PIN? Some evidences around corporate events

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Abstract

The Probability of Informed Based Trading (PIN), built on a structural sequential trade model introduced in 1987 by Easley and O'Hara, has been increasingly used in empirical research in finance. However,up to now, its behavior around corporate events has not been really investigated (at our knowledge). We present in this work a first set of results around mergers and acquisitions on a sample of 141 operations that take place on Paris stock exchange during the period 1995-2000. As our results are surprising (the PIN decreases before the event and increases after), we investigate the PIN by a simulation work in an attempt to a better understanding of its behavior. Results confirm that some concerns can be raised about the real capacity of the PIN to capture the presence of informed based trading, at least around major corporate events.

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1 Introduction

Easley et al. (1996b) propose a technique to infer the probability of information-based (PIN) trading from information contained in trade data. This technique is built on a structural sequential trade model developed in Easley and O'Hara (1987, 1992). Originally, this technique is used to investigate whether the differences in information-based trading can explain observed differences in spreads for active and infrequently traded stocks. The most important empirical result is that the probability of informed trading is negatively related to firm size. Since this paper, the PIN method has subsequently been adopted to address a variety of issues in empirical finance: the practice of payment for order flow (Easley et al.,1996a); the information content of the time between trades (Easley et al., 1997a); the importance of trade size (Easley et al., 1997b); 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, 1999); the difference between non-anonymous traditional floor trading system and anonymous computerized trading system (Grammig et al., 2001).

The initial goal of this paper is to analyze the behavior of the PIN around corporate event announcements. Indeed, up to now, it seems that there is no evidence (at least at our knowledge) about the PIN around such announcements. The corporate event announcement that we propose to study is the one of mergers and acquisitions.

The use of a sample of business combination announcements to study informed trading is motivated by the fact that these operations are known to have a large price impact (see the classical reference of Jensen and Ruback, 1983). In this context, private information strategy can be very rewarding and therefore very tempting. Consequently, if the PIN really measures information-based trading, we expect the PIN estimated before the announcement day to be greater than the one measured after. Unfortunately, we obtain surprising results. The cross-sectional average of the estimated PIN is higher for the period before the announcement day than after.

At the light of this surprising result, we attempt to investigate more in depth the PIN behavior. The initial question is whether it could be that the PIN would not capture the presence of informed based trading. The answer is clear. As the PIN is obtained by the estimation of unobservable parameters (such as e.g. the arrival rate of informed trade), such a possibility can not be ruled out. Could it be that our sample is very specific and can not be compared to the one used in other empirical works? We replicate the test introduced in Easley et al. (2001b), where the authors study the relation between the PIN based predicted opening spread and the observed one. We find qualitatively similar results during the estimation window (but not around the corporate event). In an attempt to better understand the PIN behavior, we then realize some simulation works. We first simply progressively increase the total volume on the market, anything else being kept constant (in particular, the nature of the trades that take place on the market). Our results show a systematic increase of the PIN. We see no informed based argument justifying such a result. We then play with the number of buys to number of sells ratio. The obtained results are somewhat more satisfactory but, curiously, the PIN seems to exhibit an asymmetric behavior, being more sensitive to increase in the buys. All of this leads us to raise some serious concerns on the use of the PIN to capture informed based trading, at least around major corporate events.

This paper is organized as follows. In section 2, we present the structural sequential trade model developed by Easley and O'Hara to infer the PIN from information contained in trade data. We also provide the most important empirical results known up to now. Section 3 focuses on the behavior of the PIN around merger and acquisition announcements on the French Market. Section 4 is devoted to further investigations, especially the implemented simulation work. Section 5 concludes.

2 The Probability of informed trading

2.1 The Model

Easley et al. (1996b) develop and empirically implement a structural model that builds on Easley and O'Hara (1987, 1992). In the sequel we describe this model. Individuals 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 is potentially informed.

Time within the trading day is indexed by $t[0, T]$, trading days are indexed by $i[1, I]$. 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. Information events on different days are assumed to be independent.

There are two groups of traders. Uninformed traders neither know the asset value nor do they observe whether an information event occurred. They trade for 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. This implies that they do not trade when there was no information event. On any day, arrivals of uninformed buyers and uninformed sellers are determined by independent Poisson processes. Uninformed buyers and uninformed sellers each arrive at rate ϵ where this rate is defined per minute of the trading day. On days for which information events have occurred, informed traders also arrive. Another assumption of the model is that all informed traders are risk neutral and competitive. If a trader observes a good signal, then the profit maximizing trade is to buy the stock; conversely, he will sell it if he observes a bad signal. The arrival rates of informed traders on days with information event are μ. All of these arrival processes are assumed to be independent.

The tree given in figure 1 describes the structure of the trading process. At the first node of the tree, nature selects whether an information event occurs. If an event occurs, nature then determines if it is a good news or bad news. Nodes to the left of the dotted line occur once per day.

The market maker does not observe whether an information event occurred or not, but they do know the unconditional probabilities of the information events and the order arrival rates. Throughout the trading day he uses Bayes' rule to update his beliefs about the occurrence of information events. For example, after a buyer-initiated transaction, he will revise the probability assigned to a positive information event upwards. Because days are independent, we can analyze the evolution of his beliefs separately on each day. Let $P(t) = \{P_n(t), P_b(t), P_g(t)\}$ be the market maker's prior belief about the events "no news" (n), "bad news" (b), and "good news" (g) at time t[1]. Let S_t denote that a sell order arrives at time t; similarly B_t represents a buy order at time t. Thus, $P(t|S_t)$ is the market maker's updates belief conditional on the history prior to time t and on the event that a sell order arrives at t. The market maker's posterior probability on no news if a sell order arrives $P_n(t|S_t)$ can consequently be derived by application of the Bayes' rule:

$$P_n(t|S_t) = \frac{P_n(t)\epsilon}{\epsilon + P_b(t)\mu} \tag{1}$$

The posterior probability on bad news $P_b(t|S_t)$ and on good news $P_g(t|S_t)$

[1]For example, the market maker's prior belief at time 0 is given by $P(0) = \{1 - \alpha, \alpha\delta, \alpha(1-\delta)\}$.

is derived in the same way:

$$P_b(t|S_t) = \frac{P_b(t)(\epsilon + \mu)}{\epsilon + P_b(t)\mu} \tag{2}$$

$$P_g(t|S_t) = \frac{P_g(t)\epsilon}{\epsilon + P_b(t)\mu} \tag{3}$$

The market maker sets bid and ask prices $b(t)$ and $a(t)$ equal to the conditional expectation of the asset value, given that the next trade is seller-initiated and buyer-initiated, respectively:

$$b(t) = \frac{P_n(t)\epsilon V_i^* + P_b(t)(\epsilon + \mu)V_i^b + P_g(t)\epsilon V_i^g}{\epsilon + P_b(t)\mu} \tag{4}$$

$$a(t) = \frac{P_n(t)\epsilon V_i^* + P_b(t)\epsilon V_i^b + P_g(t)(\epsilon + \mu)V_i^g}{\epsilon + P_g(t)\mu} \tag{5}$$

Note that the prior expected value of the asset at time t is:

$$E(V_i|t) = P_n(t)V_i^* + P_b(t)V_i^b + P_g(t)V_i^g \tag{6}$$

We can rewrite the bid-ask spread $s(t)$ as

$$\begin{aligned} s(t) &= a(t) - b(t) \\ &= PI_{Buy}(t)\Big(V_i^g - E(V_i|t)\Big) + PI_{Sell}(t)\Big(E(V_i|t) - V_i^b\Big) \end{aligned} \tag{7}$$

where $PI_{Buy}(t)$ ($PI_{Sell}(t)$) are the conditional probabilities that the next buyer-initiated (seller-initiated) trade is information-motivated. The spread at time t is thus equal to the probability that a buy is information based times the expected loss to an informed buyer, plus a symmetric term for sells. The probability that any trade that occurs at time t is information-based is the average of the probability of an information-based sell and the probability of an information-based buy, weighted by the probability that the next transaction is buyer- or seller-initiated, respectively:

$$\begin{aligned} PI(t) &= Prob(buy)PI_{Buy}(t) + Prob(sell)PI_{Sell}(t) \\ &= \frac{\mu\big(P_g(t) + P_b(t)\big)}{2\epsilon + \mu\big(P_g(t) + P_b(t)\big)} \end{aligned} \tag{8}$$

At the opening, using the unconditional probabilities, the probability of information-based trading is given by

$$\text{PIN} = PI(0) = \frac{\alpha\mu}{\alpha\mu + 2\epsilon} \tag{9}$$

Easley et al. (1996b) propose a method to estimate the model parameters $\Theta = \{\alpha, \delta, \epsilon, \mu\}$. These parameters can be used to obtain an estimate of the unconditional probability $PI(0)$ to encounter an informed trader. The likelihood of observing B buys and S sells on a bad-event day of total time T is given by:

$$LI_b(B,S) = e^{-\epsilon T}\frac{(\epsilon T)^B}{B!}e^{-(\mu+\epsilon)T}\frac{\left[(\mu+\epsilon)T\right]^S}{S!} \tag{10}$$

