



Legal insider trading and market efficiency

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Received 6 September 2007; accepted 15 November 2007

Available online 4 December 2007

Abstract

Does legal insider trading contribute to market efficiency? Using refinements proposed in the recent microstructure literature, we analyzed the information content of legal insider trading. We used data on 2110 companies subject to 59,244 aggregated daily insider trades between January 1995 and the end of September 1999. Our main finding is that, even though financial markets do not respond strongly in terms of abnormal returns to insider trading activities, the significant change in price sensitivity to relative order imbalance due to abnormal insider trades reveals that price discovery is hastened on insider trading days.

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JEL classification: G14; G18

Keywords: Legal insider trading; Market efficiency; Order imbalance; Price discovery

Our markets are a success precisely because Americans enjoy the world's highest level of confidence. [...] Investors trust that the marketplace is honest. They know that our securities laws require free, fair and open transactions.

A. Levitt, Chairman of the SEC, Address to the "SEC Speaks" Conference, February 1998.

1. Introduction

Does legal insider trading contributes to market efficiency? In this paper, using the refinement suggested by the recent microstructure literature, we propose to analyze the information content of *legal* insider trading. This is an important question since the regulation of insider trading

plays an important role in economies with developed stock markets. According to Battacharya and Daouk (2002), the existence of insider trading laws and their enforcement is essentially a phenomenon of the 1990s. One interesting aspect of these regulations is that they allow insiders to trade their own companies' stocks under certain conditions. For example, under US securities laws, legal insider trading occurs every day when corporate insiders – officers, directors or employees – buy or sell stock in their own companies. One of the constraints is that the insiders have to report their trading to the Securities and Exchange Commission (SEC). Once the trading is complete, files have to be sent to the SEC, which publishes them.

The social utility of regulating insiders' trading has been widely debated in the literature, and several important contributions analyze the impact of insider trading and its regulation on economic efficiency. On the one hand, the critics of insider trading regulation argue that restrictions are inefficient because insider trading allows new private information to be priced more quickly. Stock prices, therefore, reflect the intrinsic values of firms more accurately, promoting improved economic decision-making and resource

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allocation (e.g., Manne, 1966; Carlton and Fischel, 1983; Glosten, 1989; Manove, 1989; Leland, 1992). Moreover, Tighe and Michener (1994) argue that only private interests (e.g., those of brokers, arbitrageurs and portfolio managers) are served by insider trading laws, as small investors lack the political organization to lobby for such laws. On the other hand, those in favor of insider trading regulation essentially claim that regulation promotes public confidence and participation in the stock market, and allows outsiders to share in value-enhancing events on an equal footing (Ausubel, 1990).

One clear message which arises from this intensive debate is that authorizing insiders to trade should be based on a balance between allowing private information to be priced (enhancing market efficiency) and preserving market integrity (avoiding unfair enrichment by those with access to privileged information). As pointed out by Huddart et al. (2001), the regulatory objectives of the public disclosure of insider trading are to reduce the information asymmetry between insiders and outsiders. However, there is always a delay between the insider trading and public announcement of such trading.¹ Therefore, to fully justify insider trading for reasons other than diversification, we need to demonstrate a contribution to market efficiency.

Consequently, the research question we are interested in is the following: do legal insider trading activities contribute to market efficiency? In other words, does information affect prices more quickly thanks to legal insider trading activity? This is an important question because previous studies, mainly using portfolio approaches, have shown that insiders outperform the market over a time horizon ranging from one month to several months (e.g., Jaffe, 1974; Finnerty, 1976; Seyhun, 1986; and Seyhun, 1998; Lin and Howe, 1990; Jeng et al., 2003).²

Are these abnormal gains really evidence of private information being revealed by the action of better-informed agents? There are at least two other competing explanations. First, these abnormal gains could be the manifestation of some latent risk factors such as size, earnings/price or book-to-market (e.g., Rozeff and Zaman, 1988; Lakonishok and Lee, 2001). The second possible explanation is that these abnormal returns, since they are computed over an event window of several months, could reflect the price reaction to subsequent public announcement (within the event window) of previously private information. Therefore, it is still questionable whether insiders

contribute to faster price discovery. Moreover, these portfolio approaches are subject to significant bad-model problems, which are even more serious for long-term returns analysis (see Fama's (1998) comments on long-term event studies).

The relevance of our research question also stems from the fact that (informed) insider trading profit is achieved at the expense of outside investors, even if total welfare may increase or decrease depending on the economic environment (Leland, 1992). Moreover, we do not have a clear-cut answer from the literature as to whether outsiders can profit by using the publicly available information concerning insider trading once it is reported to the SEC (e.g., Seyhun, 1986; Rozeff and Zaman, 1988).³ Therefore, the necessary condition that needs to be satisfied in order to justify allowing insiders to trade on their private information is that their trading should enhance market efficiency. This is what we propose to test in this paper.

To address this question, we use an extensive US database of legal trading by insiders covering the period from January 1995 to the end of September 1999. Our sample includes 59,244 aggregated insider open market episodes. Previous studies have mostly looked at what happens *after* insider trading, in terms of abnormal gains for insiders and/or outsiders (portfolio performance), while we are more interested in what happens on insider trading days, in terms of price discovery. Our focus on the short-term impact of insiders' trading activities to capture information effects is motivated by recent evidence presented by Chordia et al. (2005). These authors show that it only takes five minutes for astute investors to begin efficiency-creating actions.

There are some studies that appraise the impact of insider trading activities over a shorter period. Seyhun (1986), and more recently Lakonishok and Lee (2001) provide short-term event-study results on legal US insider trading. They observe statistically significant, but economically unimportant, market movements around insider net purchases and net sales.⁴ Recently, within the UK context, Fidrmuc et al. (2006) have reported abnormal returns which are three times as high as those reported by Lakonishok and Lee (2001).⁵ Jenter (2005) interprets the lack of evidence for economically significant abnormal returns to insiders as indicating that corporate insiders in the US may not make much use of valid inside information.

¹ In the United States, according to Section 16(a) of the Securities and Exchange Act of 1934, insiders are required to report their transactions by the tenth day of the calendar month after the trading month. In our sample, the average reported period is around 22 days. It is important to note that since August 2002, according to the Section 403(a) of the Sarbanes-Oxley Act of 2002, insiders are required to report their transactions before the end of the second business day following the day on which the transaction is executed.

² However, there is a notable exception to this general finding, which is the study by Eckbo and Smith (1998). They report that insiders in firms on the Oslo Stock Exchange did not make abnormal profits.

³ Seyhun (1992) provides evidence that insider trading has some predictive ability for future stock returns. In the same way, Bettis et al. (1997) show that outside investors can earn abnormal profits by analyzing publicly available information about large insider trades by top executives. Lakonishok and Lee (2001) also report that insiders seem to be able to predict cross-sectional stock returns. Their result, however, is driven by insiders' ability to predict returns in smaller firms.

⁴ Note that the statistical significance of this result is subject to active debate in the literature (see e.g. Butler et al., 2005; Baker et al., 2006).

⁵ One possible explanation provided by the authors is that trading is reported more quickly in the UK than in the US.

However, it is important to note that the small returns associated with insider trades could be considered as economically significant, given that these trades combine transactions that are uninformative and others that do contain information. In addition to information-based trading, insiders trade their own company stocks mainly for diversification and liquidity reason (see [Lakonishok and Lee, 2001](#); [Iqbal and Shetty, 2002](#); [Jenter, 2005](#)). Moreover, since we focus on legal insider trading, and given that Section 16(b) of the Securities and Exchange Act of 1934 prohibits insiders from making a profit on any position held for less than six months, for the trades to be informative the insiders need to have a long-term information. To overcome this problem we analyze also abnormal insider trades after having first computed the abnormal level of insider trading by eliminating that part of the insider activity which is less likely to be information-motivated (using known determinants from the literature).

