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The PIN anomaly around M&A announcements ☆

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Abstract

The probability of information-based trading (PIN) introduced by Easley and O'Hara (1987) has been increasingly used in empirical research in finance. We investigate its behavior around a sample of merger and acquisition announcements that took place on Euronext Paris between 1995 and 2000. The behavior of the PIN seems to be in contradiction with clear evidence of information leakages in our sample during the pre-event period. We investigate the reasons for its unusual behavior and raise some concerns about its use as an information-based trading indicator, at least around major corporate events.

JEL classification: G14; G34

Keywords: Probability of information-based trading; Mergers and acquisitions; Corporate events

1. Introduction

Easley et al. (1996b) have introduced an approach to infer the probability of information-based trading (PIN) from transaction data. It is based on a structural sequential trade model developed by Easley and O'Hara (1987, 1992). Originally used to

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investigate whether discrepancies in information-based trading can explain observed differences in spreads between actively and infrequently traded stocks, the PIN method was subsequently adopted to address a variety of issues in empirical finance: the role of purchased order flow (Easley et al., 1996a); the information content of time between trades (Easley et al., 1997a); the importance of trade size (Easley et al., 1997b); the analyst coverage (Easley et al., 1998); the order flow in an electronic market (Brown et al., 1999); the difference between dealer and auction markets (Heidle and Huang, 2002); and the difference between a non-anonymous traditional floor trading system and an anonymous computerized trading system (Grammig et al., 2001).

However, most of these studies do not directly test whether the PIN truly measures information-based trading. It is implicitly assumed to be an accurate measure of information-based trading. For example, Chung et al. (2005) write: "Our study offers a more direct and discriminating test of information vs. inventory models of quote revisions using a better measure (i.e., PIN) of informed based trading." At most, indirect validations (e.g., the relation between the PIN and the bid-ask spread, which is considered to be closely linked to information asymmetry) are provided in some papers (Easley et al., 1996b, 1998, 2002).

The goal of this paper is to provide a direct validity test of the PIN as an information-based trading measure. To do so we analyze its behavior around major corporate event announcements. We focus on mergers and acquisitions (M&A). There is overwhelming evidence of illegal insider trading or information leakage prior to such events. Meulbroek (1992) analyzes illegal insider trading cases detected and prosecuted by the US Securities and Exchange Commission (SEC). In her sample, 145 cases out of the 183 insider trading episodes scrutinized occurred prior to takeover announcements. She also found that 44% of the pre-bid price run-ups occurred on insider trading days. Keown and Pinkerton (1981) also argue that the abnormal returns observed prior to the announcement of 194 future successful mergers were due to trading on private information. These results have been corroborated by Dennis and McConnell (1986), Sanders and Zdanowicz (1992), Keown et al. (1992) and Arshadi and Eyssell (1993). Case studies of illegal insider trading prior to takeover announcements have also been undertaken. For example, Cornell and Sirri (1992) have analyzed Anheuser-Bush's acquisition of Campbell Taggart, while Chakravarty and McConnell (1997, 1999) have explored Ivan Boesky's illegal trading activities prior to the acquisition of Carnation by Nestlé. It is moreover widely recognized that M&A announcements have a large stock price impact (Jensen and Ruback, 1983; Mulherin and Boone, 2000; Andrade et al., 2001; Aktas et al., 2004). Strategies based on private information can be very rewarding and very tempting. Inspecting the PIN behavior in such a context is probably one of the most natural ways to test its validity as a measure of information-based trading.

Prior to testing the ability of this proxy to capture what it claims to capture, we provide empirical evidence of information leakages before the announcement day in our sample by inspecting classical market indicators used in previous studies: cumulative abnormal volume, the bid-ask spread and the permanent price impact of trades (estimated using the Hasbrouck (1991a,b) VAR model). This investigation confirms previous studies and so confirms that testing the PIN measure with our sample makes sense.

The behavior of the PIN around the announcement date is surprising: it decreases in the pre-event period and increases after the information release. This finding is robust. It does not depend on trade misclassification problems, on particularities of our sample, on numerical convergence problems or on specific sub-samples. We then investigate why this surprising behavior arises. We show that the PIN essentially captures the ratio of the expected order imbalance (OIB) to the expected volume. The surprising behavior of the PIN is due to two defects of this measure: (1) it only reflects the number of orders, while volume is more relevant; (2) it captures the effect of public information as well as private information.

This paper is organized as follows. Section 2 introduces the structural sequential trade model developed by Easley and O'Hara to infer the PIN from information contained in trade data. Section 3 describes our data. In Section 4 we provide empirical evidence of information leakage in our sample during the pre-announcement period. We analyze the PIN behavior around the selected event dates and present a set of checks of robustness. Section 5 discusses the reasons that the PIN fails to capture information-based trading and Section 6 presents our conclusions.

2. The probability of information-based trading

Easley et al. (1996b) develop and empirically implement a structural model that builds on Easley and O'Hara (1987, 1992). Investors trade a single risky asset and money with a competitive risk-neutral market maker. The market maker quotes bid and ask prices for one unit of the risky asset. Trades arise from market buy and sell orders submitted by a large number of traders. A fraction of these traders are potentially informed.

Prior to the beginning of the trading day, nature determines whether an information event takes place. Information events are assumed to be independent across days and to occur with probability α. If no information event takes place, the asset value is V_i^*. If an information event occurs, the asset value is $V_i^b < V_i^*$ with probability δ and $V_i^g > V_i^*$ with probability $1-\delta$. The asset value is revealed at the end of the trading day.

There are two groups of traders. Uninformed traders don't know the asset value, nor do they observe whether an information event occurred. They trade for exogenous liquidity reasons. Informed traders know whether an information event took place and observe the true asset value. They buy assets when the value is high and sell when the value is low. They do not trade when there is no information event. On any day, independent Poisson processes determine the arrival rate of uninformed buyers and uninformed sellers. These both arrive at rate ε (per minute of the trading day). On event days, informed traders also arrive (with arrival rate μ). All these arrival processes are assumed to be independent. The tree diagram in Fig. 1 describes the structure of the trading process.

According to this model, Easley et al. (1996b) estimate the unconditional probability of information-based trading as

$$\mathrm{PIN} = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}. \tag{1}$$

In order to obtain this proxy of the presence of informed trades, the model parameters $\Theta = \{\alpha, \delta, \varepsilon, \mu\}$ are estimated by the maximization of a likelihood function. The likelihood

