001).

uncertainty about asset values, such as among firms with no operating revenue track record, the smaller the prior precision and the greater the risk premium.

Motivated by the mixed evidence in U.S. markets and by a likeness between the technology-dependent NASDAQ stocks and Australia's discovery-dependent resources stocks, we adopt a novel approach in considering, separately, the effects of PIN among resources sector and industrials sector stocks over the period from 1996 to 2010. We expect that PIN, as a measure of private information risk,[3] would be greater among stocks of the resources sector than those of the industrials sector. Contrary to our expectations, we find that the distributions of PIN in the resources and industrials sectors are near identical.

Next, adopting similar approaches as EHO, we examine excess returns of portfolios sorted by size and PIN, and perform monthly cross-sectional asset-pricing tests for individual stocks. Using the full sample of stocks, we find little evidence that PIN is significantly related to excess returns. However, when we consider the differential effect among industrials and resources sectors, we find that PIN has a positive and significant effect on excess returns among industrial stocks. The result provides support for the Easley and O'Hara (2004) theory and suggests that the weight of resources sector stocks in Australia accounts for our failure to observe the PIN premium in the full sample. Controlling for beta, size and book-to-market equity, a 0.10 increase in PIN in industrials stocks is associated with a 2.76% increase in annual excess returns. The result remains significant when we introduce the EHO proxies for liquidity, liquidity risk and return volatility.

Finally, we test whether PIN's association with returns is influenced by differences in prior precision as the PIN algorithm cannot discern the precision of investors' beliefs about asset values. Using the absence of operating revenues as a proxy for lack of prior precision, we find no evidence that lower prior precision is associated with higher expected returns as the Easley and O'Hara (2004) theory predicts. Furthermore, we find that there is no PIN premium among the stocks that have no operating revenue record, most of which are resources and high-tech stocks.

However, our findings are consistent with existing literature which documents an anomalously low, or even negative, risk premium among resources stocks (Ball and Brown, 1980; Finn and Koivurinne, 2000) and with the literature that shows that investors demonstrate strong behavioural biases when valuing highly-uncertain or hard-to-value stocks (Kumar, 2009). It is possible that, among resources stocks, trade aimed at exploiting investor behavioural biases and/or trade that may relate to self-promoting behaviour by mining firms (ASIC, 2006; O'Shea et al., 2008), adds noise to the PIN measure and obscures tests that use PIN as a measure of asymmetry. On the other hand, PIN may indeed measure what it is intended to measure and the absence of a PIN premium among speculative-type stocks may relate to 'mispricing' associated with those same investor biases that attract 'informed' trade or, with investors' gambling preference that others suggest underlie the anomalous returns among mining stocks (Ord, 1998).

Our paper makes a valuable contribution to the literature in three respects. Firstly, we provide additional empirical evidence in support of Easley and O'Hara's (2004) prediction that stocks with relatively greater private information should have higher expected returns using data for an alternative market. We provide new insight into the effect by highlighting an absence of the PIN premium among resources sector stocks and among stocks with no operating revenues. Our result may be reconciled to Gray et al. (2009) who use accruals quality (AQ) as a proxy for information asymmetry and find AQ is a priced risk factor in Australia. Those authors adopt sample selection criteria which likely exclude many of the speculative resources stocks where we find no PIN-price effect. Our findings have implication for trading strategies that rely on PIN as a measure of private information risk as we show its relevance to pricing is not universal.

Secondly, we demonstrate that PIN is not greater among resources stocks which are reputed to attract greater privately informed trade of the insider-type. This raises question as to whether the attributes of 'informed' trade differ between resources and industrials sectors and whether it is this difference which influences the existence of a PIN premium. In this regard we note that the informed trade that PIN captures, has been linked not just to an insider-type information advantage but, to an advantage in

[3] We use the term 'private information risk' to describe the risk of privately informed trade or the risk of asymmetric information as distinct from other information risks (i.e. information precision and prior precision) that Easley and O'Hara (2004) describe.

assessing market-wide common factor information (Evans and Lyons, 2002; Green, 2004; Pasquariello and Vega, 2007; Bardong et al., 2009) and, where there is greater analyst coverage, to a private advantage in assessing public information (Easley et al., 1998). Whether PIN also captures as informed trade, manipulative trade among speculative stocks, is an issue for further research.

Finally, but most importantly, as the first empirical research to document a distinct price effect of PIN among stocks in different industry sectors, our findings have very important implication for the existing and future research in the area. We find a strong price effect of PIN among industrial sector stocks but not among resources sector stocks and stocks without an established record of operating revenue. The results are consistent with previous empirical evidence that documents strong investor biases in pricing highly uncertain or speculative stocks. Our findings shed light on the existing mixed empirical evidence that PIN is strongly priced in the NYSE and AMEX markets but not in the NASDAQ market where hi-tech stocks are predominant, and suggest that future researchers need to be cautious when applying PIN to pricing those highly speculative stocks whether in the U.S. or in other international markets.

The remainder of the paper is structured as follows. In Section 2, we describe the sample and variables including the PIN measure. Section 3 outlines the empirical methodology and results of tests for the association between PIN and expected excess returns. Section 4 extends the tests to include the possible effect of prior precision. Section 5 discusses alternative explanations and Section 6 concludes the paper.

2. Data and variables measurement

2.1. Data and sample criteria

Our sample combines a large number of firm-level data derived from various sources over the period from 1996 to 2010. All accounting data are from the Aspect Financial database, analyst coverage is obtained from Institutional Brokers Estimation System (I/B/E/S) database while the number of shares outstanding and industry classification are obtained from the Share Price and Price Relative ('SPPR') data provided by the Securities Institute Research Centre of Asia-Pacific ('SIRCA'). SIRCA also provides the ASX Daily Trades which we use for calculating returns and volume measures, and the more detailed ASX Intraday Trade data used for PIN. Our measure of market returns uses the All Ordinaries index while our risk-free rate is the 90 day bank bill rate, both obtained from Datastream International.

We estimate PIN for individual stocks using the number of daily buy and sell trades drawn from 520 million trade observations in the ASX Intraday Trade Data commencing January 1996. Consistent with EHO we include only fully paid ordinary shares, exclude real estate investment trusts and a stock in any year where its trading days are fewer than 60.

To be included in monthly cross-sectional regressions, stocks must have at least 24 months trade history, a market value available for the preceding December and a non-negative book value of equity recorded for the financial year ended at between 3 and 14 months prior to the relevant month. Our eligibility criteria favours larger stocks and remove many of the smaller stocks, infrequently traded stocks and short-lived firms. Our final sample comprises between 265 and 765 stocks each year and 74,677 monthly return observations across the years 1997 to 2010.

2.2. PIN estimation

We use the methodology for estimating the probability of informed trade (PIN) as described in Easley et al. (1996) ('EKOP'). The measure is derived from a sequential trade market structure model where buy orders (B) or sell orders (S) arrive from two types of traders: the informed trader and the uninformed trader. Uninformed trade occurs for exogenous reasons and is also referred to as liquidity trade or noise trade. Informed trade, on the other hand, only occurs where a trader holds value-relevant information that has not been revealed to the market (referred to here as a 'news event'). At the beginning of the day there is a probability, α, that a news event occurs and a probability of $(1-\alpha)$ that there is no news event. The news may convey bad news (poor signal), with probability δ, or good news with probability $(1-\delta)$. The probability of a bad news day is therefore $\alpha\delta$ and of a good news event day is $\alpha(1-\delta)$. Trades arrive sequentially following Poisson processes. Uninformed trade is assumed constant and 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 equal.[4] Informed trades arrive randomly at the rate, μ: if the signal is bad, informed traders will sell and if the signal is good, the informed trader will buy. So, on a day where there is a poor signal, 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, if the signal is positive then both informed traders and uninformed traders arrive with buy-side trades but only uninformed traders arrive with sell-side trades. The model supposes that the observer is aware of the arrival rates and updates her beliefs with regard to the risk that she is trading against a better informed trader.

The probability that the next trade is information-based is then calculated as the expected incidence of informed trade divided by expected total trades:

$$\mathrm{PIN} = \alpha\mu / \left(\alpha\mu + \varepsilon^B + \varepsilon^S\right) \tag{1}$$

Note: ε^B is assumed to be equal to ε^S.

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. Days are assumed independent.