Apart from the debate about the economic significance of the abnormal returns around insider trading days, using these returns to infer that insiders have indulged in information-motivated trading seems to be subject at least to two shortcomings. The first relates to the likely endogenous relation between abnormal returns and insider trading: insiders may decide to purchase on a specific day because they expect stock prices to increase on that day. The second is that the abnormal returns could be a noisy proxy for private information, essentially because insiders can act strategically by timing the market, and voluntarily choosing a trading window in which they can hide their trading motivation (see [Jenter \(2005\)](#) and [Piotroski and Roulstone \(2005\)](#)). For example, the insider may submit a buying trade when the price is declining. Hence, the resulting abnormal return would be an underestimate (overestimate) of the true abnormal return for the purchase (sale). In such a context, the abnormal return for a given insider trading day could be the sum of at least two effects: (1) the price impact of the private information; and (2) the market timing of the insider.

To sum up, on the one hand, if we consider that the abnormal returns generated on insider trading days are economically important, we are not sure about the direction of causation. On the other hand, if we think that the abnormal returns are too small to be economically significant, we are left with a puzzling result. These two phenomena are likely to be present and to balance each other in a large sample of insider trades.

The contribution of this study lies in the fact that it is based on an improved measure of the incorporation of information, grounded in recent market microstructure literature and permitting insider purchase and sale activities to be examined in a large sample of firms (including those with low liquidity). Our approach is close to that of [Chordia et al. \(2005\)](#) in the sense that we measure the ‘contribution to market efficiency’ by the relationship between the return and the relative order imbalance. Moreover, focusing on the trading mechanism (the price impact of the

relative order imbalance) allows us to analyze insider purchases as well as sales and to overcome the two shortcomings affecting the abnormal return approach identified above. The abnormal price sensitivity to relative order imbalance due to abnormal insider trades is unambiguously a consequence of the trading behavior.

Our approach can be summarized as follows. We compute the abnormal returns associated with insider net purchases and net sales in order to replicate [Lakonishok and Lee’s \(2001\)](#) results. This is just to ensure that we are working in the same empirical context. Our univariate analysis highlights insiders’ market timing ability. We find that stock prices on insider net purchase (sale) days tended to be smaller (larger) than on the other days. Market liquidity seems to be weaker on insider net purchase days. Insider abnormal purchases are associated with quicker price discovery. That is, the association between the relative order imbalance and market returns is larger on days on which insiders are net purchasers. Market liquidity seems to be greater on insider net sales days. Moreover, the sensitivity of the return on the relative order imbalance is higher in absolute value on net sales days, which indicates that abnormal insider selling activities also facilitated quicker price discovery.

This paper is closely related to the work of [Damodaran and Liu \(1993\)](#), which identified an experimental context where it is possible to isolate the presence of private information and to value its economic content. Focusing on a very small sample of insider trades, Damodaran and Liu provide evidence of private information revelation through the trading of corporate insiders in real estate investment trusts, following the appraisal of their companies’ assets.⁶ Insiders seem to believe in this re-evaluation, and to trade on it to make a profit, revealing their information to the market in the process. The later public disclosure of the re-evaluation is not associated with significant market reaction. It is important to note that, in addition to the small sample size of their study, [Damodaran and Liu \(1993\)](#) do not distinguish clearly between legal and illegal insider trading.⁷ Our work can be seen as a generalization of their approach to a large sample of legal insider trading.

There are several other papers that provide indirect evidence that the stock market responds quickly to insider trades. For example, [Jeng \(1999\)](#) and [Bettis et al. \(2000\)](#) analyze the trading rates and information asymmetry during blackout periods (periods in which companies restrict trading in their stock by their own insiders). They show that trading rates are much higher during allowed trading days and that the adverse-selection component of the

⁶ Their sample only encompasses 35 transactions (23 purchases and 12 sales) in a six-month period before the appraisal, and 45 transactions (40 purchases and 5 sales) between the appraisal and its public disclosure.

⁷ There are several studies that show how information is incorporated into asset prices around the day of the illegal trading (see, *inter alia*, [Battacharya et al., 2000](#)).

spread is also higher on days on which the probability of insider trades is relatively high.

The paper is organized as follows. Section 2 introduces the method adopted to measure the contribution of legal insider trading to market efficiency. Section 3 describes the data. Section 4 presents our analysis of how legal insider trading activities contribute to market efficiency, and the final section concludes.

2. Measuring the contribution to market efficiency

The recent microstructure literature proposes three main approaches to measuring information-based trading. The first is based on spread and its adverse selection component. This method is subject to serious criticism, mainly related to the fact that competing spread decomposition models seem to provide different results (Van Ness et al., 2001; Neal and Wheatley, 1998).

Another widely used approach to measuring information-based trading is the permanent price impact measure originated by Hasbrouck (1991a,b). Here the theory is that the more informative trading is, the bigger its permanent price impact should be. By the use of a vector autoregressive model, Hasbrouck models the dynamic between the price changes and the order flow (through trading). By assuming that it is the unexpected part of the order flow which incorporates private information, Hasbrouck computes the permanent (long-term) price impact of such trading, and uses it as an indicator of information based-trading. While this method is clearly attractive, its major empirical shortcoming is the need for a large number of observations. Vector autoregressive models require a large amount of high-frequency data to be estimated, which in practice limits the applicability of the method to actively traded stocks. This weakness is not, in our case, without consequences, as we expect insider trading activities to impact more strongly on the speed of the price discovery process for stocks with low liquidity.

The last important microstructure-based information asymmetry measure is the probability of information-based trading (*PIN*) measure introduced by Easley et al. (1996). This is based on a structural sequential trade model, and has numerous applications in empirical finance. Its widespread use probably originates from the structural model on which it is based, as well as from its appealing empirical tractability. Only classified trades (buyer or seller initiated) are needed. However, its information content is not clear. The model simply suggests that the likely reason for a discrepancy (if any) between buyer- and seller-initiated trading is the trading activity of informed traders. Aktas et al. (2007) discuss the limits of such a conjecture, analyzing the behavior of *PIN* around M&A announcements.

We develop an alternative approach to analyzing whether insider trades are information-motivated. This was designed to tackle the limitation of the approaches discussed above. Aktas et al. (2007) have shown that *PIN* is simply the ratio between the expected absolute order

imbalance (absolute difference between purchases and sales, namely OIB) and the expected volume. The daily *PIN* can be proxied empirically by the daily relative order imbalance, the ratio between the daily imbalance and the daily volume. Starting from this observation, our approach is based on ideas developed by Hasbrouck (1991a,b), Chordia et al. (2005), and Aktas et al. (2007). We measure the ‘contribution to market efficiency’ by estimating the correlation between daily returns and the daily relative OIB. Only the component of the relative order imbalance that has an impact on the return is expected to convey valuable information. Its uncorrelated part is probably driven by liquidity-motivated trading (since order imbalances arise either from traders who believe themselves to be in possession of pertinent information, or from those who experience large liquidity shocks (Chordia et al., 2002)).

In order to disentangle these two components, we study the correlation between the daily return and the daily relative order imbalance. More specifically, for each of our sample securities and for each trading day, using intraday quote and transaction data, we measure the signed relative OIB (ROIB) for day t and stock i .

$$\text{ROIB}_{i,t} = (B_{i,t} - S_{i,t}) / (B_{i,t} + S_{i,t}), \quad (1)$$

where $B_{i,t}$ and $S_{i,t}$ correspond to the number of buys and sells, respectively, for day t and stock i . We also use two alternative specifications for the ROIB: the *volume ROIB*, where B and S are expressed in the number of shares exchanged, and the *value ROIB*, where B and S are the monetary value of the buy and sell volumes. The first measure of ROIB ignores the size of the trade, giving small orders the same weight as large orders. The *volume* and *value ROIB* weight large orders more heavily.