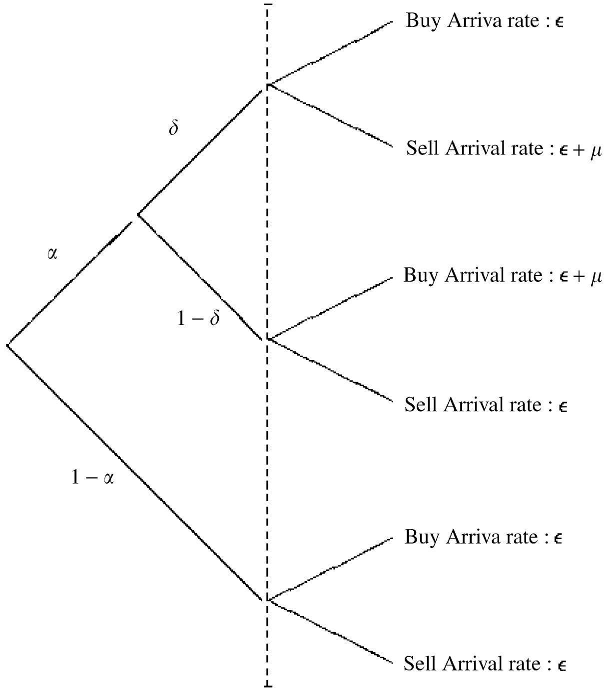


Fig. 1. The tree diagram of the pin trading model. It describes the structure of the trading process, where α is the probability of an information event, δ is the probability of a "bad" event, μ is the rate of informed trade arrival, and ε is the rate of uninformed trade arrival. At the first node of the tree, nature selects whether an information event occurs. If an event occurs, nature then determines if it is good news or bad news. Nodes to the left of the dotted line occur once per day.

of observing B buys and S sells for a single trading day is

$$
\begin{aligned}
L(B,S|\Theta) = {} & (1-\alpha)\exp(-\varepsilon T)\frac{(\varepsilon T)^B}{B!}\exp(-\varepsilon T)\frac{(\varepsilon T)^S}{S!} \\
& + \alpha\delta\exp(-\varepsilon T)\frac{(\varepsilon T)^B}{B!}\exp(-(\mu+\varepsilon)T)\frac{[(\mu+\varepsilon)T]^S}{S!} \\
& + \alpha(1-\delta)\exp(-(\mu+\varepsilon)T)\frac{[(\mu+\varepsilon)T]^B}{B!}\exp(-\varepsilon T)\frac{(\varepsilon T)^S}{S!},
\end{aligned}
\tag{2}
$$

where T corresponds to the total time (in minutes) of a single trading day. Since days are independent, across the I trading days, the likelihood to maximize is

$$
L(M|\Theta) = \prod_{i=1}^{I} L(B_i, S_i|\Theta). \tag{3}
$$

Maximization of Eq. (3), with respect to the parameter vector Θ, yields maximum likelihood estimates of the parameters of interest. Starting from the number of buys and sells, the approach developed by Easley and O'Hara allows inferences of the presence of information-based trading on the market to be made. Easley et al. (1997a) show that a 60-day trading window is sufficient to allow reasonably precise estimation of the parameters.

Let us also mention that, to reduce the convergence problem of the numerical maximization of the likelihood function when the number of buys and sells is large, Easley et al. (2001) suggest using the following rearranged log-likelihood function:

$$Log(L(M|\Theta)) = \sum_{t=1}^{T}[-2\varepsilon + M\ \ln x + (B+S)\ln(\mu+\varepsilon)] + \sum_{t=1}^{T}\ln\left[\alpha(1-\alpha)e^{-\mu}x^{S-M} + \alpha\delta e^{-\mu}x^{B-M} + (1-\alpha)x^{B+S-M}\right], \tag{4}$$

where $M = \min(B, S) + \max(B, S)/2$, and $x = \varepsilon/(\mu+\varepsilon) \in [0,1]$.

3. Our data

3.1. Sample composition

The business combinations were selected from the database of the Directorate General for Competition (DGC), which is the European Commission's antitrust authority. We have kept only operations for which at least one quoted French firm was involved. Another criterion is the availability of intraday market data.[1] These operations were announced between April 1995 and December 2000. From an initial sample of 136 firms, we are able to provide results for only 87 cases, due to numerical convergence problems in estimating Eq. (4) (see Section 4.3). Table 1 Panel A provides statistics about our sample operations. The cross-sectional average of the daily number of transactions is 795 trades per day and the cross-sectional average of the daily trading volume is \$1,707,000.[2]

The sample was also divided according to the firm's role (target, bidder and joint venture) and the presence of rumors. We used the financial press (*The Financial Times* and *Les Echos*) to check the presence of rumors before the announcement of a specific business combination. Firms are classified in the "rumor" sub-sample if there were rumors in the financial press during a six-month period prior to the public announcement day. Table 1 Panel B shows how the sample is spread over these sub-categories.

3.2. Data sources

Daily stock prices were obtained from Datastream. For announcement dates, two separate sources were checked: the financial press (*The Financial Times* and *Les Echos*) and the archive of the European Commission's DGC.[3] For every day of the period studied and for each stock, we used the Euronext database (BDM) to obtain intraday best quotes, orders and transaction prices. This database contains all the orders and trades for all the securities traded on the "Premier Marché" and the "Second Marché" of Euronext Paris. Information is time-stamped to the second. To account for abnormal trading patterns and procedures around the start and the close of each trading day, the pre-opening and

[1] Intraday data on Euronext Paris are only available from January 1st, 1995.

[2] We used time series data on the French Franc/Euro to US Dollar exchange rate to compute this statistic.

[3] Much information is available on http://www.europa.eu.int/comm/competition, the official DGC web site.

Table 1
Sample summary statistics
Panel A provides descriptive statistics about our sample of business combinations. The number of transactions, market capitalization and trading volume correspond to daily averages computed across the period studied (from day −180 to day +63 relative to the announcement date). Panel B divides the sample according to the presence of rumor and the firm's role.

Panel A. Summary statistics

Whole sample	Daily number of transactions	Market capitalization (10^3\$)	Daily trading volume (10^3\$)
Mean	795	17,338	1,707
St. dev.	729	22,620	4,000
Minimum	10	44	2
Median	634	9,341	509
Maximum	3,486	135,975	26,688

Panel B. Sub-samples

	Number of operations
No rumor	55
Rumor	32
Target	24
Bidder	38
Joint venture	25
Total	87

pre-closing periods are excluded (Biais et al., 1999).[4] Hence, only trades and quotes occurring between 10.00 a.m. and 5.00 p.m. are examined.

3.3. Trade classification

To maximize the likelihood function given in Eq. (4), and thus to compute the PIN, we need to estimate the number of buys and sells on each day for each operation. In order to determine these numbers, we need to infer the direction (buyer-initiated or seller-initiated) of each trade. Since the French market is an order-driven market, there is no designated market maker. In such a context, limit orders play a pivotal role in providing liquidity to the market. Therefore, in an order-driven market, the quoted spread corresponds to the difference between the best selling and buying limit orders. The Euronext intraday database provides these limits. A transaction is thus classified as buyer- (seller-) initiated if its price is larger (smaller) than the mid-quote (average of the corresponding best selling and buying limit orders). This method partially corresponds to the technique developed by Lee and Ready (1991) to infer trade direction in a quote-driven market. Like most trade classification methods, it generates classification errors. Boehmer et al. (2006) have shown that trade misclassifications may lead to biased results and in particular to underestimating the probability of information-based trading. Nevertheless, Declerck (2000) has shown that this algorithm classifies trades on Euronext Paris quite well. By testing this

[4]The reason for excluding pre-opening and pre-closing trades is that investors may use different trading strategies during these time periods.

classification algorithm on a sample for which the initiator of each trade was known, Declerck (2000) found that only 4.5% of trades were misclassified. Consequently, the estimated probability of information-based trading computed for our data should be only slightly affected by this potential misclassification problem.