Our ASX Intraday Trade data provide historical details of all individual trades placed on the Stock Exchange Automated Trading System (SEATS). Unlike the experience in U.S. and European markets, the ASX has held a virtual monopoly in trades of ASX-listed stocks with no competition from other trading systems.[5] The absence of an alternative trading venue in Australia limits the use of sophisticated strategies aimed at masking the information content of trade. This also reduces the noise such strategies may generate in the PIN estimates. Furthermore, SEATS is a real time electronic open limit order book and allows on-market trades to be flagged as buyer-initiated (price equals standing bid) or seller-initiated (price equals standing ask) based on the SEATS trade priority rules.[6] This obviates the need to use estimation techniques to infer trade direction, such as the Lee and Ready (1991) algorithm which has been reported to bias PIN estimates (Odders-White, 2000; Boehmer et al., 2007). Trades that are classified as neither buy nor sell (e.g. cross-trades) are excluded but comprise less than 6% of total trades. Our count on buy and sell trades are after amalgamating trades that are executed in multiple parts (e.g. one sell order may be filled by more than one smaller buy order). These are separately denoted in the database so we further benefit, relative to U.S. studies, by avoiding the use of techniques that approximate the incidence of part trades, such as suggested by Hasbrouck (1988).

We estimate the parameter vector $\theta = (\alpha, \delta, \mu, \varepsilon)$ for each firm year by using the likelihood function of the EKOP model,[7] and use a grid of initial parameter estimates for $\alpha, \delta, \mu, \varepsilon$ to minimise non-convergence issues.[8] We exclude stock year observations where non-convergence occurs (36 cases) and where we encounter violations of second-order optimality conditions (1859 cases); most being solutions that error at the bounds (0 or 1) for alpha and/or delta and related, primarily, to stocks with too few buys and sells. After merger to non-missing observations for the other variables, 6485 eligible firm-year observations remain.

2.3. PIN distribution

Table 1 provides summary statistics for PIN and its component parameters for our sample stocks. Our mean PIN (0.245) is higher than the 0.191 reported by EHO consistent with the greater preponderance of

4 This is as modelled in Easley et al. (1996).

5 This was the case until August 2011 when Chi-X Australia began trading in, initially, 8 ASX-listed stocks.

6 The ASX Market Rules which applied during the sample period allow large trades to occur off-market for single security orders of at least \$1 million or for multiple security orders comprising at least 10 stocks with a total value exceeding \$5 million. These orders are not required to be pre-disclosed and SEATS does not record the actual time of trade. It is not possible to unambiguously identify trade direction. Off-market trades are thus excluded from our sample.

7 Refer to EKOP (1996) for details of the likelihood function. The dispersion in PIN, particularly for portfolios of less actively traded stocks, is sensitive to the interval at which buy and sell trades are aggregated; greater dispersion occurring when daily intervals are used rather than smaller intervals (Kaul et al., 2008). We choose a daily time interval consistent with the related asset-pricing studies (e.g. Easley et al., 1996, 1997, 1998, 2002; Vega, 2006) and noting trade numbers at smaller intervals may be insufficient for reliable PIN estimation for many stocks in Australia.

8 We use four different starting values for alpha and five for delta, nine for mu and ten for epsilon: allowing for 1800 permutations.

Table 1
PIN parameters summary. We report the mean, median and standard deviation for the likelihood estimation for our full sample (Panel A) and for the subsamples of industrials sector and resources sector stocks (Panel B and Panel C, respectively) from 1996 to 2009. We also report the mean and maximum standard error of the estimates. PIN is the probability of informed trading calculated each calendar year for each firm as per Eq. (1), α is the probability of an information event, δ is the probability of a bad news signal, μ is the rate of arrival of informed trade, $\varepsilon^B(\varepsilon^S)$ is the rate of arrival of uninformed buy (sell) trades. N indicates the number of firm year observations. ΔPIN is the year on year change in PIN.

		Parameter estimate			Standard error	
Variable	N	Mean	Median	Std dev	Mean	Max.
Panel A: All stocks						
α	6485	0.251	0.217	0.157	0.035	0.422
δ	6485	0.477	0.467	0.202	0.080	0.264
μ	6485	51.958	18.086	95.675	1.287	9.696
$\varepsilon^B = \varepsilon^S$	6485	40.674	4.509	137.078	0.222	3.092
PIN	6485	0.245	0.238	0.081	0.031	0.107
ΔPIN	5274	0.004	0.003	0.078		
Panel B: Industrials						
α	4008	0.273	0.250	0.159	0.037	0.422
δ	4008	0.489	0.483	0.212	0.076	0.264
μ	4008	51.862	16.382	93.314	1.235	9.696
$\varepsilon^B = \varepsilon^S$	4008	43.088	4.509	128.448	0.233	2.680
PIN	4008	0.246	0.236	0.086	0.030	0.107
ΔPIN	3313	0.005	0.003	0.078		
Panel C: Resources						
α	2477	0.217	0.176	0.147	0.032	0.329
δ	2477	0.457	0.445	0.183	0.086	0.250
μ	2477	52.115	21.010	99.396	1.371	8.643
$\varepsilon^B = \varepsilon^S$	2477	36.768	4.509	149.938	0.204	3.092
PIN	2477	0.245	0.239	0.072	0.032	0.107
ΔPIN	1961	0.002	0.002	0.078		

small, illiquid stocks which typically have higher PIN (Aslan et al., 2011). The mean standard error is low providing some indication that the estimates are reliable. Epsilon, (ε), and mu, (μ), show considerable skewness reflective of the relatively few, very large, actively traded stocks.

In untabulated results we find that PIN has remained quite stable over the sample period notwithstanding significant increase in both mu (μ) and epsilon (ε). The trend is similar to that depicted in the US sample of EHO. Average monthly turnover increased significantly in 1999–2000 and again in 2003 to 2006 but then decreased slightly notwithstanding the dramatic increase in informed and uninformed trade from 2006. This suggests that the increase in mu and epsilon relate to an increased number of small-value trades, consistent with reductions in the minimum tick size occurring April 2005 and with reduced transaction costs. The changes in trade post 2006, motivate robustness tests that separately consider PIN's influence on returns in the sub-periods: 1997 to 2006 and 2007 to 2010. The latter period also captures the effects of the recent global financial crises ('GFC'). The stability of PIN notwithstanding significant changes in turnover and trades suggests that it is not a mere proxy for liquidity.

Historically, the Australian stock market has been segregated into industrials and resources sectors. The resources sector comprises both the energy sector (GICS tier 1), dominated by oil and gas companies, and the metals & mining sector (GICS tier 3); identified as CRIF Industry codes 1 and 3 on the SPPR database. Table 1 Panels B and C show that resources stocks, though on average much smaller than the industrials, have a higher average level of informed trade, μ, (insignificantly) in both nominal terms and relative to the level of uninformed trade, ε. However, a lower likelihood of information events, α, for resources sector stocks (0.217) than industrials sector stocks (0.273) tends to lower the PIN estimate. Contrary to expectation that resources stocks would reveal a higher probability of informed trade, Fig. 1 shows that the distribution of PIN is surprisingly similar between the sectors.

Fig. 2 shows the trend over time in average PIN and in the 5th and 95th percentiles. The dispersion in PIN is most pronounced when economic conditions were less buoyant in 2001–02 and in the years since

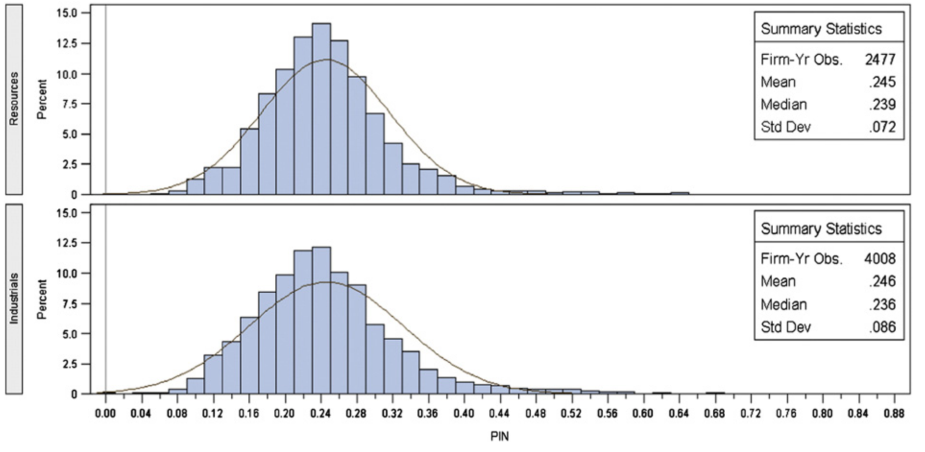

Fig. 1. Distribution of PIN by sector: Resources (top) and Industrials (bottom). Normal distribution curve is displayed.

the 2007 GFC however the dispersion is not markedly different between sectors except perhaps in 2001 when commodities prices were poised for cyclical upswing.