We can compute similarly $LI_b(B,S)$ and $LI_n(B,S)$. The overall likelihood of observing B buys and S sells for a single trading day is:

$$\begin{aligned} L(B,S|\Theta) &= (1-\alpha)LI_n(B,S) + \alpha\delta LI_b(B,S) + \alpha(1-\delta)LI_g(B,S) \\ &= (1-\alpha)\, e^{-\epsilon T}\,\frac{(\epsilon T)^B}{B!}\, e^{-\epsilon T}\,\frac{(\epsilon T)^S}{S!} \\ &\quad + \alpha\delta\, e^{-\epsilon T}\,\frac{(\epsilon T)^B}{B!}\, e^{-(\mu+\epsilon)T}\,\frac{[(\mu+\epsilon)T]^S}{S!} \\ &\quad + \alpha(1-\delta)\, e^{-(\mu+\epsilon)T}\,\frac{[(\mu+\epsilon)T]^B}{B!}\, e^{-\epsilon T}\,\frac{(\epsilon T)^S}{S!} \end{aligned} \tag{11}$$

where B and S represent total buy trades and sell trades for the day respectively, and T corresponds to the total time (in minute) of a single trading day. Since days are independent, across the I trading days the likelihood to maximize with regard to T is the following:

$$L(M|\Theta) = \prod_{i=1}^{I} L(B_i, S_i|\Theta) \tag{12}$$

Maximization of (12) with respect to the parameter vector Θ yields maximum likelihood estimates of the parameters of interest. This model allows us to use observable data on the number of buys and sells per day to make inferences about unobservable information events and the division of trade between informed and uninformed. Since the probabilities α and δ are defined on a scale from 0 to 1, we estimate unrestricted parameters and convert them via a logit transform into economically interpretable probabilities. Standard errors of the transformed coefficients are calculated using the delta method [2]. Easley et al. (1997) has shown that a sixty-day trading window is sufficient to allow reasonably precise estimation of the parameters.

2.2 Some Empirical Evidences

This section provides some empirical results obtained by using the probability of informed trading. We will see that the model initially developed by Easley and O'Hara has been used to address a variety of issues in empirical finance.

[2] We estimated the model in GAUSS. We would like to thank Joachim Grammig for providing us some precious helps during the elaboration of our econometric code.

One of the most important results in this literature is probably the one provided by Easley, Kiefer, O'Hara and Paperman (1996b). This paper investigates whether differences in information-based trading can explain observed differences in spreads for active and infrequently traded stocks. The authors show that the probability of informed trading is lower for high volume stocks. Less active stocks face a greater risk of informed trading, and so their larger spreads are consistent with the information-based explanation of the spread. Subsequently to this result, a number of researches have been undertaken. Table 2 provides a summary of the main results.

Easley et al. (1996a) use the information in the trade flow to infer any difference in information content between stock exchanges (NYSE and Cincinnati). By estimating this model on these two sites, they found that the PIN is significantly higher in New York than in Cincinnati (stocks typically employed in purchased order flow), and this difference is consistent with "cream-skimming" of orders to Cincinnati. One important issue addressed in Easley et al. (1997b) is to see whether the information content of trades differ depending on their size. They extend the model by taking into account the fact that traders can buy (sell) a large or a small quantity. They allow also the uninformed trading process to be history dependent (the stochastic process of the uninformed trade depends on the previous trade). More closely related to our work, Easley et al. (1998b) try to relate the financial analyst coverage (as a proxy for informed trading) and the PIN. They find a negative relation between the two. In fact, stocks with more analysts have more informed trade but this is not greater than the increase of uninformed trade. The authors conclude that financial analysts do not appear to create new private information. This result confirms the view that analysts' recommendations are generally based on public, rather than private information. Easley et al. (2001b) extend the initial model to allow the arrival rates of informed and uninformed trades to be time-varying and predictable. Easley et al. (2002) focus on the relation between information risk affects and cross-sectional asset returns. They present a simple model to provide the intuition for why private information affects stock returns (a more complete theoretical model is provided in Easley, O'Hara 2000). Their model concludes that between two stocks that are otherwise identical, the stock with more private information will have a larger expected excess return. Heidle and Huang (2002) examine the trading behavior in dealer and auctions markets and the effects of it on market liquidity. They investigate the degree of information asymmetry problem in dealer and auction markets and find the PIN is higher in a competing dealer market than in auction system, that trade execution costs are higher in a dealer market and that the stock liquidity is negatively correlated to the probability of informed trading.

All of this shows that the probability of informed trading has been used to address numerous issues in empirical finance. And these different results offer also an interesting observation: most of the researches use the PIN to address various kind of questions but they do not test directly if the PIN measures truly the informed trading. It is taken as granted and the PIN is used as an accurate measure of the probability of informed-trading. The main exception is the Easley et al. (2002) contribution where the relation between the spread, a measure of asymmetric information and the PIN (more exactly, a derived predicted spread obtained through the parameter estimated for the PIN) is realized. In this paper, we propose a direct test of the PIN relevance as an informed based trading indicator, using a sample of business combination announcements on the French market.

3 PIN behavior around M & A announcement: The French Evidence

We decide to investigate the behavior of the probability of informed-trading around a corporate event, especially around merger and acquisition announcements. We propose to estimate the PIN for a sample of business combination announcements on the French market[3]. If the PIN really measures information-based trading, we expect the cross-sectional average of the PIN estimated before the announcement day to be greater than the one measured after.

The use of a sample of business combination announcements to study informed trading is motivated by the fact that these operations are known to have a large price impact. Indeed, as such operations have a well-known significant impact on the prices of involved firms (at least of targets - see Jensen and Ruback (1983)), they represent an opportunity for informed investors to realize significant profits.

Related to this, we know also that significant stock price run-ups prior to the takeover announcements for the target shares have been well documented in the literature (e.g., Keown. and Pinkerton, 1981; Arshadi and Eyssell, 1993; Jabbour et al., 2000). Two main explanations have been proposed for these run-ups: the market anticipation of the takeover and the corporate insiders' activities. Jarrell and Poulsen (1989) present some evidence in support of the former but the literature gives no clear-cut answer between the two hypotheses. However more recently, Jabbour et al. (2000) using a sample of 128 Canadian acquisitions put forward a very interesting result that reconciles the two hypotheses. The early stage abnormal

[3]We provide some insight on the Paris Stock exchange organization in Appendix 1.

stock price performance is attributed to corporate insider trading while the run-up immediately prior to the takeover announcement is due to market anticipation. There are also several papers that look at the liquidity of targets around takeover announcements. They document evidence consistent with informed trading right around the day of the announcement (Jennings, 1984; Ascioglu et al., 2002).

3.1 Sample selection

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 selected only operations for which there was at least one quoted French firms involved. Another criterion is the availability of intraday market data[4]. Thus, we are able to study 141 firms. Table 3 provides for every year of our study summary statistics on the business combinations in which firms of our sample were involved. Figure 2 provides the evolution of the number of operations across years. And Table 1 lists the firms included in our sample with some more detailed descriptive statistics.

3.2 Data sources

Daily stock prices are obtained from Datastream, which is accessed at *Université de Lille 2*. For announcement dates, two separate sources are checked: the financial press (*Les Echos and Financial Times*) and the archive of the European Commission's DGC[5]. We have also used the financial press in order to check the presence of rumors before the announcement of the specific business combination. Firms are classified in the "rumor" sub-sample if there are rumors prior to the announcement of the operation in which they are involved. On the other hand, an operation will be considered rumor-less if no mention of it can be found in the financial press during a 6-month period prior to the announcement day.

For every day of the studied period and for each stock, we use the Euronext database (BDM) to obtain intraday best quotes, orders and transaction prices. This database contains the reference information, all orders and trades for all securities traded on the "Premier Marché" and the "Second Marché" of Euronext Paris. BDM set up on March 1, 1995. Information is time-stamped to the second. To account for abnormal trading patterns[6] and procedures around the start of each day and the close of the trading day, the pre-opening and pre-closing periods of trading

[4]It is important to recall that intraday data on the Paris stock exchange are only available on March 1st, 1995.

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

[6]Traders may use different trading strategies.

are excluded (Biais et al., 1999). Hence, only trades and quotes data lying between 10:00 a.m. and 5:00 p.m. are examined although the market was open for continuous trading.

To maximize the likelihood function given in equation (12), and thus to estimate the PIN, we need the number of buys and sells on each day for each of our sample firms. In order to determine these numbers we infer trade direction (buyer-initiated or seller-initiated) for each transaction. We determine these numbers by using the Euronext database. Since the French market is an order-driven market, there is no designed market maker who has the obligation to provide liquidity. In such a context, limit order traders play a pivotal role in providing liquidity to the market. Therefore, in an order-driven market the spread corresponds to the difference between the best selling and buying limit orders. The BDM Euronext intraday database provides these limits for each trade. A transaction is classified as a buyer (seller) initiated if its price is bigger (lesser) then the mid quote (average between the corresponding best selling and buying limit orders)[7]. We have matched exactly 10,866,279 transactions over the studied period. Table 3 presents some descriptive statistics about the sample firms.

3.3 Is there information leakages ?

The first question that must be addressed is whether there is effectively information leaking on the market prior to public announcement of the operation. Only in this case indeed can we expect the PIN to increase before the announcement. To validate this preliminary requirement, we analyze the behavior of the two market indicators classically used by the market supervision authorities (see e.g. Garfinkel (1997) or DeMarzo et al. (1998)): the cumulative abnormal returns and the cumulative abnormal volumes[8].