3.4. Event windows

The PIN computation requires windows of at least 60 trading days, with the announcement day being day 0. We estimated the parameters over three different event windows: [–180,–66] (the estimation window); [–65,–6] (the pre-event window); and [+3,+63] (the post-event window). We decided not to consider the window [–5,+2] because it was too small to infer values for the different PIN parameters and our interest is centered on the period just before the event (the pre-announcement period) and just after it (the post-announcement period). The first window is used as a benchmark. The pre-event window is chosen in accordance with previous evidence of information leakage. Meulbroek (1992), Keown and Pinkerton (1981) and Dennis and McConnell (1986) use a window covering the period [−20,−1], while Jabbour et al. (2000) found insider trading occurring 45–60 days before the announcement date. The well-known Ivan Boesky illegal trading, discussed in Chakravarty and McConnell (1997, 1999), occurred in the three-month period before the announcement of the acquisition of Carnation by Nestlé. Finally, Bris (2005), working with a large international sample, focused his attention on the 60-day period before the M&A announcement.[5]

4. Informed trading around M&A announcements and the PIN behavior

4.1. Are there information leakages before M&A announcements?

Even if information-based trading around M&As is well documented in the literature, the first question we need to address is whether there is evidence of information leakage onto the market prior to the public announcement of the operations in our sample.[6] Only in this situation can we expect the pre-announcement PIN to be greater than the one estimated over the benchmark period. To validate this preliminary requirement, we investigated the behavior of several market indicators used in previous studies or by market supervision authorities: the cumulative abnormal volume, the bid-ask spread, and the permanent price impact of trades.

Cumulative average abnormal volumes. We measured volumes as the natural logarithm of the daily trading volume expressed in euros. Following Ajinkaya and Jain (1989), the mean-adjusted model is used as the normal volume generating process: abnormal volumes are the differences between daily observed volumes and daily average volumes observed during the estimation window [−180,−66]. Cumulative average abnormal volumes (CAAV) are then obtained by averaging the abnormal volumes across time and sample.

[5]While estimation concerns and previous evidence of information leakage drive the choice of the time-span for the pre-announcement window, concerns could be raised about the sensitivity of our results to this choice. However, we show later on that this is not a problem.

[6]An in-depth analysis of the information leakage hypothesis on the French market can be found in Aktas et al. (2002).

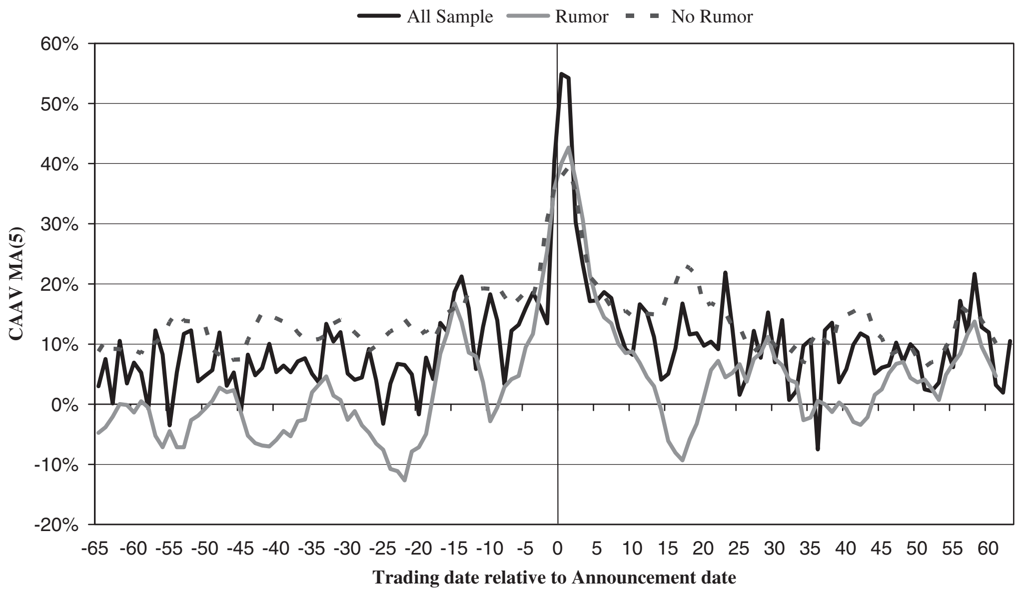


Fig. 2. Market indicators. It gives the five-day moving average evolution of the cumulative average abnormal volume (CAAV) through time for the whole sample and according to the presence or absence of rumor.

Fig. 2 presents the evolution of the five-day moving average CAAV. It shows that in the period preceding the public announcement of the acquisition or merger, the CAAV of the whole sample increased, and in particular the CAAV of the no-rumor sub-sample. As the abnormal volume is also widely used as an indication of information leakage in previous studies (Keown et al., 1992; Meulbroek, 1992), this already leaves little (if any) room for doubt concerning the presence of information-based trading.

Bid-ask spread. Microstructure theory predicts that the presence of informed traders increases the bid-ask spread.[7] Therefore, we analyzed the behavior of bid-ask spreads around the chosen corporate event. We used the percentage spread instead of the spread because it is independent of the price level. We first estimated the percentage spread, $SPREAD_{k,t}$, for each transaction k on day t by

$$SPREAD_{k,t} = \frac{Ask_{k,t} - Bid_{k,t}}{(Ask_{k,t} + Bid_{k,t})/2}, \tag{6}$$

where $Ask_{k,t}$ and $Bid_{k,t}$ are respectively best ask and best bid limit orders at time k. Then, following McInish and Wood (1992), we used a time-weighted approach to aggregate the percentage spread on day t,

$$SPREAD_t = \sum_{k=1}^{T} \frac{D_k}{L_t} SPREAD_{k,t}, \tag{7}$$

where D_k is the duration of the quotation k in seconds, L_t is the number of seconds of the trading day t and T the number of quotations for the day t.

[7]This idea was originally proposed by Treynor (alias Bagehot (1971)).

Table 2
Spread and permanent price impact
Panel A presents the bid-ask spread behavior for different event windows and Panel B gives Hasbrouck's (1991a,b) standardized permanent price impact. The percentage difference between two subsequent event windows is also provided (in brackets). To estimate significance a classical paired test of difference of means is used. * (**) represents the 10% (5%) significance level.