Finally, the cumulative distribution of the year-to-year absolute value of changes in PIN, |ΔPIN|, (not tabulated) shows that the PIN of 80% of stocks in both industry sectors changes by less than 0.09 per annum.

Overall, there is no significant difference in the PIN measure between sectors. This seems at odds with Aslan et al.'s (2011) findings, and with our expectations, but is consistent with evidence that exploration firms (mining stocks not yet in production) have similar PIN to stocks from other sectors that share similar liquidity notwithstanding evidence of the motive and opportunity for private informed trade among exploration firms (Poskitt, 2005).

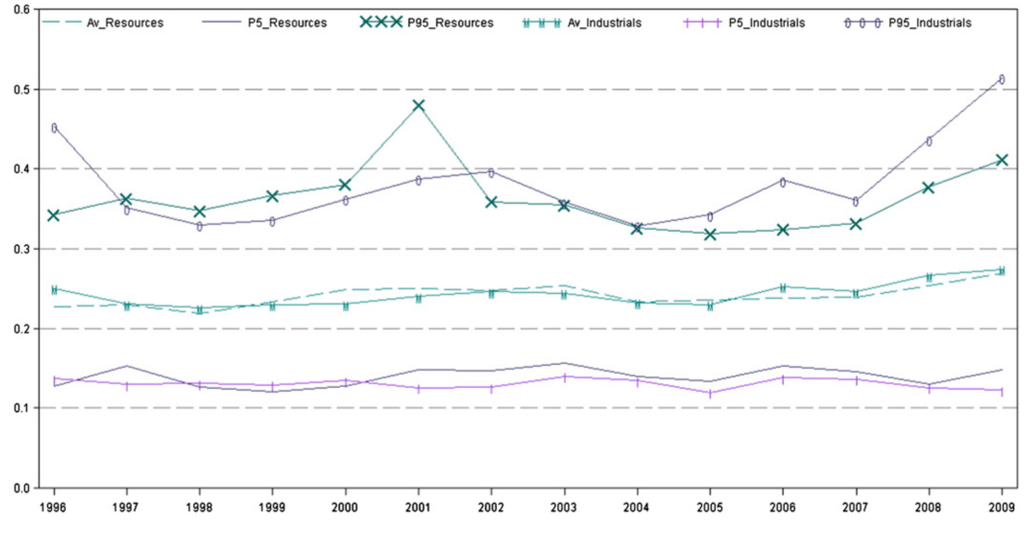

Fig. 2. PIN by sector. Average PIN and the 5th (P5) and 95th (P95) percentile of PIN for the years (x-axis) 1996 to 2009, for each of Resources and Industrials sector.

2.4. Other variables

Our asset pricing tests examine the influence of PIN controlling for beta, size, and book-to-market equity: variables which Fama and French (1992) find influence the cross-sectional variation in returns. We follow EHO in the calculation of our measure of systematic risk, *BETA*, using the adaptation of the Fama and MacBeth (1973, 'F-M') portfolio procedure to minimise within-portfolio variation in betas and including the lagged market return, as suggested by Dimson (1979), to correct for non-synchronous trade effects. Stock returns are after adjusting for dividends and capital changes and we use return data for the extended period, commencing January 1992, for our estimates of market beta. Briefly, for each estimation year, *t-2*, we regress each stock's monthly returns for the past 60 months on contemporaneous and lagged value-weighted market returns. A minimum of 24 monthly observations is stipulated. We sum the coefficients on the market return variables to arrive at *pre-ranking betas* for each stock for each estimation year. We then sort stocks at the beginning of year *t-1* into 40 portfolios based on the year *t-2 pre-ranking betas*. Then for each portfolio, we carry out a full-period regression of equal-weighted portfolio returns on contemporaneous and lagged market returns to determine 40 *post-ranking portfolio betas*, one for each portfolio, which we allocate to the component stocks so that individual stocks have a *post-ranking portfolio beta*, βETA_p, that may differ from year to year given that portfolio composition changes each year. In robustness tests, we use *BETA2*, which excludes, in the beta estimation, the effect of lagged values of the market variable.

SIZE for each firm, is the logarithm of end of year market value; *BTM*, book-to-market equity ratio, is calculated for each month l as $BTM_{i,l} = \ln(BE_{i,l}/\mathrm{MV}_{\mathrm{i,t\text{-}1}})$, where $BE_{\mathrm{i},l}$ is the book value of equity for firm i for the annual balance date occurring at least 3 months prior but not more than 14 months prior to month l, and $MV_{i,t-1}$ is the market value of equity at the end of year *t-1*. We use the lag to ensure we do not assume knowledge that the trader cannot have.[9] We exclude observations where book value of equity is negative and we set positive *BTM* values below the 0.005 fractile and above the 0.995 fractile equal to these fractiles, respectively.

PIN's influence on returns may be attributable to its association with other factors that have been shown to have some significance in explaining variations in returns. We augment our sector level asset pricing model to include controls for risk and liquidity. *STDEV* is the standard deviation of daily returns for the calendar year, and is a measure of the uncertainty associated with returns. As PIN is drawn from stock trade frequency it is related to liquidity. We use a number of liquidity variables to examine whether the effect of PIN on returns is attributable to the liquidity argument. Like EHO we calculate for each stock at each calendar year end: *lnTURN*, being the natural logarithm of the average percentage monthly share turnover over the preceding 3 years and, as a measure of variability in turnover, *CVTURN*, the logarithm of 1/100 the average coefficient of variation in monthly turnover across those 3 years. Higher variability in turnover suggests greater uncertainty as to whether liquidity demands will be met and may deter informed trade. EHO find that *CVTURN* is positively related to PIN.

In addition to the variables used by EHO, we include (in log form) a measure of illiquidity proposed by Amihud (2002) given conflicting findings of its responsibility for the PIN-price effect (Duarte and Young, 2009; Easley et al., 2010). We calculate, for each year:

$$lnILLIQ_t = \log\left(\sum_{d=1}^{n}\left(\frac{|r_{id}|}{\$volume_{id}}\right)\Big/ n\right)$$

where $|r_{id}|$ is the absolute value of daily return for stock i on day d in year t (multiplied by 1 million) and $\$volume_{id}$ is the dollar volume of shares traded on that day d. As a measure of the price impact of order flow, a high value for *lnILLIQ* suggests greater illiquidity.

Analyst coverage has been shown to be associated with higher informed trade, but also higher uninformed trade and lower PIN (Easley et al., 1998) suggesting that analysts do not create information but play a role in reducing asymmetry through greater information dispersion. We are interested to test whether this attribute of a firm's information environment affects PIN's influence on returns. We obtain

[9] ASX Listing Rule 4.5 requires disclosure to the ASX within 3 months of accounting balance date. Listing Rule 4.3A requires that within 2 months of balance date, entities (except mining exploration entities) provide details of equity changes as part of the Preliminary Final Report.

analyst coverage from the I/B/E/S Historical Summary file for International stocks. $ALYST_t$ uses the average number of monthly earnings per share estimates by analysts pertaining to the forthcoming reporting year for stock *i* in year *t*. On merger to our ASX Trade Data, firms with no matching $ALYST_t$ value have coverage set to zero. *lnALYST* is then the logarithm of $(1 + ALYST_t)$. D_{ALYST} is a dummy variable set to 1 if $ALYST_t$ is non-zero and to 0 otherwise.

2.5. Summary statistics

Table 2 reports summary statistics on the variables for the whole sample (Panel A) and separately for industrial sector (Panel B) and resources sector (Panel C) stocks.

Resources stocks are on average smaller, less liquid and riskier than industrials sector stocks. Consistent with greater information asymmetry among resources stocks, some 68% of industrials sector stocks are covered by at least one analyst while only 36% of resources stocks receive coverage.

Simple correlations (Table 3) show that PIN has weaker correlations with other variables than reported by EHO for their U.S. sample. The signs of the relationships are, however, consistent: higher PIN is associated with lower liquidity, greater return volatility (*STDEV*) and smaller firm size. As Easley and O'Hara (2004) predict, PIN is positively associated with stock returns while, consistent with Easley et al. (1998), analyst coverage is negatively related to PIN (−0.207).