As Jarrel and Poulsen (1989) present clear evidence of rumors in the financial press before the public announcement date in a significant number of cases, we also split our sample in a rumor and a no-rumor sub-samples. To be included in the no-rumor sub samples, there must be absolutely no traces of rumors in the financial press (we check both the *Financial Times* and *Les Echos* newspapers) in the six months preceding the public announcement date.

[7]The used method here corresponds partially to the technique developed by Lee and Ready (1990) to infer trade direction in a quote-driven market. Declerck (2000) has shown that this adapted algorithm does a good matching job on the Paris stock exchange.

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

3.3.1 Cumulative Abnormal Return (CAR)

In order to compute the CAR we adopt the classical event study framework (Fama et al., 1969). We use continuously compounded returns. The simple market model is used as return generating process:

$$r_{i,t} = \alpha + \beta r_{m,t} + \epsilon_{i,t} \tag{13}$$

where $r_{i,t}$ is the return of asset i at time t, $r_{m,t}$ is the return of the market index at time t, α and β are the market model coefficients and $\epsilon_{i,t}$ are the residuals. The SBF 250 Market Index is used as a proxy of the market portfolio. The estimated abnormal returns are computed as usual:

$$\hat{\epsilon_{i,t}} = r_{i,t} - (\hat{\alpha} + \hat{\beta} r_{m,t}) \tag{14}$$

They are then averaged across the time and the sample in order to get the Cumulative Average Abnormal Return (CAAR):

$$CAAR_T = \sum_{\tau=-n}^{T} \frac{1}{N} \sum_{j=1}^{N} \hat{\epsilon}_{j,r} \tag{15}$$

We finally use the Boehmer et al. (1991) approach to build a cross-sectional test of significance in order to control for the event-induced variance phenomenon.

If informed investors trade before the public announcement of the business combination, their activities should progressively reveal their information (more rapid price discovery is the most often quoted argument in favor of legalizing insider trading activities (see e.g. Meulbroek (1992)) In such circumstance, we should observe significant CAAR.

Figure 3 presents the CAAR path through time. We can see that the CAAR increases for the rumor sub-sample before the event, while it decreases for the no-rumor sub-sample. These evolutions are shown to be statistically significant at Table 4 and clearly indicate the presence of information leakages before the public announcement date.

3.3.2 Cumulative Average Abnormal Volume (CAAV)

The return approach is extended to the volume analysis with two adaptations:

- volumes are measured as the natural logarithm of daily traded volume expressed in Euro,
- following Ajinkaya and Jain (1989) and, in the French context, Mai and Tchemeni (1996), the constant mean model is used as generating process.

Figure 4 presents the evolution of the 5 days moving average CAAV. It is shown that in the period preceding the public announcement (up 80 days before), the CAAV of no rumor sub-sample is consistently higher than the one of the rumor sub-sample. The differences are statistically significant (as show in table 4) and let few (if any) place to doubts concerning the presence of information leakages.

3.4 PIN behavior

3.4.1 Parameter estimates

As the estimation of the PIN model requires windows of at least 60 days (see Easley et al. (1997)), we estimate the parameters for each of our sample firm over four different event windows. Figure 5 gives the range of the different windows around the event. The announcement day is day 0.

We estimate the parameters by numerically maximizing the likelihood function given by equation (12)[9]. We decide to not consider the window $[-5, +2]$ because this window is to small to infer values for the different parameters and furthermore the event windows of interest are especially the window just before the event (window 3) and the window after it (window 4).

Figure 6 gives the cross-sectional average of the estimated parameters for each window. Surprisingly, the estimated μ, which measures the arrival rate of informed trade, drops down the period prior to the announcement of the business combinations. We expected to have the contrary: if there is effectively information leakage before the event, we anticipate a greater value for the estimated μ for the period before the announcement. The estimated ϵ, which measures the arrival rate of uninformed trader, increases significantly in the two last windows. This result can be explain by the fact that uninformed traders have heard rumor prior to the announcement date and then decide to trade. It could be also possible that after the announcement, traders think that it's always possible to make a profit by using this information and consequently trade in the market. The estimated probability of an information event α decreases before the announcement and then increase! And, δ, the estimation that the event is bad, decreases significantly during the period just before the announcement. This result is not surprising for business combination announcements, which usually are on average classified to be value creating events.

[9]The Gauss 5.0 Constrained Maximum Likelihood Maximization has been used.

3.4.2 The Probability of Informed based Trading

The probability of informed trade is a composite variable reflecting the various parameters characterizing the trade process. This probability is given by equation (9):

$$\text{PIN} = PI(0) = \frac{\alpha\mu}{\alpha\mu + 2\epsilon} \tag{16}$$

We estimate this equation for each sample firm over the four different event windows. Table 5, Figures 7 and 8 present the cross-sectional average of the PIN for different sub-samples and event windows.

Figure 7 suggests that the PIN is more important for the period that goes from day +3 to day +63 (relative to the announcement date). The cross-sectional estimated PIN for the whole sample jumps from an estimated value of 17,84 % for the period just before the announcement to a value of 21,39 % after it. This result is at odd with both the evidences of information leakages presented at section 3.3 and the intuitively excepted behavior around a corporate event such as a business combination.

The decrease of the PIN in window 3 can be explained by the evolution of the arrival rates of both the uninformed and the informed traders. Indeed, m decreases strongly in this period while e increases, leading to a decrease of the computed PIN. It must also be recognized that the remarkable increase of the average PIN after the announcement date is particularly due to the estimated PIN for target firms, as suggest by Figure 8. The estimate jumps from 16,45 % to 29,84 % after the event. Nevertheless, the estimated cross-sectional average PIN for the sample excluding the target's firms behaves not as expected: the PIN do not increase during the period prior to the announcement date.

Are these results statistically significant ? In Table 6, we present significance test of the (cross-sectional) mean difference of the PIN between two event windows[10]. For the whole sample, the PIN is significantly different between the last three event windows. It decreases in window just prior to the announcement date and increases after. The cross-sectional average PIN between the event window 2 and the last window is also significantly different. The PIN does not clearly exhibit the expected behavior around the event date. We don't have as significant results by sub-samples due most probably to the small sample size.

[10]We use a classical paired student test of difference of means. p-value are obtained by a percentile-t bootstrap approach (see Efron and Tibshirani (1993)) with 1000 bootstrap samples.

4 Further Investigations

At the light of results presented in the previous section, the first question coming into mind is to see whether they are not due to some specificities of the used sample of cases. We try to address this question in section 4.1. We then realize a simulation work in order to better understand the behavior of the PIN indicator in response to its determinants (the observed number of buys and number of sells). Based on this simulation work, we finally provide some complementary insights on the results presented up to now.

4.1 Informed based trading and the spread

Easley et al. (2002) provide a predicted relationship between the estimated parameters and opening spreads. The sequential model that the authors use differs from the one presented in section 2. They distinguish the arrival rate of uniformed buyers and of uninformed sellers. The likelihood function induced by this model for a single trading day becomes:

$$\begin{aligned} L(B,S|\Theta) \;=\;& (1-\alpha)\, e^{-\epsilon_b T}\,\frac{(\epsilon_b T)^B}{B!}\, e^{-\epsilon_s T}\,\frac{(\epsilon_s T)^S}{S!} \\ &+\alpha\delta\, e^{-\epsilon_b T}\,\frac{(\epsilon_b T)^B}{B!}\, e^{-(\mu+\epsilon_s)T}\,\frac{[(\mu+\epsilon_s)T]^S}{S!} \\ &+\alpha(1-\delta)\, e^{-(\mu+\epsilon_b)T}\,\frac{[(\mu+\epsilon_b)T]^B}{B!}\, e^{-\epsilon_s T}\,\frac{(\epsilon_s T)^S}{S!} \qquad (17) \end{aligned}$$

where ϵ_b and ϵ_s represent respectively the arrival rate of uninformed buyers and uninformed sellers. In Figure 9, we provide the results obtained on our dataset using this modified likelihood function. They do not differ significantly from the ones obtained presented up to now. The estimated parameters can be used to construct a theoretical opening bid and ask prices. As demonstrated by Easley et al. (2002), the model predicts the percentage opening spread on day I to be:

$$\text{PISTD}_i \;=\; \mu\sqrt{\alpha\delta(1-\delta)}\left[\frac{1}{\epsilon_b+\mu\alpha(1-\delta)}+\frac{1}{\epsilon_s+\mu\alpha\delta}\right]\sigma_v \qquad (18)$$

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 by regression that indeed PISTD is significantly correlated to observed percentage opening spread.

To address the concern that the results presented in section 3 could be due to sample specificities, we replicate this analysis on our dataset. Results are presented at table 7. In the estimation window [-270,-181] and [-180,-66], we obtain (qualitatively) the same kind of results as these of Easley et al.

(2002): a significant R^2 (0.17) and a positive and significant β coefficient. While our R^2 are lower than the ones of Easley et al. (2002) (the R^2 of their regressions ranges from 0.41 to 0.71), these results lead to reject the idea that our results are sample specific. Results in the [-65,6] and [+3,+63] are particularly interesting. The relation between the observed opening spread and the predicted one disappear! This clearly reinforces the section 3 results. The PIN does not provide sensible results around a corporate event such as business combinations.