Panel A: Spread			
	[–180,–66]	[–65,–6]	[+3,+63]
All firms	0.332%	0.362% (+8.99%)**	0.337% (–6.86%)*
Target	0.344%	0.370% (+7.47%)	0.312% (–15.65%)*
Bidder	0.282%	0.301% (+6.78%)	0.271% (–10.03%)*
Joint venture	0.396%	0.446% (+12.65%)*	0.461% (+3.40%)
Panel B: Standardized permanent price impact			
	[–180,–66]	[–65,–6]	[+3,+63]
All firms	4.585E–12	5.539E–12 (+20.79%)*	2.474E–12 (–55.33%)**
Target	1.931E–12	2.733E–12 (+41.54%)	1.081E–12 (–60.43%)
Bidder	3.250E–12	3.391E–12 (+4.36%)	2.087E–12 (–38.45%)*
Joint venture	9.164E–12	1.150E–11 (+25.46%)*	4.399E–12 (–61.73%)

Table 2 Panel A shows the cross-sectional average of the bid-ask spread for our event windows. There is a significant increase in the percentage spread in the pre-announcement period, a result consistent with our information leakage hypothesis. This increase is, as expected, more pronounced for targets than for bidders. The large drift for joint ventures is partly due to a decrease in the price between the two periods. However, this analysis must be treated with caution, since the spread does not capture only the asymmetric information cost. It also includes other costs, such as the inventory holding and the order processing costs. One way to go further is to analyze the permanent price impact of trades: the more informative trades are, the larger their permanent price impact should be.[8]

Permanent price impact of trades. To study the evolution of the permanent price impact of trades, we used Hasbrouck's (1991a,b) VAR approach. The main idea is to decompose the variance of the price changes into trade-correlated and trade-uncorrelated components. Since private information is impounded into asset prices through trades, the trade-correlated variance represents a measure of the level of information asymmetry. Hasbrouck (1991a,b) introduces the following VAR model to estimate this

[8]We also estimated the adverse selection component of the spread using Lin et al.'s (1995) approach. The results obtained were similar to those presented in the following subsection.

trade-correlated component of the variance:

$$\begin{pmatrix} I & -b_o \\ 0 & I \end{pmatrix}\begin{pmatrix} r_t \\ x_t \end{pmatrix} = \begin{pmatrix} a(L) & b(L) \\ c(L) & d(L) \end{pmatrix}\begin{pmatrix} r_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} e_{1,t} \\ e_{2,t} \end{pmatrix} \text{ and } V\begin{pmatrix} e_{1,t} \\ e_{2,t} \end{pmatrix} = \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \Omega \end{pmatrix}, \tag{8}$$

where r_t represents revision in the quote midpoint (ln *Mid-Point*$_t$ – ln *Mid-Point*$_{t-1}$), x_t is a vector of two trade attributes (a signed trade indicator variable and a signed trade volume variable), and $a(L)$ to $d(L)$ are the polynomials in the lag operator.[9]

Private information resides in $e_{2,t}$, the unexpected component of the trading process. Hasbrouck (1991a,b) shows how, using the VMA representation of the VAR model, the permanent price impact of $e_{2,t}$ can be isolated. Below, we denote this as *PPI* (which corresponds to $\sigma^2_{w,x}$ in Hasbrouck's notation). Since this measure is compared for different time periods and the average trade size varies from period to period, we standardized Hasbrouck's measure by dividing it by the squared average trade size.

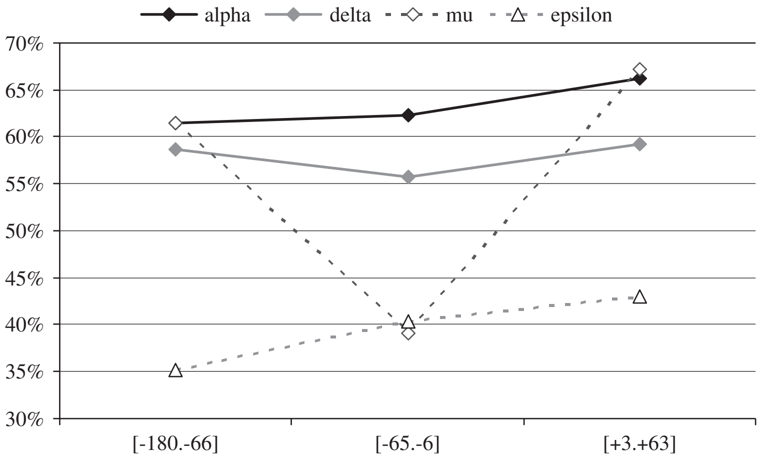
Table 2 Panel B presents the standardized *PPI* behavior for different windows and sub-samples. As expected, there is an increase in the pre-event window, one more evidence for our information leakage hypothesis. In addition, the rise is more pronounced for the target sub-sample. This result is unlikely to be innocuous, as we know that information-based trading is particularly rewarding for this sub-sample.

To sum up, the behavior of the CAAV, the spread and the permanent price impact of trades provide clear evidence that there is information-based trading prior to M&A announcements. If the PIN is an accurate measure of information-based trading, it should also detect this activity. This is the central question addressed in the next section.

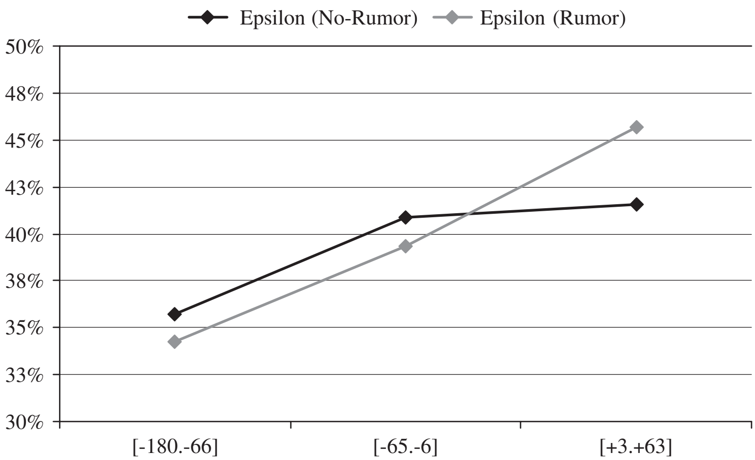
4.2. The behavior of PIN around public M&A announcements

Parameter estimates. The parameters were estimated by numerically maximizing the likelihood function given by Eq. (4). Fig. 3 Panel A gives the cross-sectional average of the estimated parameters for each window. Surprisingly, although we anticipated a greater arrival rate of informed trades during the pre-event window, the estimated μ dropped in this period. In contrast, the estimated ε, the arrival rate of uninformed trades, increases in the last two windows. The pre-announcement increase is quite logical for the rumor sub-sample (see Fig. 3 Panel B). Indeed, because of rumors, individuals trade more using the information which has been released. This phenomenon could also explain the rise in the post-announcement period for the whole sample, since traders could think that it is still possible to make a profit by using this public information and thus decide to trade. This might also be due to the impact of the activities of arbitrageurs (see Mitchell et al., 2004). The increase in the arrival rate of liquidity traders for the no-rumor sub-sample is more surprising. We cannot see any explanation for this. The estimated probability of an information event, α, only increases slightly before the event but, again astonishingly, undergoes a larger increase in the post-event window. Finally, it is worth remarking that δ, the estimated probability of a bad event, decreases during the pre-event period, as expected

[9]Following different information criteria, we decided, like Hasbrouck (1991a,b), to use a specification with five lags.



(A)



(B)

Fig. 3. PIN parameters. Panel A displays the cross-sectional parameters estimated for each window. α and δ represent the probability of an information event and of a ''bad'' event respectively, while μ and ε represent the arrival rate of informed and uninformed traders. Panel B shows the behavior of the arrival rate of uninformed traders ε according to the presence of rumor.

(business combinations are, on average, value-creating events, even if the value effect repartition between bidders and targets is highly asymmetric).