3. PIN and industry sector returns

3.1. Portfolio sorts

We first examine the PIN–return relationship at the portfolio level, sorting stocks at the end of each year into quartiles based on *SIZE* and, independently, into terciles based on PIN.

Table 2

Summary statistics. The table contains the means, medians, and standard deviations for our full sample of individual stocks across the period January 1997 to November 2010. *Rtn* is the percentage monthly return in excess of the 90 day bank bill rate. *BETA* is the portfolio beta and is the sum of the betas estimated in regressions including lagged and contemporaneous market returns, estimated from the full period using 40 portfolios, reformed annually, and assigned to component stocks in the relevant year. *BETA2* is the portfolio beta that is estimated similarly to *BETA* but without including the lagged value of market returns in regressions. *PIN* is the probability of informed trade given by Eq. (1) and estimated yearly for each stock. *SIZE* is the logarithm of end of year market value of equity. *BTM* is the logarithm of the book value of equity divided by market value of equity. *SPREAD* is the yearly average of the average daily spread. *STDEV* is the daily return standard deviation for the measurement year. *lnTURN* is the logarithm of average monthly turnover and *CVTURN* is the logarithm of the coefficient of variation of the monthly turnover both measured annually at December using the past 36 months' turnover. D_{ALYST} takes the value of 1 where at least 1 analyst provides estimate of next reporting period earnings per share and the value 0 otherwise. *lnALYST* is the logarithm of 1 plus the average number of analysts providing estimates of the stock's forthcoming earnings per share. *lnILLIQ* is the logarithm of the annual average of the daily Amihud measure of liquidity (|Rtn|/dollar volume) multiplied by 1,000,000. Panel A includes all stocks being 74,677 monthly *Rtn* observations and 6485 annual firm-year observations for other variables. Panel B and Panel C show statistics for the sub sample of Industrials sector (monthly observations: 46,062; firm-years: 4008) and Resources sector stocks (monthly observations: 28,615; firm-years: 2477), respectively.

	Panel A: All stocks			Panel B: Industrials			Panel C: Resources		
	Mean	Median	Std dev	Mean	Median	Std dev	Mean	Median	Std dev
Rtn%	1.199	0.000	18.013	0.800	0.000	15.267	1.843	0.000	21.701
BETA	1.585	1.607	0.381	1.486	1.424	0.356	1.744	1.771	0.364
BETA2	1.205	1.153	0.261	1.150	1.105	0.247	1.293	1.337	0.258
PIN	0.245	0.238	0.081	0.246	0.236	0.086	0.245	0.239	0.072
SIZE	18.675	18.479	1.945	19.044	18.853	1.889	18.079	17.762	1.885
BTM	−0.758	−0.696	0.974	−0.741	−0.668	0.941	−0.785	−0.749	1.025
SPREAD	0.025	0.018	0.024	0.020	0.014	0.021	0.033	0.028	0.026
STDEV	0.042	0.036	0.027	0.035	0.027	0.024	0.054	0.050	0.026
lnTURN	1.107	1.170	0.887	0.873	0.935	0.845	1.486	1.576	0.820
CVTURN	−0.352	−0.335	0.502	−0.432	−0.416	0.491	−0.224	−0.208	0.493
lnALYST	0.885	0.693	0.946	1.096	0.981	0.947	0.545	0.000	0.840
D_{ALYST}	0.560	1.000	0.496	0.679	1.000	0.467	0.368	0.000	0.482
lnILLIQ	−0.652	−0.194	3.060	−1.066	−0.630	3.065	0.017	0.597	2.932

Table 3
Simple correlations. The table contains the Pearson correlation coefficients for our full sample of individual stocks across the period January 1997 to November 2010. The variables are the same as described in Table 2.

	Rtn	BETA	BETA2	PIN	SIZE	BTM	SPREAD	STDEV	lnTURN	CVTURN	lnALYST	D_{ALYST}	lnILLIQ
Rtn	1.000												
BETA	0.015	1.000											
BETA2	0.017	0.665	1.000										
PIN	0.014	0.064	0.021	1.000									
SIZE	−0.040	−0.323	−0.176	−0.237	1.000								
BTM	0.055	−0.029	−0.048	0.030	−0.232	1.000							
SPREAD	0.051	0.274	0.149	0.162	−0.741	0.154	1.000						
STDEV	0.041	0.427	0.295	0.133	−0.630	0.075	0.774	1.000					
lnTURN	0.006	0.308	0.308	−0.152	−0.088	−0.081	−0.021	0.224	1.000				
CVTURN	0.015	0.312	0.165	0.282	−0.647	−0.006	0.542	0.534	0.057	1.000			
lnALYST	−0.011	−0.289	−0.137	−0.207	0.757	−0.002	−0.590	−0.513	0.031	−0.610	1.000		
D_{ALYST}	−0.006	−0.244	−0.120	−0.053	0.605	0.009	−0.562	−0.491	−0.074	−0.459	0.830	1.000	
lnILLIQ	0.034	0.247	0.106	0.342	−0.879	0.155	0.771	0.600	−0.230	0.672	−0.749	−0.573	1.000

Table 4 Panel A reports the average monthly excess returns (i.e. the return after deducting the risk-free rate) to each portfolio measured across the year following portfolio formation and reported on an equal-weighted and value-weighted basis. Average *SIZE* and PIN characteristics of our portfolios as well as the average number of stocks are reported in Panel B. The excess returns using the full sample as well as the sub-samples of industrials sector and resources sector stocks are also shown.

The data reveal, with the exception of the largest stocks, the difference between excess returns of the extreme (High-Low) PIN portfolios in the full sample is positive providing some indication of a return to PIN. Industrials sector stocks appear to account for most occurrences of the positive High-Low PIN return although, except for the 3rd size-ranked portfolio, the Wilcoxon–Mann–Whitney test shows the difference to be not statistically significant. In contrast, while there is evidence of a small-firm premium among resources stocks there is no discernible trend in returns across PIN rankings. Negative returns to the High PIN minus Low PIN hedge portfolios suggest PIN does not represent a priced risk among resources stocks.

The largest size quartile shows a negative PIN–price relationship similar to that detected by EHO. Unlike EHO we find no consistent increase in excess returns as we move from the low PIN to high PIN portfolio within each size group, and only weak evidence (again attributed to industrials sector) as we move from small to larger size quartiles, that private information has a greater impact on price for small stocks than for large stocks.

The data provides some indication that PIN may have differing price effects among sectors although the result may pertain to PIN's correlation with some other factor(s) that influences returns.

3.2. Fama and French asset pricing tests—Full sample

In this section we follow EHO and test whether PIN is priced in the cross section of returns controlling for Fama and French (1992) variables: beta, size and book-to-market equity. In Australia, Gaunt (2004), for the sample period 1993–2001, and Brailsford et al. (2012), using a database that encompasses 98% of the Australian market from 1982 to 2006, find in favour of the Fama and French three factor model (over CAPM).

We perform the following cross-sectional regression each month for the period January 1997 to November 2010.

$$R_{i,tl} = \gamma_{0t} + \gamma_{1t}\beta ETA_p + \gamma_{2t}BTM_{i,l} + \gamma_{3t}SIZE_{i,t-1} + \gamma_{4t}PIN_{i,t-1} + \eta_{i,t} \tag{2}$$

where $R_{i,tl}$ is the monthly return (continuously compounded) of stock i in month l of year t in excess of the risk-free rate, γ_{jt}, j = 0,…4, are the estimated coefficients and η_{it} is the error term. $\beta ETAp$, *BTM*, *SIZE* and PIN are estimated as described in section 2.

We provide the Fama and MacBeth (1973, 'F-M') time-series averages of the coefficients across all months. However, the measurement errors in the betas are correlated over time because 48 months of overlapping data (in each 60 month interval) are used to estimate security *pre-ranking betas* employed in successive cross-section regressions. This induces autocorrelation in the time series of estimated coefficients. We therefore use the Newey–West method to correct the standard errors for autocorrelation and heteroskedasticity.

The Fama and Macbeth (1973) approach weights the coefficients across the time series T, equally, that is by the weight $w_{jt} = 1/T$ for all j and t. This averaging is inefficient where the series' variance is not constant but varies over time. Accordingly, and to aid comparison to EHO, we also report Litzenberger and Ramaswamy (1979, 'L-R') adjusted coefficients which, in summing the coefficients across the cross-sectional regressions, weight the coefficients by their precision.