4.2 Simulations

Given the result of the previous section, we decide to look forward by analyzing the behavior of the probability of informed trading when we change the input data required for its estimation: the number buys and the number of sells (see equation (11)). Having at our disposal two variables, only two evolutions can be analyzed: either there sum changes while keeping the same relative size or their relative size changes. The first case represents a change in the total volume (the number of buys plus the number of sells is the total observed volume). The second case plays on the ratio of number of buys to the number of sells.

4.2.1 Variations of the total volume

This simulation consists in changing proportionally the number of trades initiated by the buyer and the number of trades initiated by the seller. We proceed as such: let B_0 and S_0 be respectively the vector of the initial number of buys and sells respectively observed each day in the analyzed window for a specific firm. In order to vary the total volume, we apply to this originated sample, the following transformation:

$$B_{step} = B_0 * Step \tag{19}$$

$$S_{step} = S_0 * Step \tag{20}$$

with a *Step* varying from 0.5 to 1.5 by increment of 0.05. The same transformation is realized for all firms in our sample. Suppose that, in the original sample, we have X % of informed based trades (and therefore $(100 - X)$ % of uninformed based ones). Our procedure will keep the same proportion across the different simulated samples. We thus expect to have no systematic relation between the total volume and the PIN.

We present here result for the two windows before the event. Figure 10 provides again a surprising result: it seems that the PIN increases with the volume. To validate this, we decide to regress the PIN on the step variable and we obtain a significant estimated coefficient associated with the step of 0.0146 (t stat = 6.53). This result leads us to conclude that there is a positive relation between the PIN and the volume, everything else kept constant. We do not find, up to now, any informed based argument justifying such a result.

4.2.2 Changing the ratio of the number of buys to the number of sells

We now build different samples by playing on ratio of number of buys to the number of sells. The samples are generated in such a way that the total volume stays the same across samples. Let

$$Dif = |B_0 - S_0| \tag{21}$$

$$B_{Step} = B_0 + Step * Dif \tag{22}$$

$$S_{Step} = S_0 - Step * Dif \tag{23}$$

with a *step* varying from -0.5 to 1 by increment of 0.05.

What would we expect to observe if the PIN does indeed capture informed based trading? As the ratio of number of buys to the number of sells move away from 1, we should observe a symmetric increase of the PIN. Indeed, the more the number of buys is important relative to the number of sells, the more it should reflect the fact that informed investors are buying in anticipation of a good news (and vice-versa). To sum-up, we expect to have a V-shape with a minimum when the ratio B/S equal 1. Figure 11 gives the simulated PIN found through the first two windows.

At first sight, the Figure 11 suggests that the PIN behaves as explained. But a more careful analysis put into light two somewhat strange results. First, the minimum value of the ratio B/S is not at 1 as expected but approximately at value of 1,2. Second, the slope of the PIN is not symmetric around the minimum. This result was really not excepted because the likelihood function is completely symmetric: you can reverse the number of buys and the number of sells and you will obtain the same likelihood with only one difference, the interpretation of the parameter delta.

According to this result, we are now able to understand more precisely the estimated PIN obtained in section 4.

4.3 A second look to the case of mergers and acquisitions

Table 8 provides the daily average sum of the number of buys and the number of sells and the average ratio of the number of buys to the number of sells by windows ([-180,-66], [-65,-6], [+3,+63]) and sub-samples. We also recall the estimated PIN for each window and sub-sample. The results confirm our simulations results. For example, for the whole sample, the PIN increase from 18.9% in the [-180,-66] window to 21.39% in the [+3,+63] is mainly due to a significant volume increase. For target sub-sample, the PIN goes from 17.9% to 29.8%, which is in this case due to a combined impact of a volume increase and a ratio of number of buys to number of sells decrease.

5 Conclusion

In this paper, we investigate whether the probability of informed based trading (PIN) introduced by Easley and O'Hara in successive works (from 1987 up to nowadays) does indeed capture informed base trading. While the PIN has lead to numerous applications in empirical finance, few works have been more specifically dedicated to this point up to now, Easley et al. (2002) being a major exception. To put the PIN to the test, we analyze its behavior around a major corporate event. We select the classical case of mergers and acquisitions as it is known that these operations have large value impact (see the classical reference of Jensen and Ruback, 1983). Trading on the basis of private information can therefore be very rewarding and tempting. Consequently, if the PIN really measures information-based trading, we clearly expect the PIN estimated before the announcement day to be greater than the one measured after.

Unfortunately, we do not obtain the expected result: the estimated PIN is higher for the period before the announcement day than after!

At the light of this result, we first try to test whether it is sample specific. At first, our test seems to reject this possible explanation. We then investigate by simulations the PIN behavior. We again find some troubling results. The PIN seems, anything else being kept constant, to be an increasing with the total trading volume. It moreover asymmetrically reacts to a change in the ratio of the number of buys to the number of sells.

To sum up, the main result of this paper is that the PIN behaves not as it would do if it really measures the informed based trading, at least around major corporate events.

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Appendix 1 : The Paris Stock Exchange Market Structure

The Paris Stock Exchange is based on a computerized limit-order trading system. In the limit order book, orders are prioritized for execution in terms of price and time: orders for each security are ranked by price limit as they enter the system. For example, buy orders specifying a higher limit are executed before orders with lower limits. Secondly, orders are ranked in chronological order: two buy or sell orders at the same price will be executed in the order in which they arrive on the central book.

Any order sent by a trading member to the market must indicate whether it is a buy or a sell order. It must also specify the order quantity, price and the length of time the order is active. Orders that stipulate no limit price are given priority. In an order-driven market, there is no designated market maker who has the obligation to provide liquidity. By submitting a limit order, a trader is providing other market participants with the ability to execute against his limit order. So, limit orders provide liquidity to those who demand immediacy. At the same time, other investors could trade via market orders and consume liquidity in the market. With a limit order, the investor will execute at a more favorable price than a market order. But the order can be not executed. Orders can also be partially hidden.

The trading day is ten hours, beginning at 7:15 a.m. and ending at 5:30 p.m. Paris local time. From 7:15 a.m. to 9:00 a.m., the market is in pre-opening phase and orders are fed into the centralized order book without any transactions taking place. The market opens at 9:00 a.m. The central computer automatically calculates the opening price named the call auction price at which the largest number of bids and asks can be matched. From 9:00 a.m. to 5:25 p.m., trading takes place on a continuous basis, and the arrival of a new order immediately triggers one (or several) trade(s) if a matching order exists on the other side of the book. From 5:25 p.m. to 5:30 p.m., the market is in its pre-closing period. As in the pre-opening, orders are fed into the order book. The market closes at 5:30 p.m. with a call auction that determines closing prices. Trading is anonymous. Cancellation of orders may be done at any time.

Starting January 4, 1999, tick size for equity securities is 0.01 for prices up to 50, is 0.05 for prices from 50.05 to 100, is 0.10 for prices from 100.10 to 500, is 0.50 for prices above 500. Euronext can temporarily "reserves" trading in a financial instrument if orders recorded on the central order book would inevitably result in a price beyond a certain threshold referred to as a "reservation threshold". For the CAC 40 index components, fluctuations are limited to plus or minus 10% on the previous day's close initially, followed by swings of plus or minus 5% (with a maximum of two 5% shifts). As each threshold is reached, trading is halted for 15 minutes. Euronext introduced rules on block trading to allow immediate and full execution of such trades at a guaranteed price derived from that available on the central market. Block trades must take place at a price, which falls within the weighted average spread for a standard-size block.

Table 1: FIRMS INCLUDED IN THE M&A ANALYZED SAMPLE

Table 1 shows some descriptive statistics about our sample firms. "Event date" corresponds to the announcement day of the business combination. Number of transactions, Market Capitalization and Trading Volume correspond to the daily average computed along the studied period (from day -180 to day +63 relative to the announcement date).

Name	Event Date	Number of transactions	Market capitalization (10^3\$)	Trading volume (10^6\$)
Carnaudmetalbox	05/24/95	39	3.053	34
Saint-Gobain SA	06/27/96	192	10.552	257
Pechiney	12/13/98	104	44	4
USINOR COTE	10/15/98	367	3.294	1.456
BNP PARIBAS	01/14/99	552	16.945	1.065
PARIBAS	01/22/99	526	2.267	144
VIVENDI	10/07/98	437	30.293	1.914
Renault	11/10/98	380	11.195	740
Total	11/30/98	408	28.072	953
AXA	02/01/99	581	42.540	5.006
VIVENDI	03/23/99	571	38.029	2.193
Renault	03/18/99	460	10.723	945
Sanofi-Synthelabo	12/02/98	220	15.381	1.118
Synthelabo	12/02/98	89	8.832	59
HAVAS Advertising	03/22/99	39	1.299	432
Thomson-CSF S.A.	05/07/99	151	5.793	293
UAP (CIE)	07/21/95	257	7.667	108
Thomson-CSF S.A.	04/24/95	68	3.300	226
Rhone Poulenc	09/21/95	331	1.096	139
Suez Lyonnaise des eaux	11/23/95	111	5.739	966
BIS SA	01/07/97	19	520	22
Accor SA	01/31/97	144	4.344	899
PARIBAS	03/01/97	246	1.226	67
Vallourec SA	02/11/97	30	422	45
Suez Lyonnaise des eaux	03/26/97	182	5.621	1.356
Suez (CIE)	03/26/97	230	7.190	13.492
Dexia	02/25/97	128	3.306	200
Rhone Poulenc	12/20/96	554	1.417	199
Thomson-CSF S.A.	06/16/97	130	3.624	373
L'OREAL	08/18/97	303	25.062	1.350
PARIBAS	05/26/97	276	1.265	72
Promodes	09/09/97	144	6.470	45
Casino Groupe	09/09/97	84	3.092	182
Worms et Cie	10/09/97	60	3.180	131

Table 1 shows some descriptive statistics about our sample firms. ”Event date” corresponds to the announcement day of the business combination. Number of transactions, Market Capitalization and Trading Volume correspond to the daily average computed along the studied period (from day -180 to day +63 relative to the announcement date).