The probability of information-based trading. The PIN is a composite variable reflecting the various parameters characterizing the trade process. This probability is given by Eq. (1). We estimated its value for our global sample, for each sub-sample and event window (see Table 3 and Fig. 4). Fig. 4 Panel A reveals a surprising PIN decrease during the pre-event window (from 18.61% to 17.67%), followed by a significant increase during the post-event window (from 17.67% to 20.29%)! This is exactly the opposite of what we expected. It is a mechanical consequence of the parameter estimates obtained: the sharp decrease in μ during the pre-event window, coupled with an increase in ε, leads logically to

Table 3
Cross-sectional average PIN
This table displays the cross-sectional average of the PIN for different sub-samples and event windows. The different sub-samples are derived according to the presence of rumor and the firm's role. For each sub-sample, the percentage difference between two subsequent event windows is also provided (in brackets). To estimate significance a classical paired test of difference of means is used. * (**) represents the 10% (5%) significance level.

PIN				
	N	[–180,–66]	[–65,–6]	[+3, +63]
All firms	87	18.61	17.67 (–5.1%)*	20.29 (+14.8%)**
No rumor	55	18.46	17.91 (–3%)	20.56 (+14.8%)**
Rumor	32	18.87	17.26 (–8.6%)	19.84 (+15%)
Bidder	38	18.46	17.79 (–3.6%)	17.18 (–3.4%)
Target	24	19.51	16.92 (–13.3%)*	26.85 (+58.7)**
Joint venture	25	17.97	18.21 (+1.3%)	18.72 (+2.8%)

a drop in the estimated PIN. These results are in direct contradiction both with intuition (why would a public announcement increase the level of information-based trading? See Diamond and Verrechia, 1991) and with the evidence of information leakages presented in Section 4.1 above.

It should also be noted that Fig. 4 Panel B suggests that the remarkable increase in the average PIN after the announcement date is largely due to the estimated PIN for target firms. The estimates jump from 16.92% to 26.85% after the event. Note also that, even after excluding the targets from the sample, the PIN estimation does not behave as expected: the PIN does not increase drastically during the period prior to the announcement date.

Are these results statistically significant? In Table 3, we present paired Student-t tests for comparing the (cross-sectional) means of the PIN between the event window under consideration and the preceding one. For the whole sample, the PIN is significantly different between the different event windows. The decrease in the PIN in the pre-announcement window (−5.1%) is slightly significant and allows the hypothesis of an increase in this period to be firmly rejected.

Table 3 also shows the behavior of the PIN for different sub-samples. Most of the sub-sample results (with the exception of the rumor subdivision and the target sub-sample, for which the rise following the drop comes again as a surprise) are not significant, probably because of the small sub-sample sizes. In most cases the behavior of the PIN in sub-samples does not differ from that observed for the whole sample: it decreases during the pre-event windows and increases after the event. Our results seem therefore not to be dependent on the presence of rumors and/or the role of the firm.[10]

[10]The same pattern occurs when the sample is split between value creating and value destroying operations, high and low volume assets, and high and low trade size assets (not shown). We also tried to look for M&A cases for

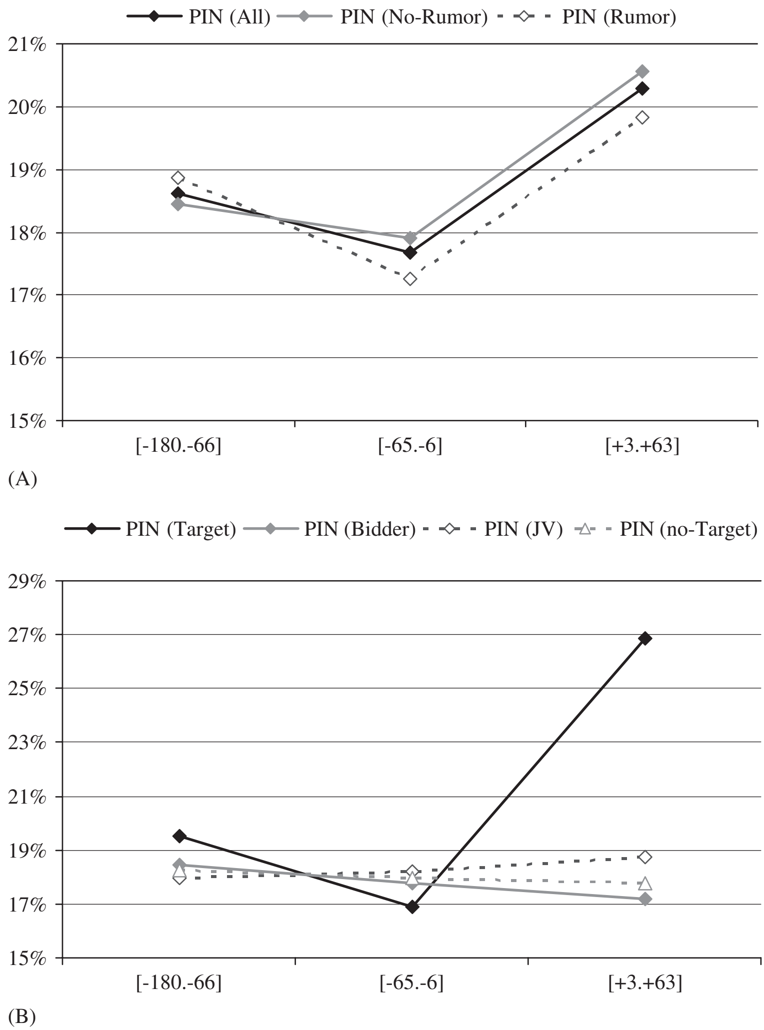


Fig. 4. PIN estimates. Panel A shows the evolution of the cross-sectional average of the PIN across our event windows and according to the presence of rumor. Panel B depicts the evolution of the PIN according to the firm's role in the business combination (bidder, target or joint venture).

4.3. Robustness checks

In this subsection we explore whether the strange behavior of the PIN might be due to trade classification errors, sample specificities or numerical convergence problems of the likelihood function.

(*footnote continued*)
which illegal insider trading had been established. Only one case was found and the PIN still decreased in the pre-event period.

Trade classification errors. We know from the literature that trade classification errors bias the PIN estimation downward (Boehmer et al., 2006). As our trade classification algorithm is not free of errors (see Section 3.3), our results might be affected. In fact, this is most probably not the case. First, the misclassification rate in Euronext Paris is smaller than that observed in other stock exchanges. According to Declerck (2000), the rate of misclassification on Euronext Paris seems to be around 5%. By comparison, using the Lee and Ready method on the Frankfurt Stock Exchange, Theissen (2000) found a rate of 27.2%. Odders-White (2000) found 15% for NYSE stocks. Second, and more importantly, Boehmer et al. (2006) found that the PIN underestimation is more pronounced for small trading volumes. In our sample, the trading activity increases in the pre-event period. So, if anything, our results are biased in favor of the PIN hypothesis, the underestimation being more pronounced for the benchmark window.