Table 5 provides the result of the cross-sectional regressions. Contrary to EHO, there is no evidence that the risk of informed trading, as captured by PIN, is priced. The coefficient on PIN is insignificantly positive under both the F-M and L-R methodologies. We do find a significant positive coefficient on *BTM* and, using the L-R method, a negative and weakly significant coefficient on *BETA*. The book-to-market effect is consistent with the Fama and French (1992) value-growth premium and with recent evidence that the HML factor is significant in explaining stock returns in Australia (Fama and French, 1998; Faff, 2001; Brailsford et al, 2012). We observe a weak size effect in the L-R result. Bollen et al (2008) note that sample selection criteria which

Table 4
Size-PIN excess portfolio returns. At the end of each year *t-1* we sort stocks into quartiles based on size (market value) and, independently, into terciles based on PIN as calculated across the year *t-1*. We form portfolios at the intersection of the sorts. For each portfolio, we calculate the mean equal-weighted and value-weighted monthly excess return (the return in excess of the risk-free rate) for the 12 months following portfolio formation and report in Panel A the average excess return (in percent) for the 167 months of our sample from January 1997 to November 2010. High–Low is the difference in excess returns for the highest ranked *PIN* portfolio and lowest ranked *PIN* portfolio in each size quartile. We report the p-value (Pr > |Z|) for the Wilcoxon–Mann–Whitney test for the statistical significance in the difference in the distributions of excess returns between the extreme *PIN*-ranked portfolios. Panel B shows the average *PIN*, average *SIZE* (the logarithm of market value) as well as the average number of stocks in each portfolio. Averages are provided for portfolios formed, separately using only Industrial sector and Resource sector stocks. Total monthly observations used in portfolio formation were 74,677 (All), 46,062 (Industrials), 28,615 (Resources).

	All stocks					Industrials					Resources				
	PIN rank					PIN rank					PIN rank				
Size rank	Low	Med	High	High-Low	*Pr* > |*Z*|	Low	Med	High	High-Low	*Pr* > |*Z*|	Low	Med	High	High-Low	*Pr* > |*Z*|
Panel A: *Average monthly excess returns*															
Equal-weighted															
Small	1.430	1.887	1.613	0.183	*0.912*	0.247	0.948	1.003	0.755	*0.475*	2.968	3.204	2.230	−0.738	*0.487*
2	0.273	0.643	0.792	0.519	*0.284*	0.550	0.338	0.846	0.296	*0.420*	0.372	1.002	0.977	0.605	*0.290*
3	0.594	0.829	0.711	0.117	*0.619*	0.069	0.638	0.603	0.535	*0.036*	0.944	0.984	0.545	−0.398	*0.972*
Big	0.524	0.571	0.378	−0.146	*0.902*	0.589	0.251	0.492	−0.098	*0.804*	0.915	1.119	0.386	−0.530	*0.337*
Value-weighted															
Small	0.607	1.202	0.956	0.349	*0.616*	−0.089	0.809	0.703	0.792	*0.285*	2.789	3.137	1.742	−1.047	*0.427*
2	0.575	0.484	0.731	0.156	*0.647*	0.674	0.369	0.815	0.142	*0.614*	0.257	1.169	0.956	0.699	*0.264*
3	0.216	0.691	0.447	0.231	*0.231*	0.175	0.576	0.458	0.283	*0.049*	0.839	1.112	0.634	−0.204	*0.733*
Big	0.630	0.485	0.396	−0.233	*0.776*	0.577	0.383	0.054	−0.522	*0.272*	0.989	0.991	0.612	−0.377	*0.876*
Panel B: *Portfolio characteristics*															
Average number of firms															
Small	38.4	40.9	36.3			22.1	24.4	24.7			16.9	14.7	12.4		
2	31.4	45.6	38.9			17.8	28.8	25.1			13.4	16.7	14.3		
3	20.6	41.4	54.1			11.2	26.1	34.6			8.9	16.5	19.1		
Big	63.8	26.8	25.1			44.1	16.4	11.0			19.4	11.4	13.2		
Average PIN															
Small	0.173	0.235	0.329			0.170	0.236	0.343			0.177	0.235	0.311		
2	0.180	0.236	0.319			0.178	0.236	0.320			0.187	0.236	0.310		
3	0.180	0.235	0.315			0.178	0.235	0.321			0.184	0.236	0.312		
Big	0.156	0.233	0.321			0.153	0.231	0.321			0.161	0.233	0.322		
Average size															
Small	16.372	16.432	16.383			16.801	16.911	16.782			15.994	16.037	15.998		
2	17.818	17.857	17.856			18.270	18.291	18.334			17.176	17.151	17.147		
3	19.130	19.137	19.176			19.568	19.496	19.522			18.255	18.356	18.315		
Big	21.818	20.693	20.607			21.951	21.008	20.930			21.375	19.954	19.973		

Table 5
Cross-sectional regressions. We report the time-series averages of the coefficients in cross-sectional asset-pricing tests using Fama and MacBeth (1973) methodology and Litzenberger and Ramaswamy (L-R; 1979) precision-weighted means (weighted least-squares). Fama–MacBeth standard errors are after applying the Newey–West adjustment for autocorrelation and heteroskedasticity. The dependent variable is the percentage monthly return (continuously compounding) in excess of the risk free rate. *BETAs* are portfolio betas calculated from the full period using 40 portfolios. *PIN* is the probability of information based trade in stock *i* of year *t-1*. *SIZE* is the logarithm of market value of equity (MV) in firm *i* at the end of year *t-1*, and *BTM* is the logarithm of the ratio of book value of equity to market value of equity for firm *i* in year *t-1*. *t*-statistic values are given in parentheses. Significance is denoted at the 10%, 5% and 1% level (*,**,*** respectively). Our sample is for the 167 months January 1997 to November 2010.

	BETA	*SIZE*	*BTM*	PIN
Fama–MacBeth	−0.771*	0.102	0.268**	0.486
	(−1.80)	(1.03)	(2.31)	(0.70)
L-R	−0.619*	0.158*	0.270**	0.931
	(−1.96)	(1.87)	(2.53)	(1.37)

serve to exclude the smallest stocks (in our case, for lack of sufficient trade) may yield a flat size–return relationship such as observed by Chan and Faff (2003) for the period 1990–1999.

Our result regarding PIN may differ from the U.S. evidence due to sample-specific issues regarding the increase post-2006 in the number of trades from which our PIN estimates are drawn (see Section 2.3) and the greater market volatility post-GFC. We use our split sample, the first sub-period being 1997 to 2006 and the second, 2007 to 2010. We repeat the tests for each of the sub-periods. In untabulated results we find the same qualitative result regarding PIN.

We also test that the result is not affected by use of the Dimson-type beta. We repeat the regressions using *BETA2* in place of βETA_p and reach the same conclusion: PIN is not significant in explaining returns in the cross section.

3.3. Fama and French asset pricing tests—by industry sector

Although Aslan et al (2011) show that industries may differ in the level of private information risk, there is nothing in the Easley and O'Hara (2004) theory to suggest that the risk should be priced in one industry and not another. However, we have argued that differences between the industrials and resources sector may be relevant to the outcome of asset-pricing tests. In this section we test for sector-level differences in PIN's influence on returns. We augment Eq. (2), with D_{IND} (a dummy variable set equal to 1 if the stock is an industrials sector stock and to 0 otherwise) and with the interactive variable, $D_{IND}{}^{*}PIN$. Specifically, we use:

$$R_{i,tl} = \gamma_{0t} + \gamma_{1t}\beta ETA_p + \gamma_{2t}BTM_{i,l} + \gamma_{3t}SIZE_{i,t-1} + \gamma_{4t}PIN_{i,t-1} + \lambda_{ot}D_{IND} + \lambda_{1t}\left(D_{IND} * PIN_{i,t-1}\right) + \eta_{i,t} \tag{3}$$

In effect, the coefficient of D_{IND} captures the difference in the regression intercept for industrials stocks over the intercept for the base case (the resources sector stocks). We are interested primarily in the coefficient of PIN, representing the price effect of PIN among resources stocks and the coefficient of $D_{IND}{}^{*}PIN$, being the incremental pricing effect of PIN among industrials stocks over/under that of resources sector stocks.

We find a striking difference in the effect of PIN between sectors. Both the F-M and L-R methods show that PIN, on its own, is significant in explaining variation in returns as shown in Table 6 Model 1. However, referring to the L-R result, the coefficient on PIN for the base sector (resources) is negative (−2.420) and significant at the 10% level while the coefficient on the interactive variable, $D_{IND}{}^{*}PIN$, is higher in absolute terms (3.857) and significantly positive at the 5% level.