Name	Event Date	Number of transactions	Market capitalization (10^3\$)	Trading volume (10^6\$)
Lafarge	10/14/97	241	6.237	343
Suez Lyonnaise des eaux	11/08/97	258	10.908	1.873
VIVENDI	10/31/97	308	16.613	1.648
AXA	11/17/97	456	22.184	4.595
Faurecia	12/11/97	34	1.091	75
Promodes	10/18/97	150	6.753	46
Promodes	12/08/97	150	7.092	45
VIVENDI	12/10/97	317	17.017	1.607
PINAULT PRINTEMPS	01/23/98	186	11.840	287
AGF	11/17/97	321	5.914	866
Elf Aquitaine	01/28/98	595	31.697	1.040
Thomson-CSF S.A.	04/15/98	571	4.015	329
Alcatel Alsthom	04/15/98	147	24.873	4.211
AXA	05/05/98	521	30.575	4.514
VALEO SA	06/26/98	164	5.935	223
Elf Aquitaine	07/14/98	516	33.430	993
AGF	07/17/98	329	9.609	925
Suez Lyonnaise des eaux	07/17/98	285	19.733	2.729
Renault	05/07/98	300	9.228	615
CASTORAMA DUBOIS	09/25/98	114	2.716	357
BNP PARIBAS	09/14/98	558	15.215	1.032
Thomson-CSF S.A.	11/19/98	150	5.575	324
Peugeot SA	10/16/98	215	8.588	1.388
USINOR COTé	03/03/99	360	3.105	1.541
Danone	01/16/99	322	19.767	672
RHODIA	03/16/99	199	3.046	469
PINAULT PRINTEMPS	03/20/99	294	19.798	239
Rhone Poulenc	12/01/98	549	2.773	221
Suez Lyonnaise des eaux	06/28/99	443	27.181	2.708
PARIBAS	08/06/99	542	2.562	114
VIVENDI	06/08/99	680	39.745	2.230
AXA	08/13/99	562	45.248	4.427
LAGARDERE GROUPE	12/05/95	94	1.877	286
Crédit Commercial de France (CCF)	03/29/96	110	3.355	223
Thomson-CSF S.A.	04/05/96	81	2.841	237

Table 1 shows some descriptive statistics about our sample firms. ”Event date” corresponds to the announcement day of the business combination. Number of transactions, Market Capitalization and Trading Volume correspond to the daily average computed along the studied period (from day -180 to day +63 relative to the announcement date).

Name	Event Date	Number of transactions	Market capitalization (10^3\$)	Trading volume (10^6\$)
Thomson-CSF S.A.	03/25/96	80	2.827	232
Suez (CIE)	04/29/96	185	6.369	10.183
Poliet	05/08/96	193	2.518	107
Saint-Gobain SA	05/08/96	25	10.522	269
Havas SA	01/10/96	93	28.316	157
Thomson-CSF S.A.	01/05/96	78	2.857	247
SOMMER-ALLIBERT	07/09/96	18	600	42
Alcatel Alsthom	12/20/95	263	14.127	2.749
AXA	11/12/96	569	11.874	3.138
UAP (CIE)	11/12/96	218	7.231	176
Elf Aquitaine	07/05/99	534	38.960	1.005
TotalFina Elf	07/05/99	502	34.961	1.312
Air Liquide	07/13/99	349	13.177	226
VIVENDI UNIVERSAL	06/21/00	1470	55.517	2.962
Renault	04/26/00	459	11.337	705
France Telecom	05/30/00	1591	135.975	2.147
Canal Plus	05/18/00	1464	19.966	26.688
VIVENDI UNIVERSAL	05/18/00	729	55.013	2.895
Pechiney	04/04/00	140	62	2
Lafarge	02/02/00	409	10.084	509
Carrefour	08/31/99	157	34.252	1.615
Promodes	08/31/99	442	14.111	48
Carrefour	07/26/00	1006	51.631	1.578
Saint-Gobain SA	02/01/00	364	14.422	322
SOMMER-ALLIBERT	10/26/00	82	783	71
VIVENDI UNIVERSAL	09/30/00	77	55.879	3.440
Canal Plus	01/05/00	1748	14.684	25.181
LAGARDERE GROUPE	01/05/00	378	6.451	644
De Dietrich	11/01/00	499	365	8
AXA	02/12/00	17	46.382	3.947
AGF (Assurance Générale de France)	10/11/00	555	9.822	333
Atos	08/29/00	209	2.580	92
Moulinex	09/28/00	258	316	225
CAP GEMINI	10/26/00	121	20.476	521
Alcatel Alsthom	06/14/00	1034	53.853	5.664

Table 1 shows some descriptive statistics about our sample firms. "Event date" corresponds to the announcement day of the business combination. Number of transactions, Market Capitalization and Trading Volume correspond to the daily average computed along the studied period (from day -180 to day +63 relative to the announcement date).

Name	Event Date	Number of transactions	Market capitalization (10^3\$)	Trading volume (10^6\$)
VIVENDI UNIVERSAL	06/14/00	1414	55.409	2.954
Hurel Dubois	09/14/00	1478	116	2
Total Fina Elf	03/22/00	250	82.880	1.680
Accor SA	11/27/99	5	8.490	854
Saint-Gobain SA	04/07/00	727	13.939	327
France Telecom	03/24/00	358	125.560	2.087
Suez Lyonnaise des eaux	08/08/00	383	32.244	3.186
Thales	06/07/00	1457	6.410	411
Aventis	03/16/00	692	4.943	288
Pechiney	04/25/00	225	62	2
Labinal	05/02/00	592	928	22
VALEO SA	05/02/00	137	5.277	361
CAP GEMINI	08/07/00	348	19.901	481
BNP PARIBAS	04/19/00	44	36.183	1.657
VIVENDI UNIVERSAL	06/29/00	837	55.565	2.975
VALEO SA	06/28/00	701	4.898	387
Marine Wendel	05/05/00	1488	1.454	20
RHODIA	02/01/00	350	3.448	564
Danone	03/20/00	27	17.308	531
Saint-Gobain SA	06/05/00	183	13.287	324
Plastic Omnium	05/10/00	456	358	4
Canal Plus	01/14/00	395	15.184	25.766
LAGARDERE GROUPE	01/14/00	27	6.578	644
Thales	01/13/00	397	6.035	420
Crédit Commercial de France (CCF)	04/01/00	534	9.341	246
Carrefour	03/30/00	210	47.583	1.716
Alcatel Alsthom	02/23/00	223	37.921	5.231
CAP GEMINI	12/06/99	860	13.615	417
Michelin	03/02/00	1085	5.351	524
Equant	02/04/00	436	19.177	1.298
Carrefour	03/06/00	319	46.395	1.748
France Telecom	01/26/00	420	113.568	1.964
Danone	12/17/99	843	17.967	520
Thales	12/01/99	1315	5.762	428
PINAULT PRINTEMPS	11/30/99	410	22.020	294

Table 1 shows some descriptive statistics about our sample firms. ”Event date” corresponds to the announcement day of the business combination. Number of transactions, Market Capitalization and Trading Volume correspond to the daily average computed along the studied period (from day -180 to day +63 relative to the announcement date).

Name	Event Date	Number of transactions	Market capitalization (10^3\$)	Trading volume (10^6\$)
Faurecia	10/26/00	202	562	23
Peugeot SA	06/14/00	341	9.631	973

Table 2: SUMMARY OF THE MAIN EMPIRICAL RESULTS BY USING THE PIN

Table 1 provides a summary of the main empirical evidences by using the probability of informed trading. This table specified the authors, the concern of their research and in some cases the modifications of the model done.

Authors	Concern	Modifications of the sequential model
Easley, O'Hara & Paperman (1996)	The difference in spread for active and infrequently traded stocks	None
Easley, Kiefer & O'Hara (1996)	The difference in information content between trading locales	None
Easley, Kiefer & O'Hara (1997a)	The information content of the time between trades	Include the role of trade size
Easley, Kiefer & O'Hara (1997b)	The difference of information content of stocks with different trade size	Traders can buy (sell) a large or a small quantity. The uniformed trading process is history dependent
Easley, O'Hara & Srivinas (1998)	The informational role of transactions volume in options markets	Informed traders may trade in option or equity markets
Easley, O'Hara & Paperman (1998)	Financial analyst as a proxy for informed trading ?	None
Easley, O'Hara & Saar (2001)	How stock splits affect trading ?	None
Easley, O'Hara & Wu (2001)	Investigation of the correlation between the arrival rates and trade composition on market volatility and liquidity	The arrival rates of trades is time-varying and forecastable
Easley, O'Hara & Hvidkjaer (2002)	Information risk affect cross-sectional asset returns ?	None
Heidle & Huang (2002)	The trading behaviour in dealer and auction markets	None
Grammig, Schiereck & Theissen (2001)	The difference between non-anonymous traditional floor trading system and anonymous computerized trading system	Simultaneous estimation of the model for two parallel markets
Brown, Thomson & Walsh (1999)	The characteristics of the order flow through an electronic open limit order book	Market participants can learn from the 'openness' of the limit order book.Extension also to allow for limit/market order choice

Table 3: SUMMARY STATISTICS ABOUT SAMPLE OPERATIONS

Table 3 provides the evolution of the number of business combination across years. It gives also the evolution of the number of firms implied and their proportion according their role in the business combination (bidder, target or joint-venture).