Sample specificities. Some concerns might also be raised about the nature of our sample, especially its representativeness. We investigate this issue by repeating some of the Easley et al. (2002) analyses. In this article the authors explore a theoretical relationship between the PIN and the predicted opening spread. The sequential model they use differs slightly from the one presented in Section 2. They allow for different proportions of liquidity traders on each side of the market by distinguishing the arrival rate of uninformed buyers (ε_{b}) from uninformed sellers (ε_{s}).[11] Using the estimated parameters obtained through the maximization of the likelihood function, the authors derive the theoretical opening bid and ask prices. As a consequence, the model predicts the percentage opening spread on day *i* as

$$PISTD_i = \mu\sqrt{\alpha\delta(1-\delta)}\left[\frac{1}{\varepsilon_{\mathrm{b}} + \mu\alpha(1-\delta)} + \frac{1}{\varepsilon_{\mathrm{s}} + \mu\alpha\delta}\right]\sigma_v, \tag{9}$$

where σ_v is the standard deviation of the daily percentage price change and $PISTD_i$ is the predicted percentage spread for stock *i*. The authors show, using a regression equation, that the observed percentage opening spread and $PISTD_i$ are significantly positively correlated.

To address the concern that our results are not due to some sample specificities, we repeated this analysis with our dataset. Table 4 Panel A gives the slope coefficient of the regression where *PISTD* is used to explain the observed percentage opening spread. We obtained qualitatively similar results to Easley et al. (2002) in the different estimation windows: significant positive slope coefficients. This result leads us to reject the idea that our results are sample-specific. We also notice that the tested relationship seems to be weaker in the post-event period. This could well be explained by a more pronounced convergence problem due to the fact that: (1) we have an additional parameter to estimate with our 60-day observations (since ε is split into ε_{b} and ε_{s}), and (2) we face an increasing trading volume in this period. We discuss the numerical convergence issue below.

Numerical convergence. As indicated in Section 3.1, from an initial sample of 136 cases, we can only provide results for 87 firms due to numerical convergence problems. In order to have a homogeneous sample across the event windows, we used listwise deletion: if the estimation does not converge in a specific window, the firm is excluded from our sample.

[11]We do not reproduce the estimated parameters for this new likelihood function because the results do not differ significantly from those presented in Section 4.2. This reinforces our conclusion, because even when we allow for different proportions of liquidity traders on each side of the market, the model predicts that the proportion of informed trades will decrease during the pre-event period.

Table 4
Robustness checks
Table 4 provides robustness checks. Panel A shows the relationship between the observed opening spread and the theoretical one obtained using Eq. (9). Regression slope coefficients, corresponding p-values and the R^2 for the model where we regress the observed opening spread on *PISTD* are provided. Panel B presents the number of estimations that converge (good) or do not converge (bad) across windows. Panel B also shows the average total number of trades for the two samples across windows.

Panel A. Observed spread as a function of theoretical spread

	[–180,–66]	[–65,–6]	[+3,+63]
Slope	0.248	0.182	0.115
P-value	0	0.012	0.259
R^2	0.254	0.094	0.023

Panel B. The convergence problem

	[–180,–66]	[–65,–6]	[+3,63]
Number of estimations			
All	141	141	141
Converge (good)	123	114	118
Do not converge (bad)	18	27	23
% bad	12.80%	19.10%	16.30%
Average B+S			
Converge	525	609	688
Do not converge	1835	1745	2241

Table 4 Panel B gives, across event windows, the number of cases for which the estimations converge and the number of cases for which the estimations do not converge. The rate of "bad convergence" is 12.80%, which is substantially higher than the rates found in previous studies. Easley et al. (2002), for example, document a no-convergence rate of 4.6%. In addition, our rates increase significantly for the following windows, due to the increase in trading volumes. As shown in Table 4 Panel B, the number of trades in cases of no convergence is considerably larger than the number obtained when the estimation procedure converges. This feature was recently emphasized by Easley et al. (2004). They face more computational problems for the later years of their sample and in particular for the most actively traded stocks. They attribute these difficulties to the increased number of trades in recent years.

Consequently, by excluding from our sample the cases for which the total number of trades is too large, our result could suffer from a selection bias. Information-based trading is indeed more likely to occur in these particular cases, especially in the pre-announcement window. However, we will show later (at the end of Section 5.1) that this issue does not affect our results.

5. Why does the PIN fail to detect information-based trading around M&A announcements?

The PIN is based on a model where informed traders use market orders. It seems likely that, in practice, informed traders use other channels to exploit their private information (e.g., limit with/without hidden quantity). Another explanation could be that the PIN, being based exclusively on classified trades, misses two important dimensions of the trading process: the volume (the number of shares involved in each transaction) and the value (the price at which trades are executed). Finally, the PIN might reflect public- as well as private-information-motivated trades. We will explore each of these trails. To dig deeper into these issues, however, we face a serious difficulty: the PIN estimation requires not only a rather broad time span (60 days seems to be the minimum requirement – see Section 2) but, because of the numerical limits of current computers, buys and sells involved in the log-likelihood computation (see Eq. (4)) must remain relatively small. This precludes the replacement of B (the number of buys) and S (the number of sells) by volume information (the number of shares bought or sold) or value information (the value of the transaction, i.e., the number of shares exchanged times their price). To overcome this problem, we first introduce a PIN approximation, based on the relations provided by Easley et al. (2001) between the expected volume ($B+S$) and the order imbalance (B–S).

5.1. A PIN approximation and its relation to the relative OIB

Easley et al. (2001) provide the relations between the different parameters of their model, the total number of trades $B+S$ and the order imbalance $B-S$. In particular, according to the model, the expected total number of trades per day is equal to the sum of the Poisson arrival rates of informed and uninformed trades,

$$\mathrm{E}[B+S] = \alpha\mu + 2\varepsilon. \tag{10}$$

Furthermore, the expected daily order imbalance (OIB) is related to the arrival rates by

$$\mathrm{E}[B-S] = \alpha\mu(1-2\delta). \tag{11}$$

And since each day is either a good day ($\delta = 0$), a bad day ($\delta = 1$), or a no-event day ($\alpha = 0$), the expected daily absolute OIB is

$$\mathrm{E}[|B-S|] = \alpha\mu. \tag{12}$$

Consequently, the PIN is given by

$$\mathrm{PIN} = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} = \frac{E[|B-S|]}{E[B+S]}. \tag{13}$$

Eq. (13) shows that the PIN is the ratio of the expected OIB to the expected volume (which we will call the relative OIB). Eq. (13) holds exactly on a daily basis but is only an approximation for larger time windows if the probability of information arrival, α, varies across days. Approximating the PIN by the relative OIB is attractive because the latter can easily be estimated by the sample average: this allows us to focus on short time windows (even within a day!) and also to circumvent any numerical convergence problems. This remarkably simple PIN approximation will help us to explore the grounds for the unexpected PIN behavior in depth.

Table 5 Panel A shows the PIN for each window and its approximation by the relative OIB. We see that the relative OIB is indeed only an approximation to the PIN (there is a bias due to the averaging process on a multi-day window) but, as expected, it faithfully reproduces the PIN behavior (a decrease in the pre-event window followed by an increase in the post-event window). Table 5 Panel A also shows the median of the ratio of the

Table 5
PIN approximations using relative OIB

Panel A shows the average PIN, its average approximation by the absolute relative order imbalance $|B–S|/(B+S)$ and the median ratio B/S across windows. Panel B presents the PIN approximation using either limit orders (B_{LO} and S_{LO}), displayed volume of limit orders (B_{QDISP} and S_{QDISP}) or hidden volume of limit orders (B_{QHIDD} and S_{QHIDD}). Panel C gives the PIN approximation using either the trading volume (the quantity exchanged B_{VOL} and S_{VOL}) or the trading value (the quantity exchanged times the trade price B_{VAL} and S_{VAL}). In Panels B and C the percentage difference between two subsequent event windows is also provided (within brackets). To estimate significance a classical paired test of difference of means is used. * (**) represents the 10% (5%) significance level.