The contrasting PIN-price effect between sectors is similar in Model 2 which includes the effect of the Fama and French variables. The L-R result reveals a highly significant coefficient on the interactive PIN variable (4.029) while PIN itself is no longer significant. The result indicates that PIN is positively associated with excess returns among industrial stocks and not among resources stocks. We interpret the result to mean that a 0.10 increase in PIN is associated with an additional 0.23% monthly return (2.76% per annum) among industrial stocks. Referring to the F-M result, the negative influence of PIN on returns to the resources sector

Table 6
Cross-sectional regressions with industry sector. We report the time-series averages of the coefficients in cross-sectional asset-pricing tests using Fama and MacBeth (1973) methodology and Litzenberger and Ramaswamy (L-R; 1979) precision-weighted means (weighted least-squares). Fama–MacBeth standard errors are after applying the Newey–West adjustment for autocorrelation and heteroskedasticity. The dependent variable is the percentage monthly return (continuously compounding) in excess of the risk free rate. *BETAs* are portfolio betas calculated from the full period using 40 portfolios. *PIN* is the probability of information based trade in stock *i* of year *t-1*. *SIZE* is the logarithm of market value of equity (MV) in firm *i* at the end of year *t-1*, and *BTM* is the logarithm of the ratio of book value of equity to market value of equity for firm *i* in year *t-1*. D_{IND} is a dummy variable which equals 1 for stocks in the industrials sector and 0 otherwise. Interactive variable, $PIN^{*} D_{IND}$ represent D_{IND} multiplied by PIN. *t*-statistic values are given in parentheses. Significance is denoted at the 10%, 5% and 1% level (*,**,*** respectively). Adjusted R-Squared is shown where applicable. Our sample is for the 167 months January 1997 to November 2010.

Model	1		2	
	F-M	L-R	F-M	L-R
Intercept	0.170	0.309	−0.909	−2.188
	(0.21)	(0.49)	(−0.43)	(−1.22)
D_{IND}	−0.821	−1.061**	−1.013*	−1.286***
	(−1.33)	(−2.06)	(−1.82)	(−2.63)
BETA			−0.702*	−0.659**
			(−1.91)	(−2.49)
SIZE			0.124	0.187**
			(1.27)	(2.27)
BTM			0.271***	0.284***
			(2.63)	(2.85)
PIN	−2.876**	−2.420*	−2.181*	−1.725
	(−2.24)	(−1.76)	(−1.70)	(−1.29)
$PIN^{*}D_{IND}$	3.756**	3.857**	3.740**	4.029***
	(2.31)	(2.55)	(2.41)	(2.68)
Adjusted R-Squared	0.024		0.051	

stocks is only weakly significant but suggests, whatever PIN captures, that it may contribute to mispricing among these stocks.

3.4. The effect of liquidity and other risk variables

We test for the robustness of the PIN premium by augmenting our regressions with the EHO controls for liquidity and risk: turnover (*lnTURN*), bid-ask-spread (*SPREAD*), the variability in turnover (*CVTURN*) and the volatility of returns (*STDEV*). Table 7, Models 1 to 5, show that, in the presence of each and all of the control variables, PIN's differential effect on returns to industrials relative to resources stocks (as captured by the coefficient estimate for the variable $D_{IND}{}^{*}PIN$) is somewhat reduced but remains statistically significant. The variability of turnover (*CVTURN*) and the variability of returns (*STDEV*) are each negatively and significantly related to excess returns, the opposite to what we might expect if risk is compensated. However, while these variables do not fully subsume the PIN effect among industrials stocks, they appear to reduce the (negative) influence of PIN among resources stocks to a level insignificantly different from zero (Models 2 and 4).

In Model 6, we introduce our measure of illiquidity, *lnILLIQ*, given its correlation with PIN (see Table 3 correlation 0.342) and in the light of Duarte and Young's (2009) evidence that the variable may account for PIN's influence on average returns. We find that PIN's price effect is largely unchanged: the coefficient on $D_{IND}{}^{*}PIN$ is significantly positive at the 10% level of significance using both the F-M and L-R approaches. Notably, *lnILLIQ* is not significant in the regression.

Overall, our results suggest that PIN captures something more than illiquidity among industrials sector stocks and has a significant and positive influence on excess returns among those stocks controlling for Fama–French variables, liquidity risk and return uncertainty. PIN has no robust influence on resources sector returns.

3.5. The effect of analyst coverage

In Table 7 Model 7 we introduce our proxy for analyst coverage, *lnALYST*, as we have noted a significant difference in this information attribute between industrials and resources sector stocks (Table 2). We

Table 7

Cross-sectional regressions with industry sector and with liquidity and other risk variables. We report the time-series averages of the coefficients in cross-sectional asset-pricing tests using Fama and MacBeth (1973) methodology (Panel A) and Litzenberger and Ramaswamy (L-R; 1979) precision-weighted means (Panel B). Fama–MacBeth standard errors are after applying the Newey–West adjustment for autocorrelation and heteroskedasticity. The dependent variable is the percentage monthly return (continuously compounding) in excess of the risk free rate. *BETAs* are portfolio betas calculated from the full period using 40 portfolios. *PIN* is the probability of information based trade in stock *i* of year *t-1*. *SIZE* is the logarithm of market value of equity (MV) in firm *i* at the end of year *t-1*, and *BTM* is the logarithm of the ratio of book value of equity to market value of equity for firm *i* in year *t-1*, *SPREAD* is the yearly average of the average daily spread for year *t-1*. *STDEV* is the standard deviation of daily return for year *t-1*. *lnTURN* is the logarithm of average monthly turnover year *t-3* to *t-1*. *CVTURN* is the logarithm of the coefficient of variation of the monthly turnover year *t-3* to *t-1*. *lnALYST* is the logarithm of 1 plus the average number of analysts, in year *t-1*, providing estimates of stock *i*'s forthcoming earnings per share. *lnILLIQ* is the logarithm of yearly average of 1,000,000 times the daily Amihud measure of liquidity (|Rtn|/dollar volume) calculated for each stock *i* for year *t-1*. D_{IND} is a dummy variable which equals 1 for stocks in the industrials sector and 0 otherwise. The interactive variable ($PIN^{*} D_{IND}$) represents D_{IND} multiplied by *PIN*. *t*-statistic values are given in parentheses. Significance is denoted at the 10%, 5% and 1% level (*,**,*** respectively). Adjusted R-Squared is shown where applicable. Our sample is for the 167 months January 1997 to November 2010.