Year	Bidder	JV	Target	# Firms	# Operations
1995	4	1	2	7	7
1996	3	7	3	13	11
1997	11	2	9	22	20
1998	12	5	5	22	19
1999	13	6	6	25	23
2000	17	27	8	52	46
Firm Type	60	48	33	141	126

Table 4: CAAR AND CAAV ACROSS EVENT WINDOWS

Table 4 provides the cumulative average abnormal return (CAAR) and the cumulative average abnormal volume (CAAV) variations for different event windows. All p-value are bootstrap percentile t p-value. The last part of this table 4 gives the difference between the rumor and no-rumor sub-sample.

		$[-65, -6]$	$[-5, +2]$	$[+3, +63]$
		ALL SAMPLE		
CAAR	Variations	-0.019	0.013	0.008
	p-value	(0.196)	(0.008)	(0.113)
CAAV	Variations	4.585	2.586	6.044
	p-value	(0.000)	(0.000)	(0.000)
		RUMOR		
CAAR	Variations	-0.032	0.01	0.011
	p-value	(0.078)	(0.138)	(0.327)
CAAV	Variations	-0.047	2.527	2.681
	p-value	(0.26)	(0.007)	(0.027)
		NO RUMOR		
CAAR	Variations	-0.047	0.015	0.006
	p-value	(0.004)	(0.024)	(0.120)
CAAV	Variations	7.379	2.621	8.093
	p-value	(0.000)	(0.000)	(0.000)
		NO RUMOR <> RUMOR		
CAAR	Variations	0.079	-0.005	0.005
	p-value	(0.000)	(0.599)	(0.742)
CAAV	Variations	-7.426	-0.094	-5.411
	p-value	(0.000)	(0.817)	(0.028)

Table 5: CROSS-SECTIONAL AVERAGE OF THE PIN

Table 5 gives the cross-sectional average of the PIN for different sub-samples and event windows. The different sub-samples are derived according to the existence or not of rumors in the financial press before the announcement day and according to the firm's role.

	PIN				
	N	$[-270, -181]$	$[-180, -66]$	$[-65, -6]$	$[+3, +63]$
All Firms	141	18.41 %	18.95 %	17.84 %	21.39 %
Rumors less	90	18.65 %	18.96 %	17.87 %	21.74 %
Rumors	51	18.01 %	18.94 %	17.80 %	20.76 %
Bidder	60	18.20 %	19.63 %	18.41 %	18.28 %
Target	28	18.68 %	17.94 %	16.45 %	29.84 %
JV	48	18.48 %	18.86 %	18.31 %	19.45 %

Table 6: MEAN DIFFERENCE AND SIGNIFICANCE TEST

Table 6 presents significance test of the (cross-sectional) mean difference of the PIN between two event windows, for each sub-sample. We use a classical paired student test of difference of means. p-value are obtained by a percentile-t bootstrap approach (see Efron and Tibshirani (1993)) with 1000 bootstrap samples.

		PIN Difference		
		$[-180, -66] - [-65, -6]$	$[-65, -6] - [+3, +63]$	$[-180, -66] - [+3, +63]$
All Firms	mean difference	1.11 %	-3.54 %	-2.44 %
	p-value	(0.000)	(0.000)	(0.007)
Rumors less	mean difference	1.10 %	-3.87 %	-2.78 %
	p-value	(0.313)	(0.089)	(0.114)
Rumors	mean difference	1.14 %	-2.96 %	-1.82 %
	p-value	(0.267)	(0.285)	(0.335)
Bidder	mean difference	1.22 %	0.13 %	1.36 %
	p-value	(0.147)	(0.898)	(0.171)
Target	mean difference	1.49 %	-13.39 %	-11.90 %
	p-value	(0.501)	(0.006)	(0.021)
JV	mean difference	0.55 %	-1.14 %	-0.59 %
	p-value	(0.871)	(0.567)	(0.765)

Table 7: REGRESSION ANALYSIS

Table 7 provides the regression's estimation of the observed opening spread by the theoretical opening spread given in equation (11):

$$Spread_i = \beta_0 + \beta_1 PISTD_i + \epsilon_i$$

β_1 is the estimated coefficient associated with the theoretical opening-spread. Table 7 gives also the p-value associated with this coefficient and the R^2 of the regression.

	$[-270, -181]$	$[-180, -66]$	$[-65, -6]$	$[+3, +63]$
β_1	0.177	0.182	0.091	-0.001
p-value	(0.000)	(0.000)	(0.025)	(0.988)
R^2	0.179	0.173	0.036	0.000

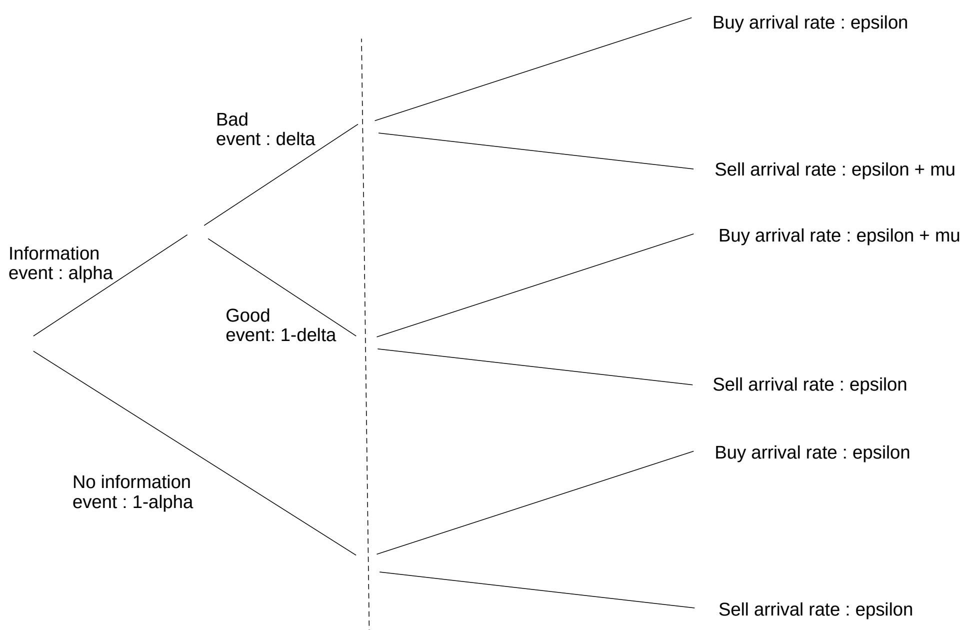
Table 8: DAILY AVERAGE $B{+}S$ AND B/S IN EACH EVENT WINDOW

Table 8 provides the daily average of B+S and of the ratio B/S for the event windows of interest. Table 8 gives also the percentage change of this two variable across windows and remembers the estimated PIN for the three windows.

		$[-180, -66]$	$[-65, -6]$	$[+3, +63]$
All Firms	PIN	18.95 %	17.84 %	21.39 %
	$B + S$	717	861	946
	% change		20.1 %	9.8 %
	B/S	0.936	1.042	1.067
	% change		11.4 %	2.4 %
Target	PIN	17.94 %	16.45 %	29.84 %
	$B + S$	428	502	628
	% change		17.4 %	25.1 %
	B/S	0.884	1.001	0.715
	% change		13.2 %	-28.6 %
No Target	PIN	18.80 %	17.73 %	18.34 %
	$B + S$	818	963	1019
	% change		18.2 %	5.8 %
	B/S	0.948	1.047	1.129
	% change		10.4 %	7.8 %

Figure 1: THE TREE DIAGRAM OF THE TRADING MODEL

This figure gives the structure of the trading process, where a is the probability of an information event, d is the probability of a "bad" event, is the rate of informed trade arrival, and e 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 a good news or bad news. Nodes to the left of the dotted line occur once per day.



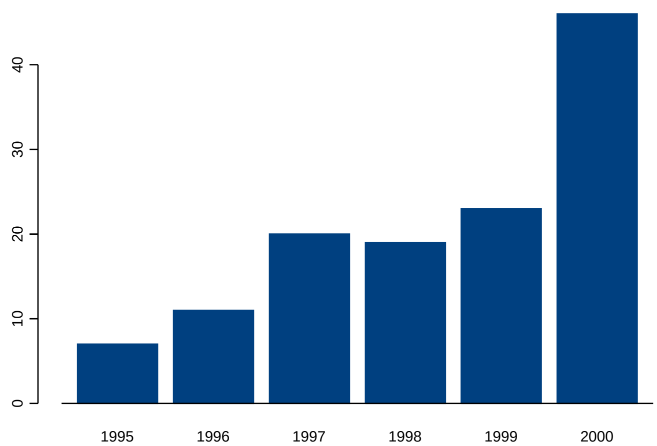


Figure 2: EVOLUTION OF THE NUMBER OF OPERATIONS ACROSS YEARS

Figure 2 provides the evolution of the number of business combinations of our sample across years.