Since only the component of the ROIB that generates a price impact is expected to signal private information, then we analyze the sensitivity of the daily return to the daily ROIB (computed using intraday transaction data) within a panel regression framework. This is given by

$$R_{i,t} = \alpha_i + \beta \text{ROIB}_{i,t} + \varepsilon_{i,t}. \quad (2)$$

The coefficient β measures the normal level of sensitivity of prices to the ROIB. Our aim is to measure the impact of insider trades on this coefficient, which corresponds to the abnormal change in sensitivity due to insider trading. The reasoning underlying our test is summarized in Fig. 1. The coefficients δ_{BUY} and δ_{SELL} capture the abnormal change in sensitivity induced by insider buy and sell transactions, respectively. If insider trades are information-motivated, insider purchases should increase the price sensitivity to a positive order imbalance (Panel A), and decrease the price sensitivity to a negative order imbalance (Panel B). With a negative order imbalance, information-motivated insider purchases should attenuate the sell-order imbalances of other traders. Indeed, if ROIB is positive, then its coefficient should be larger on days when insiders also purchase, but when ROIB is negative, the price sensi-

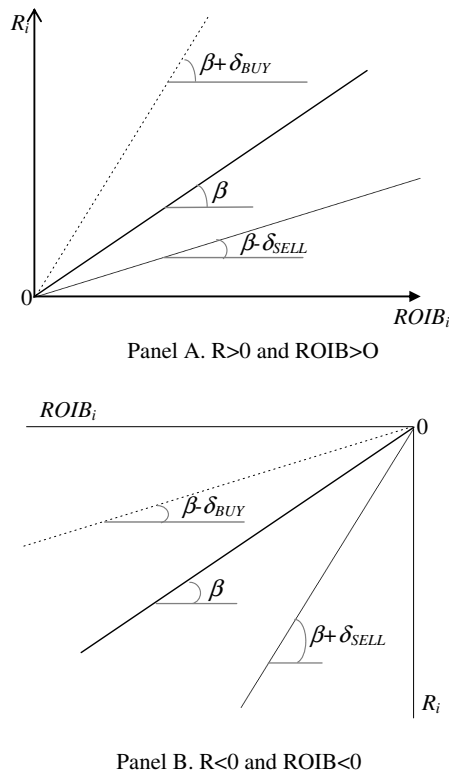


Fig. 1. Abnormal price sensitivity to relative order imbalance. This figure displays the expected change in abnormal price sensitivity to relative order imbalance due to insider trading. The X-axis and Y-axis represent the relative order imbalance (ROIB) and the return (R) for stock i , respectively. Panel A (Panel B) depicts the case where a positive (negative) return is associated with a positive (negative) ROIB. The coefficient β measures the normal level of the price sensitivity to the ROIB. The coefficients δ_{BUY} and δ_{SELL} capture the abnormal change in the sensitivity induced by insider buy and sell transactions, respectively.

tivity to order imbalances on insider purchase days should be smaller in absolute value than on the other days. The reasoning is the same for insider sells.

To capture the asymmetric relationship between the return and the interaction of the ROIB and insider trades, we consider the absolute value of ROIB, and estimate the following general equation within a panel framework⁸:

$$R_{i,t} = \alpha_i + \beta ROIB_{i,t} + \delta_{BUY}(|ROIB_{i,t}| \times IBUY_{i,t}) + \delta_{SELL}(|ROIB_{i,t}| \times ISELL_{i,t}) + \varepsilon_{i,t}. \quad (3)$$

Here $IBUY_{i,t}$ ($ISELL_{i,t}$) measures the intensity of insider net purchases (sales) on day t for stock i , and $|ROIB_{i,t}|$ is the relative order imbalance in absolute value for stock i . To validate our ‘information incorporation’ hypothesis on insider trading days, the coefficient δ_{BUY} (δ_{SELL}) should be positive (negative) and statistically significant for insider purchases (sales). Once controlled for the general relation between the return and the ROIB, this result indicates that

the ROIB observed on insider purchase (sale) days impacts marginally more on the return than on other days, and this is attributed to the differential incorporation of information into the price occasioned by insider purchases (sales). Such a result is only compatible with information incorporation into prices on insider trading days. Moreover, the use of a fixed-effect panel regression approach allows us to control for omitted variables (e.g., the characteristics of the firm) that are constant through time.

To conclude this section, we want to stress that the biases potentially affecting the abnormal return as a proxy of information incorporation into price (the causation problem and the strategic behavior of informed investors) are less likely to affect our approach. This is because our measure captures something that is specific to the functioning of the market, which is the speed of convergence to market efficiency. This dimension is less subject to manipulation/strategic action by insiders. What we really want to do is to assess empirically whether insiders bring new and useful (long-term) information into asset prices with their trading activities, controlling as far as possible for other impacts.

3. Data sources and summary statistics

3.1. Trade, quote and imbalance data

Trade and quote data come from the NYSE’s TAQ database, over the period January 1995 until the end of September 1999. The TAQ database includes intraday transaction data for all securities listed on the NYSE, AMEX and the NASDAQ stock exchanges. We drop NASDAQ stocks from our sample because it is difficult to sign these trades (see Christie and Schultz, 1999). Intraday data are known to be prone to a number of anomalous records. We use the same rules as Chordia et al. (2002) to filter out the data. We exclude trades:

- with no price information, a negative price or a price above \$999;
- with no quantity;
- recorded before or after the closing time.⁹

For the quotes, we delete records:

- with a negative bid–ask spread;
- with negative quoted depth;
- established before or after the closing time.

At this stage, from an initial sample of 329,705,317 quotes and 208,732,464 trades, we retain 329,687,111 filtered quotes and 208,472,712 filtered trades.

⁸ We owe particular thanks to Richard Roll for having suggested this specification.

⁹ The last trade is assumed to occur no later than 4:05 p.m., since transactions are commonly reported up to five minutes after the official close at 4:00 p.m.

The next step is the determination of the number of buys and sells for each day and each stock, which are essential to compute the imbalance data. We use [Lee and Ready's \(1991\)](#) algorithm to infer trade direction. This algorithm classifies a particular trade as buyer- (seller-)initiated if its price is larger (smaller) than the prevailing mid-quote (average of the ask and the bid prices). A trade at the mid-quote is classified as buyer- initiated if the last price change prior to the trade was positive, and conversely if the last prior price change was negative it is counted as seller-initiated.

3.2. Legal insider trading data

We use the Securities and Exchange Commission (SEC) Ownership Reporting System (ORS) data files to extract corporate insider purchases and sales. These data come from First Call/Thomson Financial Insider Research Services Historical Files. The ORS systems contain records of security transactions by people with beneficial ownership of securities, primarily officers, directors and principal stockholders of a corporation. We retain only SEC Form 4 data from the ORS database, which corresponds to the statement of changes in beneficial ownership of securities. For intraday stock data availability reasons, we study the period from January 1995 to the end of September 1999. We keep only open market and private transactions and we exclude those with fewer than 100 shares, so as to focus on the more meaningful events. The initial sample contains 113,506 insider transactions. Following [Lakonishok and Lee \(2001\)](#), we apply filter rules to eliminate records which are duplicated, amended, have no price information, have a recorded date preceding the transaction date, or have a recorded date occurring more than 30 days after the due date. As a last filter, we cross-check the ORS price and volume information against that reported by the TAQ database, and then drop from the sample records with a price outside the range of prices for that day, or with a volume exceeding the number of shares exchanged on that day. The application of these filters results in a sample of 109,847 insider trades.