	Panel A: *Fama–Macbeth*							*Panel B*: *Litzenberger–Ramaswamy*						
	Model							Model						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Intercept	−0.313	0.782	−0.738	1.858	2.181	2.013	4.462**	−1.870	−1.071	−1.436	0.942	0.952	0.109	3.569**
	(−0.15)	(0.38)	(−0.36)	(1.00)	(1.12)	(0.77)	(2.30)	(−1.06)	(−0.62)	(−0.82)	(0.58)	(0.55)	(0.05)	(2.02)
D_{IND}	−1.185**	−0.925	−0.982*	−0.952*	−1.001*	−0.978*	−1.020*	−1.453***	−1.220**	−1.245**	−1.233**	−1.293**	−1.275**	−1.290**
	(−2.17)	(−1.62)	(−1.80)	(−1.71)	(−1.78)	(−1.72)	(−1.81)	(−2.96)	(−2.46)	(−2.56)	(−2.53)	(−2.59)	(−2.55)	(−2.57)
BETA	−0.534	−0.638*	−0.694*	−0.467	−0.265	−0.282	−0.229	−0.472*	−0.599**	−0.648**	−0.402	−0.222	−0.248	−0.184
	(−1.55)	(−1.76)	(−1.90)	(−1.40)	(−0.89)	(−0.96)	(−0.79)	(−1.96)	(−2.25)	(−2.45)	(−1.61)	(−0.99)	(−1.11)	(−0.83)
SIZE	0.110	0.000	0.115	−0.011	−0.054	−0.044	−0.190**	0.188**	0.103	0.154**	0.043	0.033	0.055	−0.129
	(1.13)	(0.00)	(1.30)	(−0.13)	(−0.61)	(−0.32)	(−1.99)	(2.29)	(1.29)	(1.99)	(0.59)	(0.43)	(0.47)	(−1.52)
BTM	0.249**	0.215**	0.276***	0.212**	0.132	0.132	0.095	0.265***	0.239**	0.282***	0.218**	0.160*	0.166*	0.121
	(2.50)	(2.16)	(2.87)	(2.34)	(1.47)	(1.47)	(1.12)	(2.73)	(2.42)	(2.91)	(2.31)	(1.72)	(1.82)	(1.36)
PIN	−3.062**	−1.283	−2.181*	−1.709	−1.750	−1.690	−1.579	−2.469*	−0.966	−1.718	−1.423	−1.380	−1.457	−1.167
	(−2.43)	(−0.95)	(−1.72)	(−1.34)	(−1.34)	(−1.29)	(−1.20)	(−1.82)	(−0.71)	(−1.30)	(−1.08)	(−1.01)	(−1.06)	(−0.85)
$PIN^{*}D_{IND}$	3.937**	3.362**	3.620**	3.002*	2.960*	2.830*	2.584	4.058***	3.709**	3.865***	3.354**	3.068**	2.935*	2.492
	(2.56)	(2.10)	(2.37)	(1.91)	(1.82)	(1.74)	(1.56)	(2.70)	(2.45)	(2.63)	(2.25)	(2.05)	(1.96)	(1.64)
lnTURN	−0.329***				−0.262***	−0.265**	−0.372***	−0.323***				−0.262***	−0.222*	−0.375***
	(−3.58)				(−2.62)	(−2.05)	(−3.49)	(−3.53)				(−2.78)	(−1.87)	(−3.59)
CVTURN		−0.684***			−0.591***	−0.578***	−0.487***		−0.536***			−0.411**	−0.446***	−0.311*
		(−3.92)			(−3.31)	(−3.12)	(−2.83)		(−3.36)			(−2.54)	(−2.69)	(−1.94)
SPREAD			−2.044		11.242	11.637	9.738			−1.528		10.942	11.187	9.228
			(−0.26)		(1.21)	(1.17)	(1.05)			(−0.24)		(1.42)	(1.39)	(1.19)
STDEV				−18.025***	−19.200**	−19.376**	−18.129**				−20.099***	−22.963***	−23.294***	−22.042***
				(−2.96)	(−2.58)	(−2.58)	(−2.47)				(−4.38)	(−4.58)	(−4.62)	(−4.45)
lnILLIQ						0.002							0.030	
						(0.03)							(0.41)	
lnALYST							0.396***							0.416***
							(2.96)							(3.19)
Adj. R-Squared	0.052	0.051	0.055	0.055	0.061	0.061	0.062							

observe the coefficient on *lnALYST* to be positive and highly significant at the 1% level. Furthermore, the difference in PIN's effect between the sectors is now statistically insignificant. The result tends to support PIN's relevance to a firm's information environment and suggests that differences in analyst coverage may capture the 'private' information advantage that is relevant to PIN's influence on prices.

Given the role that analysts play in evaluating and disseminating information widely, and the more speculative nature of many resources sector stocks, this result raises the possibility that the lack of a PIN-price effect among those stocks may relate to the precision of knowledge that exists for a firm.

4. PIN, information precision and industry sector returns

In this section we examine whether the effect of PIN on excess returns among resources sector stocks is obscured by the 'prior precision' of information concerning the firm. Information asymmetry and precision need not work in concert; precision may encourage informed trade as it provides greater assuredness the informed trader will realise profits (McNichols and Trueman, 1994) but greater asymmetry may reduce the average precision if the informed trader's information is not fully revealed for want of sufficient liquidity (Lambert et al, 2012). Easley and O'Hara (2004) show that firms with smaller precision in beliefs about value, such as those without a track record of earnings, are likely to suffer a higher cost of capital. If lower precision is associated with lower PIN stocks then the effect one has on returns may confound the effect of the other.

We use the existence or absence of operating revenues as a proxy for prior precision and test whether PIN has a positive influence on returns controlling for the effect of the precision variable. We extract annual operating revenues at each annual balance date for each firm and create a dummy variable, D_{OPR}, which is set equal to 1 for stocks with annual operating revenues greater than 5% of market value and equal to 0 otherwise.[10]

Our reduced sample comprises non-missing observations for 4991 firm-years. Table 8 shows that a third of the sample has no operating revenues and 78% of these are from the resources sector. A further 14% are from technology-related industries (Health and Biotechnology, Software Services, Hardware Technology). Thus our classification appears to distinguish speculative-type stocks which rely on 'discovery' for success, and are likely associated with high uncertainty about asset values.

We perform cross-sectional regressions using the same methodology as the above but include interactive variables: $PIN^{*}D_{OPR}$, to capture the differential effect of PIN on the returns of stocks with operating revenues, and; $PIN^{*}D_{OPR}{}^{*}D_{IND}$, to identify whether PIN is priced differently for industrial stocks with operating revenues compared to resources sector stocks with operating revenues. We allow for the intercept to vary by operating revenue status, and by sector, by including D_{OPR} and $D_{OPR}{}^{*}D_{IND}$, respectively, in the regressions.

If PIN's differing effect on prices among sectors relates to a negative PIN-imprecision association among resources stocks and if the Easley and O'Hara (2004) theory holds, we expect the coefficient of PIN to be significantly positive capturing the higher average return to PIN among stocks that have low information precision (no operating revenues). We expect the coefficient of $PIN^{*}D_{OPR}$ to be insignificant if PIN is priced equivalently for stocks that have greater precision (positive operating revenue). If industry sector remains significant to the PIN-price effect, even after allowing for the influence of 'precision', then $PIN^{*}D_{OPR}{}^{*}D_{IND}$ may have significant positive influence.

Referring to Table 9, looking first at the intercepts, we find no evidence stocks with low precision (no operating revenues) receive a significantly greater return than those with higher precision (positive operating revenues). Indeed D_{OPR} is statistically significant and positive suggesting that resources stocks with a revenue track record offer higher returns than the more speculative low-precision stocks. A significant negative estimate for the coefficient of $D_{OPR}{}^{*}D_{IND}$ largely mitigates this effect in the case of industrials but the net effect is not as predicted by Easley and O'Hara (2004).

Referring to the L-R result, while the coefficient on PIN in both Models 1 and 2 is positive it is not statistically significant: stocks with low precision show no evidence of a PIN premium. It appears that the PIN premium may indeed be sector-related and confined to industrial sector stocks with positive revenues if we consider both the significance of the coefficient on $PIN^{*}D_{OPR}{}^{*}D_{IND}$ (the differential effect of PIN among

[10] The 5% benchmark is consistent with the classification used to identify 'development stage entities' in the resources sector (Ferguson et al., 2011a, 2011b).

Table 8
Operating revenue sample by industry. We show the number of firm-year observations by sector and by industry for our reduced sample of stocks that have an annual operating revenue observation recorded for their reporting year ending in year *t-1*. Our sample period is from 1997 to 2010. Revenue ($D_{OPR} = 1$) [No revenue ($D_{OPR} = 0$)] refers to firm-year observations where operating revenue is greater [less] than 5% of the market value as at end of year *t-1*. CRIF Industry is the CRIF Industry recorded in the SPPR database.

Industry	CRIF Industry	Revenue $D_{OPR} = 1$		No revenue $D_{OPR} = 0$		Total	
Resources sector							
Energy	1	278		284		562	
Mining	3	578		978		1556	
		856	*25%*	1262	*78%*	2118	*42%*
Industrials sector		*40%*		*60%*			
Health care and biotechnology	14&15	297	*9%*	192	*12%*	489	*10%*
Software services	21	223	*7%*	14	*1%*	237	*5%*
Technology hardware & equipment	22	67	*2%*	24	*1%*	91	*2%*
Other		1921	*57%*	135	*8%*	2056	*41%*
		2508	*75%*	365	*22%*	2873	*58%*
		87%		*13%*			
Total firm-year observations		3364	*100%*	1627	*100%*	4991	*100%*
		67%		*33%*			

industrial stocks with operating revenues), and the insignificance of the $PIN^{*}D_{OPR}$ coefficient. The result suggests that an increase in PIN of 0.10 among industrial stocks that have operating revenues may lead to an additional monthly excess return of 0.308% (i.e. one-tenth of 4.569–2.939 + 1.447). Illiquidity (*lnILLIQ*) does not explain the differential PIN-price effect, and while analyst coverage (*lnALYST*) has an effect of similar magnitude to that reported in Table 7, it does not explain the difference in PIN's positive pricing-effect among revenue-generating industrial stocks (Model 3).