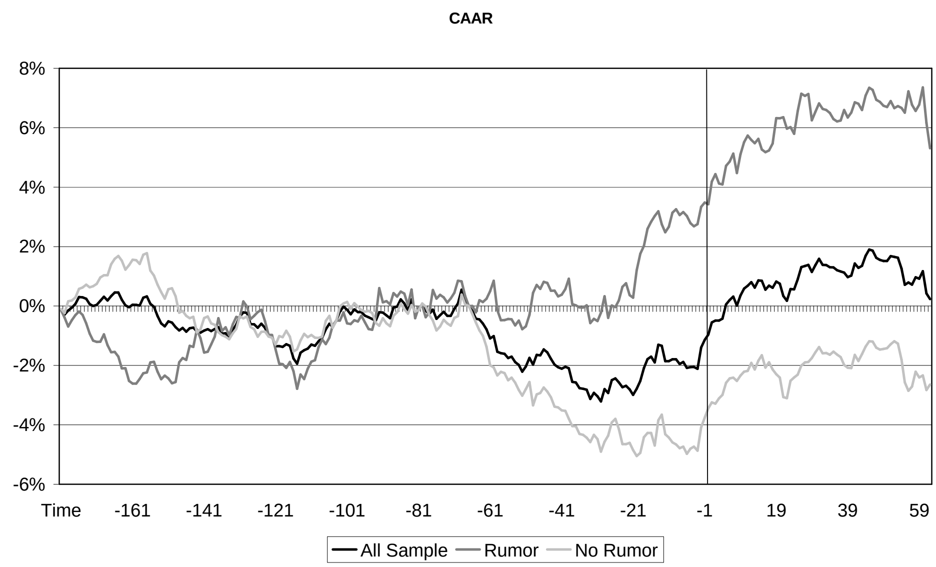


Figure 3: EVOLUTION OF THE CAAR

Figure 3 gives the evolution of the Cumulative Average Abnormal Return through time.

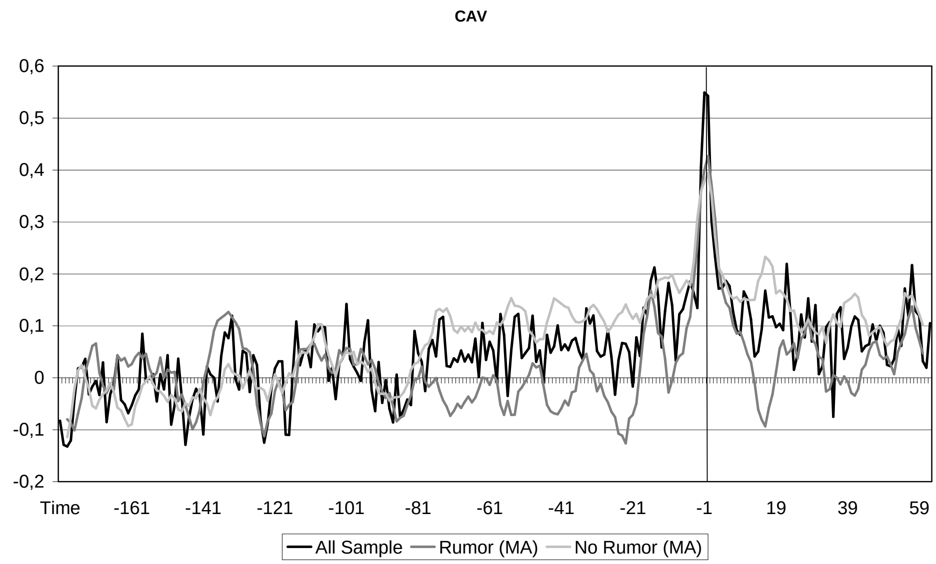


Figure 4: EVOLUTION OF THE CAAV

Figure 4 gives the evolution of the Cumulative Average Abnormal Volume through time.

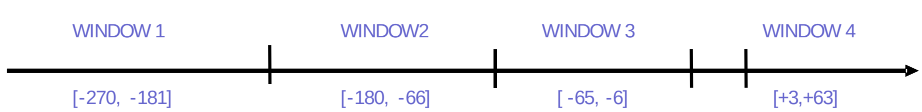


Figure 5: RANGE OF THE DIFFERENT WINDOWS OF STUDY

This figure presents the range of the different event windows of interest. The announcement day is on day 0.

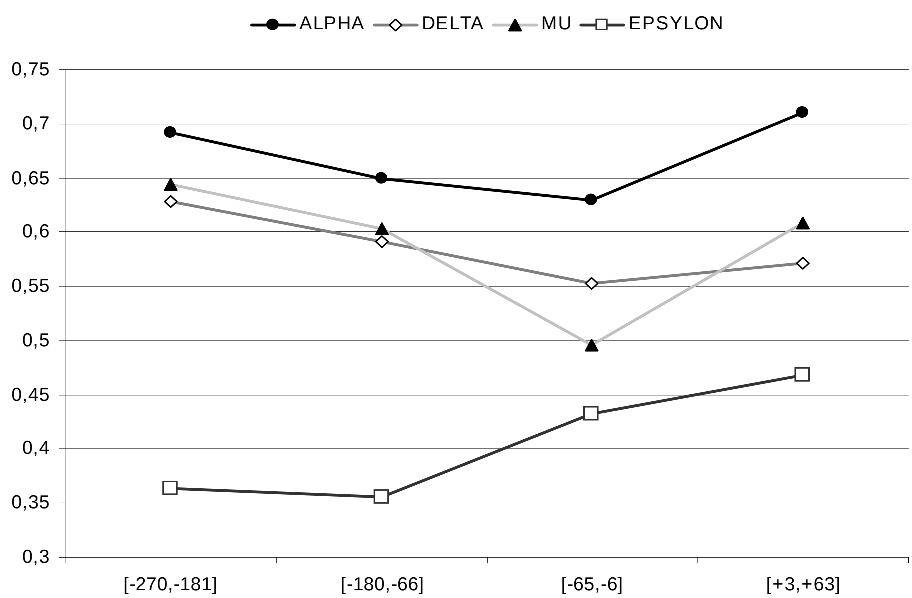


Figure 6: CROSS-SECTIONAL AVERAGE PARAMETERS ESTIMATED

Figure 6 gives the cross-sectional parameters estimated for each window. The estimates are obtained through the maximization of the likelihood function given in equation (6).

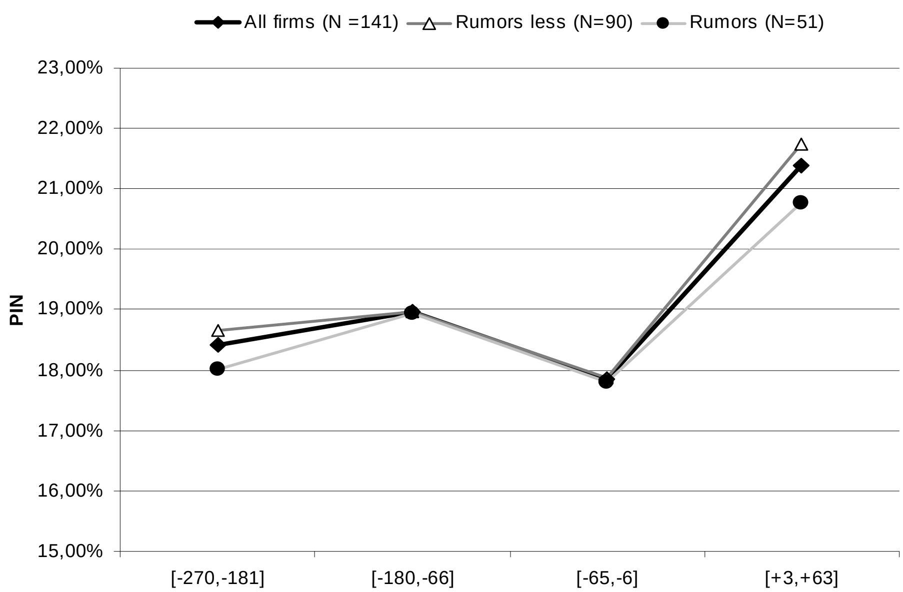


Figure 7: CROSS-SECTIONAL AVERAGE OF THE PIN (RUMORS OR NOT)

Figure 7 gives the evolution of the cross-sectional average of the PIN across event windows and for different sub-samples. Firms are classified in the "rumor" sub-sample if there are rumors prior to the announcement of the operation in which they are involved.On the other hand, an operation will be considered rumor-less if no mention of it can be found in the financial press (we check both the *(*Financial Times) and *Les Echos* newspapers) during a 6-month period prior to the announcement day.