To define event days (days on which we have an insider purchase or an insider sale) we use the same method as in [Fidrmuc et al. \(2006\)](#). This consists of taking the net transaction for days for which there is more than one transaction (e.g., a purchase of 300 shares and a sale of 150 shares on a given day become a net purchase of 150 shares for that day, and a purchase of 300 shares and a sale of 400 shares become a net sale of 100 shares). Following this adjustment, our sample covers 59,244 daily aggregated insider trades in 2110 firms. The number of insider purchase days is 20,023 and the number of insider sales days is 39,221.

[Fig. 2](#) shows the average proportion of aggregated insider net purchases and net sales per month. The proportion of insider purchases (sales) for a given month is computed with respect to the total insider purchases (sales) in the cor-

responding year. Panel A shows the number of insider trades and Panel B the volume in dollar. These two panels suggest that insider purchases and sales seem to have a common seasonality.

3.3. Summary statistics, abnormal returns and market conditions

3.3.1. Summary statistics

[Table 1](#) presents the summary statistics for insider trading activities for all NYSE/AMEX common shares between January 1995 and September 1999. Panel A focuses on insider net purchases. The average number of insider net purchase days is 9 per company. The average company subject to an insider purchase has a market value of circa USD 2.6 billion, and the mean number of shares purchased is 14,612 per event, the median being 2270 shares. In dollar value, the average net purchase transaction amounts to USD 298,350, the size of the median transaction being USD 44,820.

Panel B contains the same statistics for the insider net sales. The trading volume is larger for sales, which suggests that insiders are more likely to be sellers than buyers. Insider selling activity tends to be concentrated in larger firms than insider buying activity. This accords with [Jenter's \(2005\)](#) results.

In order to analyze the relative size of insider transactions, we compute two ratios: the first is the ratio of the net insider purchase to the volume of the corresponding day's transactions (*Percentage Volume*); the second is the ratio of the net insider purchase to the market capitalization of the corresponding day (*Percentage Mkt Cap*). The mean insider net purchase is 12.35% of the daily volume of transactions (the median being 3.60%). The ratio of net insider purchases to market capitalization ranges from 0 percent to 3.12 percent. In terms of relative size, insider sales and purchases are comparable.

[Table 1](#) shows two important statistics on the time at which insider trades are reported to the SEC: the disclosure and the resting times. The disclosure time is the difference (in days) between the trading day and the reporting day. The average reporting delay is 22.11 days for purchases and 22.75 days for sales. [Table 1](#) also shows the resting time, which is the gap (in days) between the theoretical due date and the recorded time. The median of the resting time is 1 day, and the first quartile is 0, for both purchases and sales. Thus, 25% of insider trades are reported within 30 days. Some 75% of insiders submit their reports before the due date.

3.3.2. Market reactions

In this part, we replicate [Lakonishok and Lee's \(2001\)](#) event study approach to check whether we are working within the same empirical context. [Table 2](#) displays the market reaction to insider net purchases and sales around the transaction dates. We compute the daily abnormal returns using a Beta-one model, which consists of subtract-

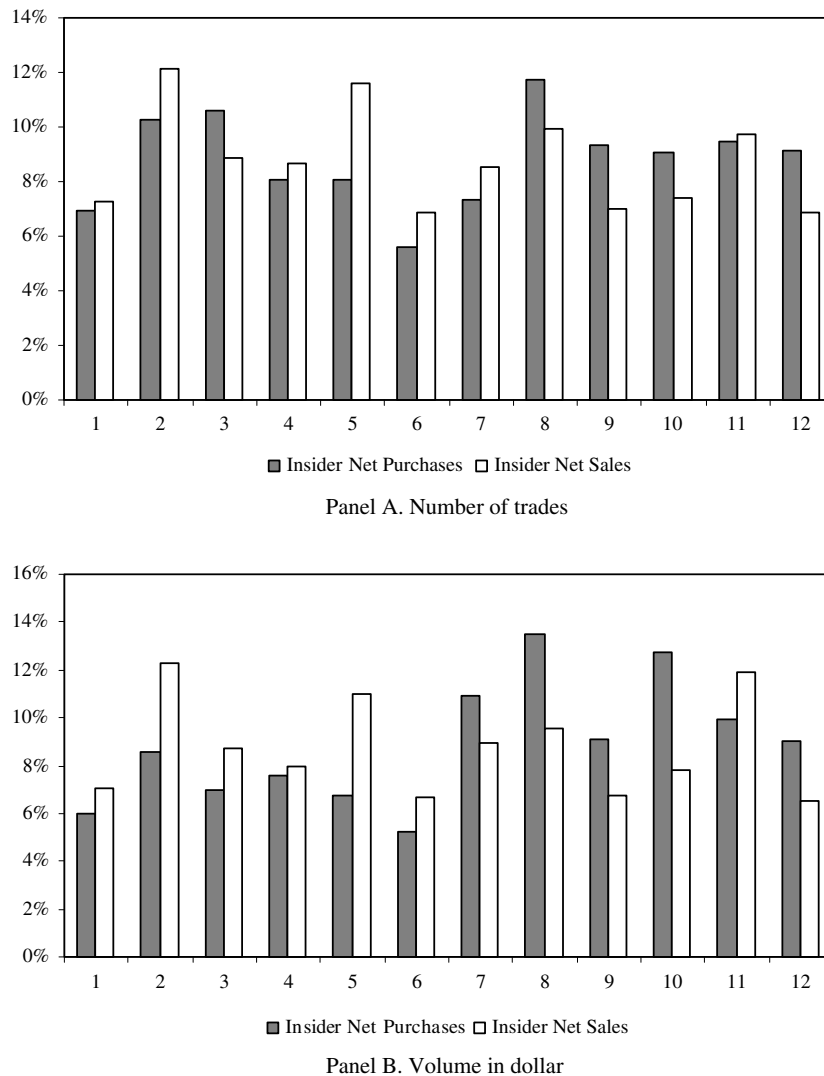


Fig. 2. Insider trades aggregated per month. This figure displays the evolution of the average proportion of the aggregated insider net purchases and net sales per month. The X-axis represents the month of the year. Panel A and Panel B consider the number of insider trades and the volume in dollar, respectively.

ing the daily market portfolio return from the daily return of each company. We use the daily equally weighted CRSP index as a proxy for the market portfolio. We calculate both two-day ($CAR_{0,1}$) and five-day ($CAR_{0,4}$) average cumulative abnormal returns by taking the average of the abnormal returns for each insider transaction.

For the entire sample, the two-day abnormal returns are 0.144% and 0.278%, respectively, for net purchases and net sales. The corresponding figures for the five-day returns are 0.417% and 0.225%. The two-day average CAR for purchases is lower than that for sales. However, when we increase the length of the event window, the average CAR on insider net sale days is smaller than the average CAR on insider net buy days. We also examine the average CAR as a function of trade size. As expected, the market impact appears to increase with trade size. Although these abnormal returns are statistically significant at conventional levels, they represent a weak economic

response to insider trades, which is consistent with [Lakonishok and Lee's \(2001\)](#) results.

It is quite puzzling to observe positive abnormal returns for insider sales. There are at least four possible explanations for this result. First, in comparison to buys, insider sells are more likely to be driven by motives other than private information (e.g. diversification and liquidity reasons, see [Lakonishok and Lee, 2001](#); [Jeng et al., 2003](#); [Fidrmuc et al., 2006](#)). Second, insiders may sell stock when the market is dominated by the buy side, probably due to positive public announcements. Indeed, [Huddart et al. \(2007\)](#) have documented that insiders sell after good earnings announcements. The third and fourth potential explanations have already been mentioned in the introduction. It is possible that insiders have some market timing ability ([Jenter, 2005](#); [Piotroski and Roulstone, 2005](#)). And finally, it is also possible that using CAR is not a good way to capture information asymmetry.