Our results suggest that the difference in the PIN-price effect between sectors is not related to any opposing relationship between PIN and precision. Rather, speculative stocks which we associate with the lack of a revenue track record are part of the subset of stocks which show no robust evidence of the positive association between expected returns and private information risk that Easley and O'Hara (2004) describe. Among Australian listed stocks any PIN premium appears confined to industrials sector stocks with operating revenues.

5. Possible explanations

In offering possible explanations, we note that the PIN premium is not evident among stocks where mispricing (inadequate return for risk) is most prevalent. Ball and Brown (1980) in a sample of stocks for the period 1958 to 1979 show there is no return for the additional risk posed by mining sector stocks relative to industrial stocks. Resources sector's underperformance has since been found for the period 1980 to 1996 especially the solid fuels industry which underperforms the risk free rate (Finn and Koivurinne, 2000). The same factors that cause this mispricing of risk may extend to an 'anomaly' in the pricing of information risk among speculative stocks.

The mining industry is replete with examples of dramatic stock price hikes and falls. During the Poseidon-led nickel boom of 1969–70, for example, Tasminex NL's stock price went from $2.80 to highs of $75 within a week on speculation of a nickel discovery which never eventuated (Simon, 2003). More recently, on January 7, 2013, a rumour that Whitehaven Coal had lost support from its bankers caused the company's stock price to slump almost 9% before the shares were placed on trading halt at around midday.[11] Kumar (2009) shows that investor behavioural biases are greatest among speculative stocks and these stocks are characterised by high PIN. If the type of trade that PIN captures as 'informed' among these stocks is a consequence of rumour, hoax or of 'manipulative' efforts to exploit the behavioural biases of investors who favour these stocks, PIN may

[11] Refer to Australian Financial Review, 8 January 2013, the company stock price recovered shortly after the company and its bankers clarified that the news was a hoax.

Table 9
Cross-sectional regressions with industry sector and operating revenue status. We report the time-series averages of the coefficients in cross-sectional asset-pricing tests using Fama and MacBeth (1973) methodology and Litzenberger and Ramaswamy (1979) precision-weighted (weighted least squares) means. Fama–MacBeth standard errors are after applying the Newey–West adjustment for autocorrelation and heteroskedasticity. The dependent variable is the percentage monthly return (continuously compounding) in excess of the risk free rate. D_{OPR} is a dummy variable which equals 1 (0) for firm-year observations where operating revenue is greater [less] than 5% of the market value as at end of year t-1. Other variables are as described in Table 7. Interactive variables (eg. $PIN^{*}D_{OPR}{}^{*}\ D_{IND}$) represent the result from multiplying the relevant variables (PIN, D_{OPR} and D_{IND} in the example). *t*-statistic values are given in parentheses. Significance is denoted at the 10%, 5% and 1% level (*,**,*** respectively). Adjusted R-Squared is shown where applicable. Our sample is for the 167 months January 1997 to November 2010. Average monthly observations are 344.

	Fama–MacBeth			Litzenberger–Ramaswamy		
Model	1	2	3	1	2	3
Intercept	−1.506	0.893	2.697	−2.974	−0.791	−0.095
	(−0.66)	(0.36)	(0.82)	(−1.54)	(−0.37)	(−0.03)
D_{OPR}	1.849**	2.222***	2.224***	1.609**	1.880**	1.808**
	(2.55)	(3.18)	(3.16)	(2.11)	(2.44)	(2.33)
D_{OPR} *D_{IND}	−1.152	−1.693**	−1.711**	−1.247**	−1.711***	−1.670***
	(−1.46)	(−2.17)	(−2.18)	(−2.01)	(−2.69)	(−2.61)
BETA	−0.381	−0.034	−0.016	−0.364	−0.043	−0.048
	(−0.97)	(−0.11)	(−0.05)	(−1.22)	(−0.17)	(−0.19)
SIZE	0.027	−0.103	−0.210	0.103	0.010	−0.054
	(0.27)	(−0.92)	(−1.20)	(1.22)	(0.11)	(−0.37)
BTM	0.202**	0.106	0.073	0.207**	0.132	0.114
	(2.01)	(1.10)	(0.78)	(2.07)	(1.36)	(1.21)
PIN	2.464	3.132*	3.371*	1.447	1.791	1.610
	(1.38)	(1.79)	(1.92)	(0.70)	(0.88)	(0.79)
PIN*D_{OPR}	−4.111	−6.499**	−6.903**	−2.939	−4.568	−4.501
	(−1.43)	(−2.28)	(−2.38)	(−0.99)	(−1.52)	(−1.49)
PIN*D_{OPR}*D_{IND}	4.710*	6.677**	6.428**	4.569**	5.951**	5.298**
	(1.72)	(2.34)	(2.21)	(2.05)	(2.56)	(2.25)
lnTURN		−0.250**	−0.344**		−0.171	−0.171
		(−2.26)	(−2.14)		(−1.63)	(−1.18)
CVTURN		−0.472**	−0.333		−0.230	−0.168
		(−2.23)	(−1.54)		(−1.18)	(−0.82)
SPREAD		14.515	14.461		15.993*	13.332
		(1.45)	(1.34)		(1.79)	(1.43)
STDEV		−19.827**	−19.404**		−25.593***	−25.267***
		(−2.34)	(−2.32)		(−4.44)	(−4.39)
lnILLIQ			−0.002			0.078
			(−0.02)			(0.93)
lnALYST			0.346**			0.346**
			(2.04)			(2.25)
Adj. R-Squared	0.050	0.060	0.062			

have no price effect. Of course behavioural bias itself may manifest in mispricing irrespective of what it is that PIN or other information proxies may capture.

Finally, we need to bear in mind the assumptions underlying the PIN model when interpreting the results. It seems reasonable to assume that for each price-sensitive good (bad) news event, rational informed traders enter the market on the same side of the order book and will cross the spread to trade at the standing limit ask (bid). However, more sophisticated strategies may be employed to camouflage the information content of trade. These strategies such as splitting orders into smaller quantities, trading over time or even evoking others to trade, may have different relevance to resources versus industrials sector stocks and may cause sector-level differences in the noise associated with our estimation of information risk.

6. Conclusion

Given the mixed empirical evidence from the U.S. markets regarding the theory of information–asymmetry–risk premium proposed by Easley and O'Hara (2004), we examine the price effect of PIN, a proxy for information asymmetry (or private information risk), in an alternative market with information attributes that differ significantly to those of the U.S. markets. Using a large number of data sets for the Australian market over the period from 1996 to 2010, we investigate three specific issues: 1) whether there is a PIN premium among Australian listed stocks, 2) whether PIN has a similar price effect for the country's historically dichotomous sectors notable for their different information attributes–resources and industrials sectors, 3) whether lower prior information precision is linked to higher expected return, as predicted by Easley and O'Hara (2004), and affects the PIN premium.

We find that PIN is only weakly priced for the full sample of all Australian listed stocks; the relationship between PIN and stock expected returns is positive but not statistically significant. However, we observe a considerably different picture when examining the price effect of PIN among the stocks of the two industry sectors. Despite similar distribution of PIN among the stocks of both industrials and resources sectors, we find that PIN is a significant determinant of returns among industrials sector stocks. This result is robust to the controls for market risk, size, book-to-market ratio, liquidity, variability in liquidity and return volatility, providing empirical evidence in support of Easley and O'Hara (2004). We detect no PIN premium among stocks of the resources sector, which leads to an overall weak price effect of PIN in the Australian market renowned for its abundance of resources stocks.

Using the absence of operating revenue as a proxy for lack of prior precision, we observe no PIN premium among stocks that we classify as having low prior precision, most of which are resources and high-tech stocks. Nor do we detect a link between expected return and prior precision.

In summary, we find strong evidence of a PIN premium among industrials sector stocks but not among resources stocks and stocks without an established record of operating revenue, both distinguished for their speculative business nature and uncertainty about true asset values. Our results are consistent with previous evidence that documents strong investor behaviour biases when valuing extremely uncertain stocks or hard-to-value stocks (Kumar, 2009), and have very important theoretical and practical implications. Our findings shed light on the existing mixed empirical evidence that a strong PIN premium exists in the NYSE and AMEX markets but not in the NASDAQ where high-tech stocks are prevalent, and suggest that caution needs to be taken when applying PIN to pricing highly speculative stocks or when relying on PIN in trading strategies. Therefore, our findings extend the current research on the PIN premium by linking it to research related to investor behaviour biases, and open up fruitful avenues for future research on the price effect of PIN.

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