Panel A. PIN approximation

	[–180,–66]	[–65,–6]	[+3,+63]
PIN	18.61%	17.67%	20.29%
$\lvert B–S\rvert/(B+S)$	22.38%	20.83%	23.69%
B/S	0.904	0.957	0.931

Panel B. Limit and hidden orders

	[–180,–66]	[–65,–6]	[+3,+63]
$\lvert B_{LO}–S_{LO}\rvert/(B_{LO}+S_{LO})$	0.1538	0.1479	0.1660
		(–3.83%)	(+12.26%)**
$\lvert B_{QDISP}–S_{QDISP}\rvert/(B_{QDISP}+S_{QDISP})$	0.2418	0.2431	0.2589
		(+0.53%)	(+6.48%)
$\lvert B_{QHIDD}–S_{QHIDD}\rvert/(B_{QHIDD}+S_{QHIDD})$	0.1941	0.1863	0.2028
		(–4.02%)	(+8.81%)*

Panel C. Volume and value effects

	[–180,–66]	[–65,–6]	[+3,+63]
$\lvert B_{VOL}–S_{VOL}\rvert/(B_{VOL}+S_{VOL})$	0.2305	0.2337	0.2304
		(+1.39%)	(–1.42%)
$\lvert B_{VAL}–S_{VAL}\rvert/(B_{VAL}+S_{VAL})$.	0.2305	0.2337	0.2305
		(+1.39%)	(–1.39%)

number of buys to the number of sells for each window.[12] This ratio exhibits a very different (and more intuitively comprehensible) behavior: it increases between the benchmark and the pre-bid period. Obviously, before a value-creating event such as M&A announcements, informed traders are expected to be on the buy side of the market. So buys and sells do not convey the same information and taking the absolute value of their difference might not be the best way to reveal information arrival phenomena. We explore this issue below.

Since the relative OIB appears to be a good approximation to the PIN, we can turn back to the whole sample (136 cases) to see if our results are altered by the convergence problem. In fact they are not (results not shown): the PIN, proxied by the relative OIB, declines uniformly during the pre-bid period, providing evidence that convergence problems have

[12]In this particular case, we use the median instead of the mean statistic to lessen the impact of outliers.

not biased our results. The uniform decline observed also suggests that our results are not sensitive to our (subjective) time-span choice.

5.2. Do informed traders use limit and/or hidden orders?

In an order-driven market, limit orders generally play the role of liquidity providers (see Biais et al., 1995). However, we could ask whether informed traders would not prefer to use limit orders with or without a hidden quantity to hide themselves and limit the price impact of their own trading. Table 5 Panel B provides some tentative answers to this question. Each section shows the evolution of the relative OIB (the PIN approximation) estimated from the number of buying and selling limit orders $|B_{LO}-S_{LO}|/(B_{LO}+S_{LO})$. The results are self-explanatory: this ratio exhibits the same behavior as the PIN. Taking into account the quantity exchanged and splitting this between the displayed and hidden volume of the limit orders ($|B_{QDISP}-S_{QDISP}|/(B_{QDISP}+S_{QDISP})$ and $|B_{QHIDD}-S_{QHIDD}|/(B_{QHIDD}+S_{QHIDD})$, respectively) shows that displayed limit orders are almost stable between the estimation window and the pre-event one, before rising from 24.31% to 25.89% in the post-event window. However, hidden limit orders reproduce the PIN behavior. These results seem to indicate that the use of limit orders by informed traders is not the reason that the PIN does not capture information-based trading in our data sample.

5.3. Are volume and/or value the missing dimensions?

The PIN indicator is based on the number of buying and selling trades. It does not take into account in any way the number of shares involved in a given transaction and/or the value of the transaction. Are these two missing dimensions the sources of the failure of PIN? Table 5 Panel C explores this issue. Again the relative OIB approximation to the PIN is used to produce estimates taking into account the transaction volumes $|B_{VOL}-S_{VOL}|/(B_{VOL}+S_{VOL})$ and transaction values $|B_{VAL}-S_{VAL}|/(B_{VAL}+S_{VAL})$. The results are strikingly different from the ones shown in Table 5 Panel A (using either the PIN or its approximation). The relative OIB increases in the pre-event window and decreases after the public announcement. We obtain almost the same results working in volume and in value. These movements are of small amplitude (the approximate probability of information-based trading goes from 23.05% during the estimation window to 23.37% during the pre-event window) and insignificant, but at least these results are more in accordance with the results established in Section 4.1 (using the cumulative abnormal volume, the spread and the permanent price impact measure employed by Hasbrouck (1991a,b)) and previous literature. The volume and value dimensions of the trading process convey important information; omitting this information completely is a serious shortcoming of the PIN indicator.[13]

5.4. Is the PIN too broad to be an indicator of private information arrival?

In Section 4.1 we introduced the use of Hasbrouck's (1991a,b) permanent price impact measure as an indicator of information-based trading on the market. The VAR approach suggested by the author is built on a fundamental idea

[13] Easley et al. (1997b) do consider the information content of stocks with different trade size but they are only able to distinguish large trades from smaller ones.

common to numerous microstructure models: private information is impounded into prices through trading process innovations. The key element is the notion of innovation: the trading process conveys all the information (either public or private) but only its unexpected part reveals the presence of private information. Might it be that the PIN, based on the total number of buys and sells, encompasses the whole trading process and is therefore sensitive to the whole information flow coming to the market?

To explore this suggestion, we start from Fig. 5 Panel A which presents the evolution (three-day moving average) of the relative OIB approximation. As expected in the light of previous results, it declines during the pre-event window. Fig. 5 Panel B presents the evolution (still a three-day moving average) of the signed relative OIB approximation $(B-S)/(B+S)$. The picture is now completely different: the estimation window exhibits a clear disequilibrium between the number of buys and the number of sells (there are significantly more selling trades than buying ones). This imbalance diminishes (more buying transactions occur) as we get closer to the announcement date, and then expands again. The rise in the arrival of buying trades in the pre-event window does not come as a surprise. It is the natural consequence of the information-based trading revealed in Section 4.1. But why is there such a disequilibrium in the estimation window? Fig. 5 Panel C, which presents the equally weighted (cross-sectional) average of the CAC40 market indicator behavior across windows, provides the first part of the answer. Our sample of M&As was taken during a clearly upward-trending market period. Shouldn't we then observe more buying than selling?