Table 1
Summary statistics of insider trading activities

	Mean	Min	Q1	Median	Q3	Max
<i>Panel A. Insider net purchases</i>						
Events by firm	9	0	2	6	12	286
Mkt Cap (\$'000)	2,632,963	11,337	289,311	606,308	1,670,704	209,144,834
Trade quantity	14,612	100	1,000	2,270	10,000	5,799,432
Trade value (\$)	298,350	200	15,000	44,820	155,000	50,446,608
Percentage Volume (%)	12.35	0.00	0.70	3.60	15.49	99.43
Percentage Mkt Cap (%)	0.03	0.00	0.00	0.01	0.03	3.12
Disclosure time	22.11	0.00	14.00	21.00	30.00	70.00
Resting time	2.47	−30.00	0.00	1.00	4.00	38.71
<i>Panel B. Insider net sales</i>						
Events by firm	19	0	2	9	26	233
Market Value (\$'000)	7,217,954	11,337	526,281	1,591,086	6,032,857	209,144,834
Trade quantity	25,561	100	2,500	7,400	20,000	6,610,129
Trade value (\$)	1,031,844	114	74,380	237,420	753,800	243,529,545
Percentage Volume (%)	11.91	0.00	1.34	4.88	15.05	99.80
Percentage Mkt Cap (%)	0.05	0.00	0.00	0.01	0.04	19.16
Disclosure time	22.75	0.00	14.20	22.00	30.00	70.00
Resting time	1.89	−30.00	0.00	1.00	3.00	38.00

This table reports summary statistics of insider net purchases (Panel A) and net sales (Panel B) for all NYSE/AMEX common shares over the period from January 1995 to the end of September 1999. The total number of firms in our sample is 2110. ‘*Events by firm*’ corresponds to the number of insider trade days (net purchase or net sell days) for a sample firm. ‘*Mkt Cap*’ is the market capitalization on the month of the insider trade (number of shares outstanding multiplied by the share price of the corresponding month). The descriptive statistics have been computed with respect to the considered events. ‘*Trade quantity*’ refers to the size in number of shares of the insider net purchases (sales) per event. ‘*Trade value*’ is the net insider purchases (sales) in USD. ‘*Percentage Volume*’ is the ratio of the net insider purchases (sales) to the volume of the corresponding day. ‘*Percentage Mkt Cap*’ is the ratio of the net insider purchases (sales) to the market capitalization of the corresponding month. ‘*Disclosure time*’ is the time (in number of days) between the recorded time and the transaction time. ‘*Resting time*’ is the time (in number of days) between the theoretical due date and the recorded time. Q1 and Q3 correspond to the first and third quartile, respectively.

Table 2
Market reactions to insider trading activities

	Net purchases		Net sells	
	CAR _{0,1}	CAR _{0,4}	CAR _{0,1}	CAR _{0,4}
<i>Panel A. All sample</i>				
Abnormal returns	0.144	0.417	0.278	0.225
p-value	0.000	0.000	0.000	0.000
<i>Panel B. Split by trade size</i>				
Trade Value ≤ Q1				
Abnormal returns	0.023	0.187	0.104	0.021
p-value	0.729	0.033	0.009	0.718
Q1 < Trade Value ≤ Q2				
Abnormal returns	0.200	0.522	0.274	0.214
p-value	0.001	0.000	0.000	0.000
Q2 < Trade Value ≤ Q3				
Abnormal returns	0.130	0.524	0.325	0.333
p-value	0.033	0.000	0.000	0.000
Q3 < Trade Value				
Abnormal returns	0.225	0.435	0.411	0.331
p-value	0.000	0.000	0.000	0.000

This table reports average cumulative abnormal returns in percentage around insider net purchases and insider net sells for all companies in the sample. Panel A deals with the all sample, and Panel B provides a split of the sample by trade size. Q_x denotes the quartile x reported in Table 1, and CAR_{0,1} (CAR_{0,4}) corresponds to the average of the cumulated abnormal return between day 0 and day +1 (+4) relative to the transaction date. As in Lakonishok and Lee (2001), we calculate daily abnormal returns by subtracting the equally weighted CRSP index daily return from the daily return of a firm's stock.

3.3.3. Market conditions

Table 3 displays some simple and intuitive measures for comparing market conditions on insider trading (IT) and other (NoIT) days, using both intraday transaction and quote data. The variables are first measured for each stock and for each day. Once we have our daily observations, we compute the percentage difference for each stock by averaging the variable over IT (\bar{X}_i^{IT}) and NoIT (\bar{X}_i^{NoIT}) days, and dividing the difference by the average on NoIT days. This gives us a percentage abnormal change in price due to insider trading for each of our sample stocks over the period being studied. To get the average percentage difference (%difference), we average across our stocks according to the following equation:

$$\% \text{difference} = \frac{1}{N} \sum_{i=1}^N \frac{\bar{X}_i^{IT} - \bar{X}_i^{NoIT}}{\bar{X}_i^{NoIT}}, \quad (4)$$

where N denotes the number of firms in the sample. Table 3 also provides the p -values to check whether the %difference is statistically different from 0. The variables (X_i) are either daily averages (e.g., price, percentage quoted spread) or daily accumulations (e.g., trade volume, quantity volume).

Although the abnormal returns are significantly positive, the price is on average lower on insider net purchase days (and higher on insider net sale days) than on other days. Insider purchase days are days of high volume, both in terms of trade and of share exchanged. However, on

Table 3
Comparison of market conditions between days of insider trading and other days

Market variables	Description	Net purchases		Net sales	
		%Difference	p-value	%Difference	p-value
Price	Average transaction price	−7.7	0.00	4.0	0.00
Trade volume	Number of trades	2.8	0.00	−1.4	0.00
Quantity volume	Number of shares exchanged	5.5	0.00	−2.8	0.00
\$ volume	Number of shares exchanged in dollar value	−2.5	0.00	1.3	0.01
Percentage quoted spread	Average of (<i>quoted spread</i> /midpoint)	7.0	0.00	−3.5	0.00
Percentage effective spread	Average of (<i>effective spread</i> /midpoint)	1.5	0.00	−0.7	0.00
Ask depth	Average depth at the ‘ask’ side	4.0	0.00	−2.0	0.00
Bid depth	Average depth at the ‘bid’ side	6.4	0.00	−3.3	0.00
Depth	Average of ‘ask depth + bid depth’	5.2	0.00	−2.7	0.00
Composite liquidity	Average of ‘percentage quoted spread/dollar depth’	12.8	0.00	−6.5	0.00
Relative order imbalance	Buys minus sells, divided by buys plus sells (in number)	−84.0	1.00	42.9	0.43
Volume relative order imbalance	Buys minus sells, divided by buys plus sells (in volume)	86.0	0.71	−43.9	0.80
Value relative order imbalance	Buys minus sells, divided by buys plus sells (in dollar)	−654.5	0.05	334.1	0.40

This table compares market conditions between days of insider trading and other days. The considered variable are either daily average (e.g., ‘price’, ‘percentage quoted spread’) or daily accumulation (e.g., ‘trade volume’, ‘quantity volume’). ‘%Difference’ corresponds to the difference in percentage between these two categories of days, averaged across stocks. The ‘ask’ (‘bid’) price is the price at which the market maker is willing to sell (buy) the stock. The ‘quoted spread’ corresponds to the difference between the ask price and the bid price. The ‘midpoint’ is the average of the ask price and the bid price ($(ask+bid)/2$). The ‘effective spread’ corresponds to the absolute difference between the transaction price and the midpoint, divided by 2. The ‘ask depth’ (‘bid depth’) is the maximum quantity of stock the market maker is willing to sell (buy) at the ask price. The ‘dollar depth’ is the weighted sum of the ask depth and the bid depth, the weights being the ask price and the bid price. The reported *p*-value tests whether the ‘%Difference’ is statistically significant or not.

insider net sale days the volume of trade is lower than, and the dollar value is not statistically different from, that on other days. These results are consistent with recent findings by Jenter (2005) and Piotroski and Roulstone (2005) suggesting that insiders have market timing ability.