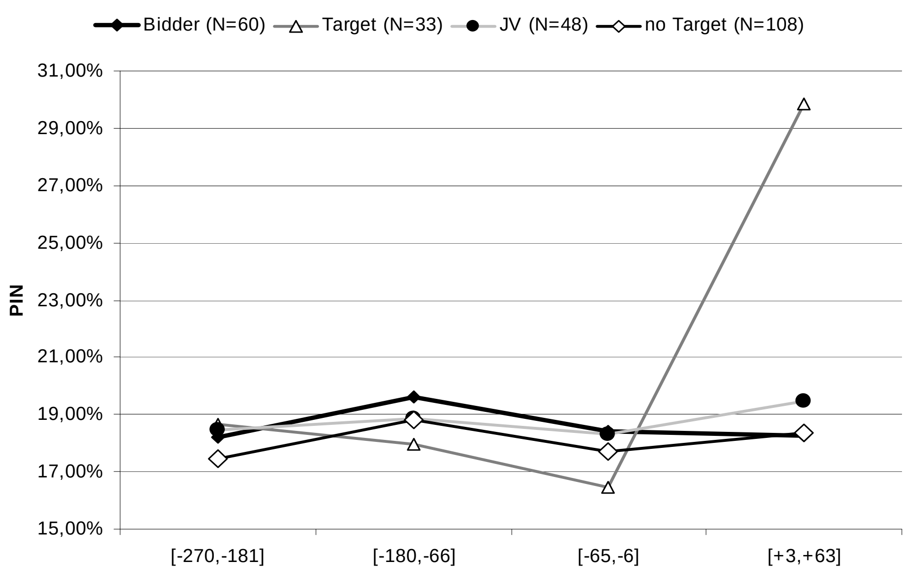


Figure 8: CROSS-SECTIONAL AVERAGE OF THE PIN ACCORDING TO FIRM'S ROLE

Figure 8 gives the evolution of the PIN for each event windows according to the firm's role in the business combination (bidder, target or joint-venture).

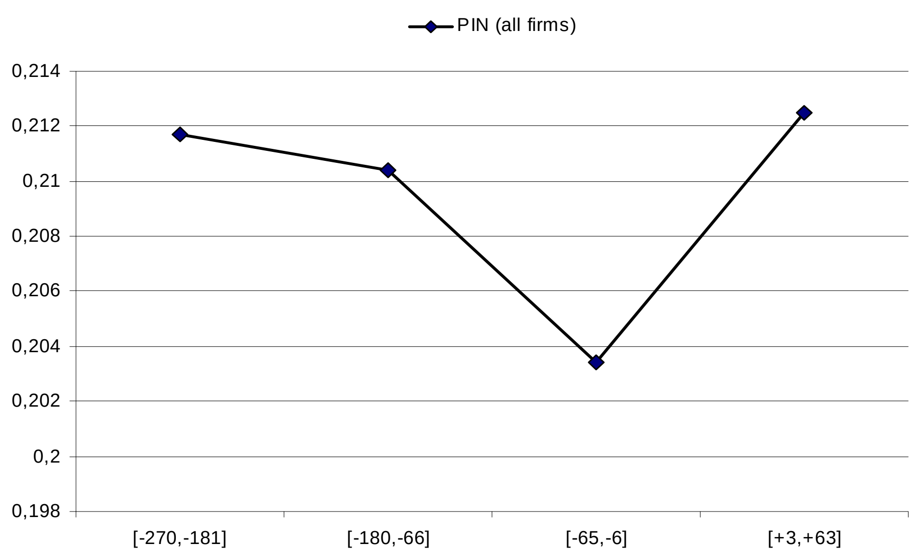


Figure 9: ESTIMATED PIN THROUGH EASLEY ET AL. (2002) MODEL

The figure 9 presents the evolution of the estimated cross-sectional PIN using the likelihood function which distinguishes arrival rates of uninformed sellers from uninformed buyers (see equation (17)). This likelihood function is given in Easley et al. (2002). The result observed is similar to the results in section 3: the PIN decreases strongly the period prior to the announcement date and increases after it.

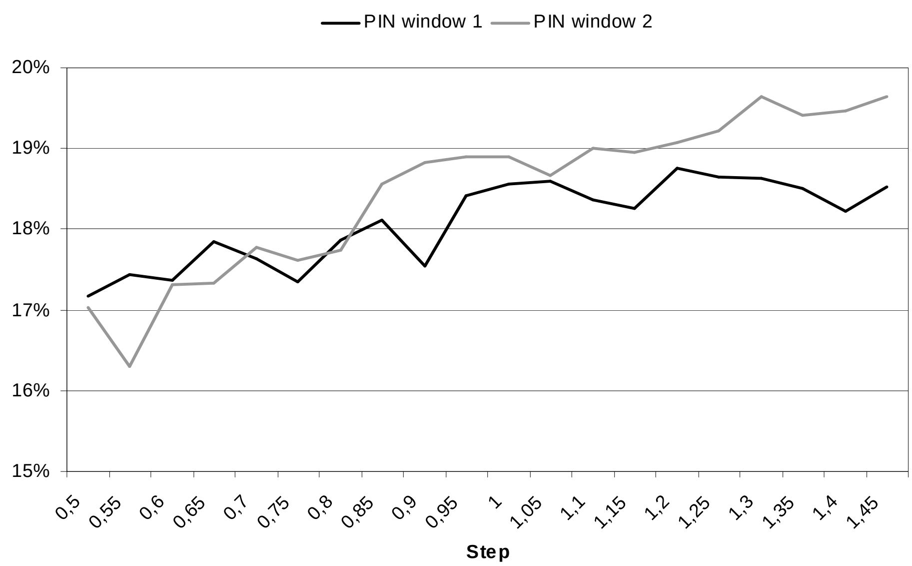
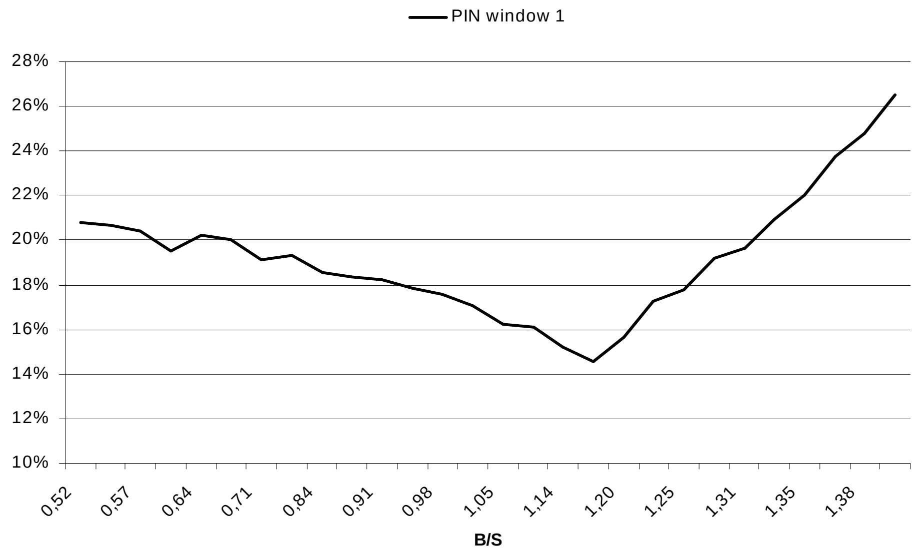


Figure 10: SIMULATED PIN WITH DIFFERENT VOLUME

Figure 10 gives the evolution of the simulated PIN according to different level of volume. The PIN is simulated for the first two event windows.



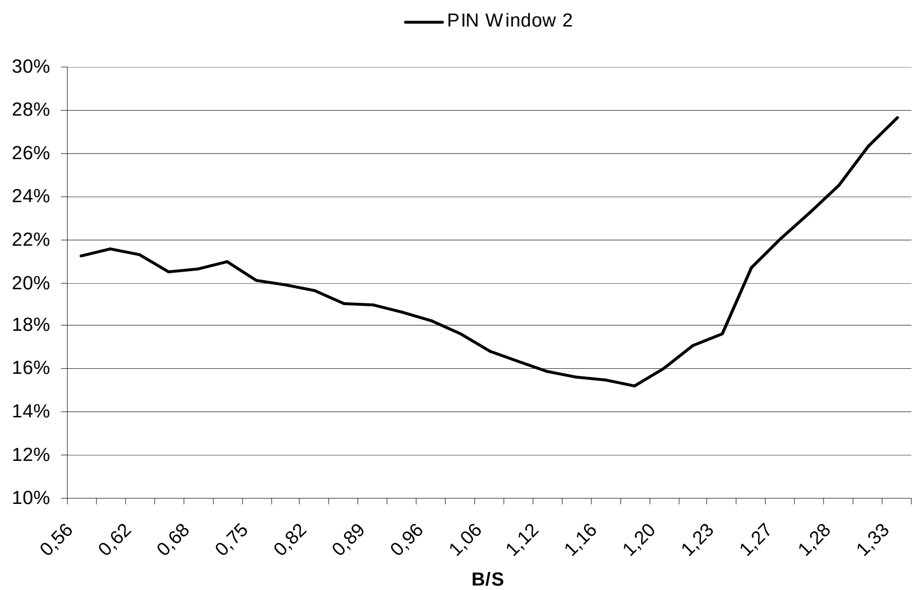


Figure 11: SIMULATED PIN WITH DIFFERENT RATIO B/S

Figure 11 shows the evolution of the PIN for the period from day -270 to day -181 (window 1) and from day -180 to day -66 (window 2) with different level of the ratio B/S.