Table 6 gives the second part of the answer. It shows the average buying and selling trade size by window. On average, purchases were significantly larger than sales during the estimation window. The upward trend was caused by large purchases, with a lot of small sales (probably initiated by investors wishing to take their profits). As we come into the pre-event window, more buying trades occur (but, interestingly, their average size diminishes, as if informed traders were trying to hide themselves): the imbalance thus decreases. The post-event window is characterized by a rise in the size of sales, probably due to the activity of arbitrageurs. The PIN, by focusing only on the imbalance between the number of buying and selling transactions, leads to misleading interpretations: from its point of view, the initial situation (the estimation window) appears to be a situation of high information asymmetry, while in fact it just reflects a trending market; the pre-event window appears to be a period of information asymmetry resolution, while it is in fact the arrival of informed traders that reduces the initial imbalance. This sends us back to Hasbrouck's (1991a,b) intuition: it is the innovations in the trading process that reveal the presence of private information, and not the trading process in itself.

To sum up, Section 5 shows that the PIN measure might be a misleading indicator of information-based trading, at least around M&A announcements. In particular, it ignores the volume/value dimension of the trading process and is also insensitive to market-wide trends.

6. Conclusion

Information asymmetry measures play an important role in empirical finance. Three main approaches have emerged from the previous literature: spread-based measures

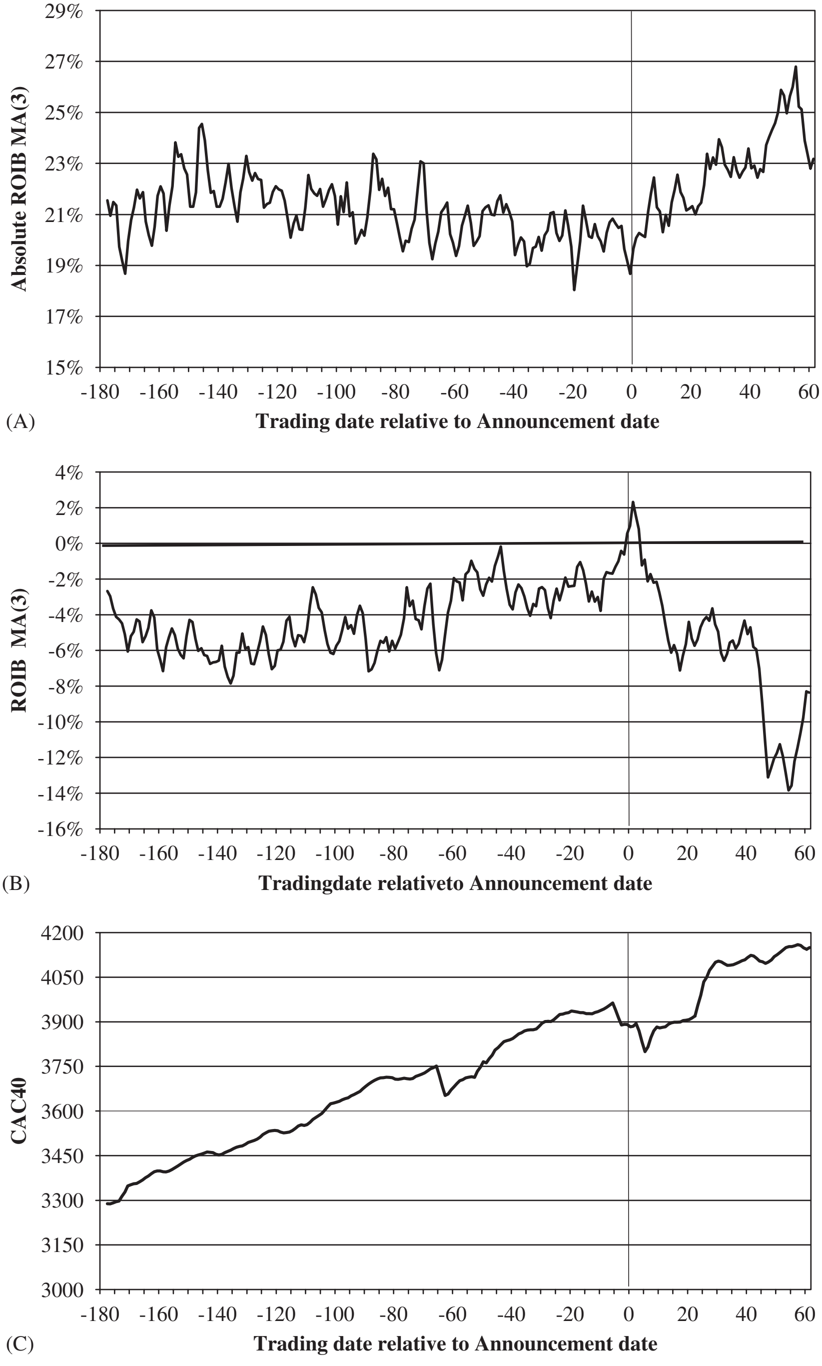


Fig. 5. Order imbalance statistics and market indicator. Panel A gives the three-day moving average evolution of the PIN approximation $|B-S|/(B+S)$ through time. Panel B shows the three-day moving average evolution of the relative order imbalance $(B-S)/(B+S)$ through time. Panel C shows the evolution of the equally weighted (cross-sectional) average of the CAC40 market indicator.

Table 6
Trade size patterns across windows
This table provides the average trade size for buy and sell trades and their ratio during the estimation, pre-event and post-event windows.

Average trade size			
	[–180,–66]	[–65,–6]	[+3, +63]
Buy trade size	572	503	551
Sell trade size	493	481	525
Sell size/buy size	86.29%	95.49%	95.11%

(including their decomposition) (Bagehot, 1971); permanent price impact measures (Hasbrouck, 1991a,b); and the probability of information-based trading (Easley and O'Hara, 1987).

In this paper, we proposed an empirical test of the ability of the PIN to capture information asymmetry. Our test is simple and intuitive: we explore the behavior of the PIN around M&A announcements. Information leakages are known to exist prior to such public announcements (see, for example, Keown and Pinkerton, 1981; Meulbroek, 1992). Moreover, the value effects of announcements are large (especially for targets) (Jensen and Ruback, 1983; Mulherin and Boone, 2000; Andrade et al. 2001; Aktas et al., 2004). This provides us with an almost ideal natural experiment to test the ability of the PIN to detect the presence of informed traders.

Using a sample of 87 operations from the 1995–2000 period on Euronext Paris, we first confirmed the presence of informed traders by analyzing cumulative abnormal volumes, spreads and permanent price impacts (following Hasbrouck, 1991a,b). We expected to observe an increase in the PIN before M&As. However, our empirical analysis reveals the opposite effect: on average the PIN dropped before the announcement of M&As and increased after the information release. We show that our results are most probably not biased by trade classification errors, atypical sample composition and/or numerical convergence problems.

To explore the PIN anomaly more fully, we show that the PIN can be approximated by a simple and easy-to-compute trade-imbalance statistic. Using this approximation, we show that the PIN's failure to detect information-based trading is to due two major shortcomings:

- the PIN does not incorporate the volume/value dimensions of the trading process;
- the PIN reflects many factors other than private information, for example global market trends.

Our work therefore suggests that caution is necessary when asserting that the PIN is a "better" asymmetric information measure than other such measures. More research should be directed to identifying accurate measures of asymmetric information. For example, as suggested by Chordia and Subrahmanyam (2004), an analysis of the imbalances generated by different categories of agents (institutions and individual investors) could represent a promising avenue for future research.

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