Table 3 shows that the percentage quoted spread widens on insider purchase days. This contrasts to some extent with Chung and Charoenwong’s (1998) results. According to their analysis, market makers establish larger spreads for stocks where insider trading is more prevalent, but there is no evidence of spread changes on insider trading days. Table 3 also shows that the percentage quoted spread narrows on insider sale days. Combined with the result reported above on *CAR*, this could suggest that there is a reduction in the information asymmetry on the market, probably due to public announcements. In fact, Huddart et al. (2007) have documented that insider trades tend to cluster on days after earning announcements, and Chae (2005) has shown that volume is higher and measures of information asymmetry lower after earning announcements.

The impact of insider trades on market depth goes in the opposite direction. Our depth measures are greater on insider purchase days and lower on insider sale days. To gain a better understanding of the impact of insider trading on market liquidity, we use the *composite liquidity* measure proposed by Chordia et al. (2001), which corresponds to the ratio between the *percentage quoted spread* and the *dollar depth*. This measure suggests that insider purchase days are days of low liquidity, and insider sale days are days of high liquidity. The increase in spread on purchase days is not compensated for by an increase in depth, nor is the decrease in spread on sale days offset by a decrease in depth.

Table 3 also compares trade imbalance measures for insider trading days with similar measures for other days. It is important to note that, on neither insider purchase nor sale days do the *ROIB* or the *volume ROIB* differ statistically from their values on other days.¹⁰ Based on these two measures, insider trades do not, on average, modify the trade imbalance. The question of the sensitivity of the return to the trade imbalance is explored in the next section.

4. Results

4.1. Are insider trades informative?

The analysis of abnormal returns in the previous section showed that financial markets only respond weakly to insider purchases, and the response to insider sales does not have the expected sign. Moreover, insiders do not significantly modify the trade imbalance with their transactions. This result is important because in Eq. (3) we assumed a linear relation between *ROIB* and the return. If this relation is not linear (but is, for example, a quadratic function), and if the trade imbalance is significantly different from other days on insider trading days, our specification would conclude that there had been a change in the slope while in reality there might be only a location change on the *Y*-axis.

Next we turn to the analysis of the sensitivity of the return to the order imbalance on insider purchase and sale days using Eq. (3). Remember that if insider trades convey

¹⁰ This result for the value *ROIB* is quite puzzling, but seems to be driven by some extreme values.

valuable information about future prices, we expect to observe increasing price sensitivity in absolute value on insider trading days. According to Eq. (3), this corresponds to a significant positive δ_{BUY} or negative δ_{SELL} coefficient. Table 4 shows the fixed effect panel regression estimation of this equation. The dependent variable is the daily return over time.

4.1.1. Price sensitivity change due to insider trades

Model 1 provides an analysis of the change in price sensitivity induced by insider trades. The independent variables are the signed relative order imbalance (ROIB), the cross product between the absolute ROIB and the ratio of insider net purchases on a given day to the total volume of that day (*insider buy*), and the cross product between the absolute ROIB and the ratio of insider net sales on a given day to the total volume of that day (*insider sell*). The coefficients of these two cross-product variables measure the abnormal price sensitivity change induced by insider purchases and sales, respectively. They correspond to the coefficients δ_{BUY} and δ_{SELL} in Eq. (3). The coefficient of ROIB is 0.02410, which is statistically significant, showing that a positive imbalance (number of buys > number of sells) impacts positively on the return. The coefficient of $|\text{ROIB}| \times \text{insider buy}$ is also positive and statistically significant. This indicates that the sensitivity of the return to trade imbalance on insider purchase days is higher than on other days, which is a clear indication that information is being incorporated into prices. The coefficient of $|\text{ROIB}| \times \text{insider sell}$ is not significant, and does not have the expected sign. This result suggests that insider sales are either not information-based (on average) or that the other investors (and/or the market makers) are not able to detect their presence in the market.

4.1.2. Price sensitivity change due to abnormal insider trades

Since their physical and human capital is invested disproportionately in their company (see, for example, Hall and Murphy, 2002; Becker, 2006), insiders are known to be structurally more frequently sellers than buyers of their own company stocks, mainly for diversification and liquidity reason (e.g., Lakonishok and Lee, 2001; Iqbal and Shetty, 2002; Jenter, 2005). In order to isolate the effect of information-based insider trading on price sensitivity we need to control for managers' incentives to diversify. To estimate the normal level of insider trading, we regress the percentage of insider net purchases (and net sales) on a set of determinants (as Jenter (2005) did). Abnormal insider purchases (sales) correspond to the unexplained part of the regression. We include the following variables in the regressions: *total return over the last 12 months* (corporate insiders are more likely to rebalance their portfolios after large price changes); *market capitalization* (insiders in large firms are more likely to sell company shares than insiders in small firms); *total stock return volatility over the last 12 months* (Meulbroek (2000) shows that managers in more risky companies tend to sell equity more aggressively). We also control for the changing firm risk by including the volatility change between the two successive 6-month periods immediately prior to the insider trade under consideration. These first step regressions (for both purchases and sales) have significant Fisher statistics, with all the estimated coefficients being statistically significant. For ease of exposition, these first step regressions are not displayed in Table 4.

The estimation of Eq. (3) using insider abnormal trades is given in the Model 2 column in Table 4. In order to have robust standard errors, the regressions are estimated using a GMM estimator. When trades which are probably under-

Table 4
Insider trades and price sensitivity change to relative order imbalance

Independent variables	Model 1	Model 2	Model 3	Model 4
ROIB	0.02410 (0.00)	0.02410 (0.00)	0.02330 (0.00)	0.02046 (0.00)
$ \text{ROIB} \times \text{insider buy}$	0.01656 (0.00)			
$ \text{ROIB} \times \text{insider sell}$	0.00167 (0.27)			
$ \text{ROIB} \times \text{insider abnormal buy}$		0.01720 (0.00)	0.01672 (0.00)	0.01725 (0.00)
$ \text{ROIB} \times \text{insider abnormal sell}$		−0.02361 (0.00)	−0.02367 (0.00)	−0.02384 (0.00)
ROIB \times percentage volume			0.01393 (0.25)	
ROIB \times composite liquidity			6.39934 (0.00)	
ROIB \times % quoted spread				0.37446 (0.00)
ROIB \times depth				−0.20369 (0.00)
Fisher Test	64,422 (0.00)	64,432 (0.00)	40,010 (0.00)	42,179 (0.00)
N	2,042,438	2,042,438	2,042,438	2,042,438
Adjusted R^2	0.086	0.086	0.089	0.093

This table provides fixed effect panel regression estimation of Eq. (3). For each model, the dependent variable is the daily return. Model 1 provides an analysis of the price sensitivity change induced by insider trades. ROIB is the signed order imbalance, $|\text{ROIB}|$ is the absolute value of ROIB, '*insider buy*' ('*insider sell*') corresponds to the ratio of the insider net purchases (sales) on a given day to the total volume of that day. To compute the *p*-value we use White's heteroscedasticity-consistent covariance matrix estimators. Model 2 provides an analysis of the price sensitivity change induced by insider abnormal trades. '*insider abnormal buy*' ('*insider abnormal sell*') corresponds to the unexplained part of a first step regression, where '*insider buy*' ('*insider sell*') are regressed on a set of determinants. Model 3 and Model 4 extend the specification of Model 2 by controlling for volume and liquidity. The used control variables are '*percentage volume*' (volume of the trading day divided by the total number of shares outstanding), '*composite liquidity*', '*% quoted spread*', and '*depth*'. In order to have robust standard errors, the regressions have been estimated using GMM estimator. *p*-values are within brackets. We do not report firm specific fixed effects in the table. '*N*' denotes the number of observations entering into the panel estimation.

taken for diversification reason are controlled for, both insider purchases and sales significantly hasten price discovery. The coefficient of the cross product variable $|\text{ROIB}| \times \text{insider abnormal sell}$ is -0.02361 . It has the expected negative sign and is statistically significant, suggesting that the returns on insider sale days are more sensitive to the order imbalance of other traders. If the imbalance is negative on insider sale days, insiders' trading amplifies the impounding of the order imbalance into (negative) returns. If the imbalance is positive, insider sale trades attenuate the buy order imbalances of other traders. This is a clear indication that insiders allow information incorporation into prices by their abnormal selling activities.

Models 3 and 4 extend the specification of Model 2 by controlling for market conditions on insider trading days. According to Table 3, insider trading days have market conditions (in terms of volume and liquidity) which differ from other days. Ignoring this in the specification could lead to the conclusion that price sensitivity is increasing, when in fact any change is a consequence of, for example, a difference in liquidity. Model 3 shows that, once we control for the volume of the trading day (in percentage of the total number of shares outstanding) and the liquidity (measured as in Table 3 by the ratio of the *percentage quoted spread* to the *dollar depth*), the coefficients of interest remain significant. Our results seem not to depend on different market conditions prevailing on insider trading days. Note that the control variables in Models 3 and 4 have the expected sign with respect to the liquidity measures. The lower the market liquidity, the higher is the sensitivity of the return to the order imbalance, and the higher the spread (or the lower the depth), the higher is the sensitivity of the return to the order imbalance.

Overall, our results suggest that insider (abnormal) trading allows faster price discovery.

4.1.3. Is there any price reversal on subsequent days?

It could be argued that the price sensitivity changes on insider trading days are not due to the incorporation of private information into the price, but rather to price pressure caused by the intensity of insider trading. At first sight, this is unlikely given the fact that the average level of the ROIB on insider trading days is not significantly different from the level on other days (see above). However, to demonstrate more convincingly that the price sensitivity change is not driven by temporary price pressure, we need to show that there is no price reversal in the days following insider trading. In other words, once we control for both the general level of the ROIB and the insider trading intensity on day t , where there is a price reversal, the contemporaneous return should be negatively associated with the previous day's ROIB weighted by a measure of insider net purchase. For sales, the association should be positive. To implement a test for price reversal, we estimate an equation similar to Eq. (3) with the addition of the one day lagged cross product variable between the ROIB and a measure of insider

trading activity. The estimated equation, for both insider purchase and sale days, has the following structure:

$$\begin{aligned} R_{i,t} = & \alpha_i + \beta \text{ROIB}_{i,t} + \delta_{\text{BUY}}(|\text{ROIB}_{i,t}| \times \text{IBUY}_{i,t}) \\ & + \delta_{\text{SELL}}(|\text{ROIB}_{i,t}| \times \text{ISELL}_{i,t}) \\ & + \gamma_{\text{BUY}}(|\text{ROIB}_{i,t-1}| \times \text{IBUY}_{i,t-1}) \\ & + \gamma_{\text{SELL}}(|\text{ROIB}_{i,t-1}| \times \text{IBUY}_{i,t-1}) + \varepsilon_{i,t}. \end{aligned} \quad (5)$$

If there is a price reversal, the coefficient γ_{BUY} should be negative and the coefficient γ_{SELL} positive. For ease of discussion, only one lag is used in Eq. (5), but in Table 5 we report estimations with five lags. Table 5 shows that the ROIB on a given insider purchase day, weighted by the abnormal insider purchase, does not have a significant negative impact on the return on the subsequent five days. In other words, there is no price reversal, suggesting that the price sensitivity change to ROIB on insider purchase days is not driven by price pressure. We also got the expected result for insider sales. None of the coefficients associated with the lagged cross product variable is statistically significant.

4.1.4. Price sensitivity on reporting days

Table 6 shows the analysis of reporting days. The official reporting day does not always correspond to the day on which the reporting is made public. There can be a time delay of a few days, varying from case to case (Chang and Suk, 1998). This is why we also analyze the days subsequent to the reporting day. We estimate the same panel

Table 5
Is there any price reversal on subsequent days?

Independent variables	Coefficient	p-value
ROIB	0.02410	0.00
$ \text{ROIB} \times \text{insider abnormal buy}$	0.01466	0.00
$ \text{ROIB} \times \text{insider abnormal sell}$	-0.02368	0.00
$(\text{ROIB} \times \text{insider abnormal buy})_{t-1}$	0.00674	0.04
$(\text{ROIB} \times \text{insider abnormal buy})_{t-2}$	0.00535	0.11
$(\text{ROIB} \times \text{insider abnormal buy})_{t-3}$	0.00051	0.87
$(\text{ROIB} \times \text{insider abnormal buy})_{t-4}$	0.00372	0.18
$(\text{ROIB} \times \text{insider abnormal buy})_{t-5}$	-0.00006	0.98
$(\text{ROIB} \times \text{insider abnormal sell})_{t-1}$	-0.00214	0.29
$(\text{ROIB} \times \text{insider abnormal sell})_{t-2}$	0.00397	0.11
$(\text{ROIB} \times \text{insider abnormal sell})_{t-3}$	0.00129	0.52
$(\text{ROIB} \times \text{insider abnormal sell})_{t-4}$	-0.00068	0.72
$(\text{ROIB} \times \text{insider abnormal sell})_{t-5}$	-0.00087	0.68
Fisher test	14,827	0.00
N	2,042,438	
Adjusted R^2	0.087	

This table provides fixed effect panel regression estimation of Eq. (5) to check whether there are price reversals on subsequent days to insider trading days. The dependent variable is the daily return. ROIB is the signed order imbalance, $|\text{ROIB}|$ is the absolute value of ROIB, 'insider abnormal buy' ('insider abnormal sell') measure insider trading intensity and corresponds to the unexplained part of a first step regression, where 'insider buy' ('insider sell') is regressed on a set of determinants. In order to have robust standard errors, the regression has been estimated using GMM estimator. p-values are within brackets. We do not report firm specific fixed effects in the table. 'N' denotes the number of observations entering into the panel estimation.

Table 6
Insider reporting days and price sensitivity change to relative order imbalance

Independent variables	Coefficient	p-value
ROIB	0.02410	0.00
ROIB × insider abnormal buy	0.01666	0.00
ROIB × insider abnormal sell	−0.02357	0.00
ROIB × Reporting0_buy	0.00084	0.03
ROIB × Reporting1_buy	0.00021	0.26
ROIB × Reporting2_buy	0.00203	0.00
ROIB × Reporting3_buy	0.00053	0.22
ROIB × Reporting0_sell	0.00008	0.85
ROIB × Reporting1_sell	−0.00096	0.05
ROIB × Reporting2_sell	−0.00038	0.40
ROIB × Reporting3_sell	−0.00025	0.63
Fisher Test	17,573	0.00
N	2,042,438	
Adjusted R ²	0.086	

This table provides fixed effect panel regression estimation of Eq. (3) where we have also identified insider reporting days ('Reporting0') and the successive days. The variable 'Reporting0_buy' ('Reporting0_sell') takes the value of the aggregated insider net purchases (sales) expressed in percentage of the daily trading volume on the reporting day and 0 otherwise. The following three subsequent days to the reporting day are identified by 'Reporting1', 'Reporting2' and 'Reporting3', respectively. In order to have robust standard errors, the regressions have been estimated using GMM estimator. *N* denotes the number of observations entering into the panel estimation.

regression model. As well as of identifying days of insider trading, we also identify days of reporting. The variable 'Reporting0_buy' ('Reporting0_sell') takes the value of the aggregated insider net purchases (sales) expressed as a percentage of the daily trading volume on the reporting day and 0 otherwise. The three days subsequent to the reporting day are identified as *Reporting1*, *Reporting2* and *Reporting3*.

The results in Table 6 suggest that information is significantly incorporated into prices on the reporting day of an aggregated insider net purchase. The coefficient associated with the cross product variable |ROIB| × *Reporting0_buy* is positive (0.00084) and statistically significant. This result indicates the importance of the reporting imposed by regulation, because this activity allows additional information to be incorporated into asset prices. The change in the return sensitivity to an order imbalance due to the reporting of insider purchases is also significant two days after the recording day and is in fact much stronger. For the reporting of aggregated net insider sales, additional information seems to be incorporated the day after the reporting.

4.2. Robustness checks

This sub-section is devoted to some analyses of robustness. First, we want to be sure that our results were not due to chance. Then, we consider the value of the insider trades in dollars, and perform the same empirical analysis using two alternative measures of ROIB. Finally, we remove days for which the abnormal insider purchases or

sales are below the first decile or above the ninth decile from our insider events.

4.2.1. Are our results due to chance?

We implement a model-based bootstrap (MbM) scheme to test whether our results were due to chance (see Davison and Hinkley, 1997). The used bootstrap scheme has six steps:

1. First, we estimate Eq. (3) without taking into account the cross product variable between the ROIB and net abnormal insider purchases and sales: $R_{i,t} = \alpha_i + \beta \text{ROIB}_{i,t} + \varepsilon_{i,t}$.
2. Then we compute the residual of the estimated model ($e_{i,t}$) as $\hat{e}_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta} \text{ROIB}_{i,t})$ for each stock.
3. For each stock, we randomly draw a residual from the corresponding previous series, and then we recompose the initial return series by adding this residual ($\hat{e}_{i,t}^*$) to the estimated return: $\hat{R}_{i,t}^* = (\hat{\alpha}_i + \hat{\beta} \text{ROIB}_{i,t}) + \hat{e}_{i,t}^*$.
4. With our new return series we re-estimate the model in Eq. (3).
5. We save the heteroscedastic consistent *t*-statistic.
6. Steps 3 to 5 are repeated 1,000 times.

In this way, we derive simulated distributions for the *t*-statistics under the null hypothesis that insider trading do not contribute to market efficiency. If our results are not due to chance, we expect the *t*-statistics of the coefficients δ_{BUY} and δ_{SELL} to be significantly larger than those obtained through the MbB simulations. Panel A of Table 7 gives the number of times the simulated *t*-statistics are larger than the original *t*-statistics, as well as the number of times the simulated *p*-value is equal to or below 0.05. These results clearly show the robustness of our finding that abnormal insider purchase and sale days permit faster price discovery.

4.2.2. Insider trades in dollar

Panel B displays the estimation of Model 2 from Table 4 using abnormal insider dollar trades instead of the number of shares. The use of dollar volumes does not alter the results presented in Table 4 substantially.

4.2.3. Trade ROIB versus volume and dollar ROIB

We replicated Model 2 from Table 4 using alternative measures of ROIB. Panel C of Table 7 shows the estimations of Eq. (3) using the *quantity ROIB* and the *dollar ROIB*. It is clear that the results are almost identical.

4.2.4. Truncating insider trades

To check that our results are not driven by larger insider trades, we remove days on which the abnormal insider purchases or sales are below the first decile or above the ninth decile from the insider episodes. The changes in the sensitivity of the return to order imbalance due to purchases and sales remain significant and with the expected sign.

Table 7
Robustness checks

	Count	Proportion		
<i>Panel A. Are our results due to chance?</i>				
Abnormal insider purchase				
T _{MbB} > T _{BUY}	0	0.00%		
p-value _{MbB} < 0.05	48	4.80%		
Abnormal insider sell				
T _{MbB} > T _{BUY}	0	0.00%		
p-value _{MbB} < 0.05	59	5.91%		
Number of simulation	1,000			
<i>Panel B. Insider trades in dollar</i>				
Independent variables	Coefficient	p-value		
ROIB	0.02410	0.00		
ROIB × \$ insider abnormal buy	0.01511	0.00		
ROIB × \$ insider abnormal sell	−0.02506	0.00		
Fisher Test	64,433	0.00		
N	2,042,438			
Adjusted R ²	0.086			
Independent variables	Volume ROIB		Dollar ROIB	
	Coef.	p-value	Coef.	p-value
<i>Panel C. Volume and dollar ROIB</i>				
ROIB	0.01864	0.00	0.01864	0.00
ROIB × insider abnormal buy	0.00864	0.00	0.00860	0.00
ROIB × insider abnormal sell	−0.01116	0.00	−0.01120	0.00
Fisher Test	74,162	0.00	74,186	0.00
N	2,196,212	2,196,212		
Adjusted R ²	0,098	0.098		
Independent variables	Coefficient		p-value	
<i>Panel D. Truncating the data</i>				
ROIB	0.02452		0.00	
ROIB × insider abnormal buy	0.02415		0.00	
ROIB × insider abnormal sell	−0.08874		0.00	
Fisher Test	61,197		0.00	
N	1,899,108			
Adjusted R ²	0.088			

Panel A shows the results obtained through a model-based bootstrap (MbB) approach to check whether our result is not due to chance. T_{BUY} corresponds to the *t*-statistic of the coefficient δ_{BUY} in Eq. (3). T_{Mbb} corresponds to the *t*-statistic of the same coefficient obtained through the MbB procedure at each iteration. Panel B displays the estimation of Model 2 in Table 4 using insider abnormal dollar trades instead of number of shares. Panel C replicates also Model 2 in Table 4 using volume ROIB and dollar ROIB, instead of trade ROIB. Panel D considers only insider abnormal trades within the first and last deciles.

This suggests that it is not just a small sub-set of large trades that carry private information.

5. Conclusion

So far, empirical evidence supporting the contribution of insiders to information efficiency is limited. Studies relying on short-term abnormal returns are at best ambiguous and show only limited impact, being hampered by potential

endogeneity problems and insiders' strategic behavior. The long-term abnormal performance of insiders' portfolios may simply be due to the public release of information in the months following insider trades.

The contribution of this paper stems from our method. Using insights from the recent microstructure literature, we studied, in a panel data analysis setting, the change in sensitivity of the return to the relative order imbalance induced by insider trading. The modest data requirements of our approach allowed us to deal with a very large sample of 59,244 daily aggregated insider trades in 2110 firms quoted on either the NYSE or the AMEX during the period 1995–1999.

Our results are unambiguous and robust with respect to several definitions of the relative order imbalance: insiders do contribute significantly to faster price discovery on insider trading days; disclosure requirements also contribute (although to a lesser extent) to market efficiency. The necessary condition for allowing regulated insider trading is fulfilled. Is this contribution sufficient, given the price paid by uninformed agents? This is an ethical question which remains open.

Acknowledgement

This paper was reviewed and accepted while Prof. Giorgio Szego was the Managing Editor of The Journal of Banking and Finance and by the past Editorial Board. We are grateful to Pascal Alphonse, Asli Asciglu, Luc Bauwens, Pierre Giot, Charles Jones, Maureen O'Hara, Christophe Perignon, Michel Robe, Avandhar Subrahmanyam, Giorgio Szego (the editor), Richard Roll, Antonio Rubia, participants at the University of Alicante seminar, the CORE Econometrics seminar and the Dauphine Workshop on Financial Market Quality, and an anonymous referee and associate editor for useful comments. We gratefully acknowledge financial support from the Europlace Institute of Finance.

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