Stock Price Patterns Around the Trades of Corporate Insiders on the London Stock Exchange

By

Sylvain Friederich, Alan Gregory,
John Matatko and Ian Tonks

DISCUSSION PAPER 332

September 1999

FINANCIAL MARKETS GROUP
AN ESRC RESEARCH CENTRE

LONDON SCHOOL OF ECONOMICS

E·S·R·C
ECONOMIC
& SOCIAL
RESEARCH
COUNCIL

ISSN 0956-8549-332

Stock Price Patterns around the Trades of Corporate Insiders on the London Stock Exchange[1]

Sylvain Friederich,[2,3] Alan Gregory, John Matatko, and Ian Tonks.

September 1999

[1]We thank Margaret Bray, Bob Nobay, Richard Payne, seminar participants at the LSE for comments. Remaining errors are, of course, ours.

[2]Corresponding author. Tel: (+44-207) 955-7893. Email: s.j.friederich@lse.ac.uk

[3]The authors are respectively affiliated with the Financial Markets Group, London School of Economics and TEAM, Université de Paris - I (Friederich), the School of Business and Management, University of Exeter (Gregory and Matatko), and the Financial Markets Group, LSE and Department of Economics, University of Bristol (Tonks).

Abstract

This paper examines the patterns of security returns around the trades of corporate insiders in the shares of their own company. We find patterns in abnormal returns in the days around a director's trade that are consistent with directors engaging in short-term market timing: they sell (buy) after an increase (decline) in prices, and their trades are followed by a partial price reversal. This provides strong evidence that directors trade to exploit patterns in share prices. We also find positive gross, but not net, abnormal returns to imitating some of the trades of directors once transactions costs implicit in the bid-ask spread are taken into account.

We also report that some types of trades have superior predictive content over future returns. In particular, we find that medium-sized trades are more informative for short-term returns than large ones, consistent with Barclay and Warner's (1993) "stealth trading" hypothesis.

Keywords: market efficiency, corporate insiders, insider trading, Directors' trading, informed trading.

JEL Classification: G 14

1 Introduction

Do the actions of corporate insiders convey information about future company prospects which are not available elsewhere? From the point of view of testing for market efficiency, one issue is whether corporate insiders have the ability to time the market, and consequently generate benefits, either for their firms, or for themselves personally. If they are able to generate abnormal profits, this could be interpreted as evidence against strong-form efficiency. Typically, financial regulators assume that corporate insiders' information is superior, and require that their actions be disclosed to the market. This leads to a second issue, of whether outsiders may obtain excess returns from mimicking the signals sent by the insiders' actions.[1] Significant abnormal returns following an insider's trade could be interpreted as evidence against semi-strong efficiency. Examples of actions potentially timed to benefit the firm are stock splits or issues, corporate repurchases or restructurings. An example of an action timed to benefit the corporate insider personally, and which typically must be disclosed after it has occurred is the trade of a corporate insider in the shares of his company.[2] This is the event that this paper focuses on.

In previous work, although there was evidence of long-run abnormal returns following the trades of corporate insiders, returns during the month (or even the two weeks) containing the trade were found to be not significantly different from zero. The current paper therefore examines the behaviour of daily returns immediately around the trades of corporate insiders. First, we identify *patterns* of price movements around the directors' trades which may provide evidence of trading on short-lived information as defined for instance in Admati and Pfleiderer (1988). This takes us closer to strong-form efficiency tests and to the debates on the detection and regulation of insider trading. Secondly, we ascertain the *size* of excess returns over the first month around the director's trade, in

[1] Appendix 1 gives more evidence on the interest that currently surrounds data on these trades among professional investors.

[2] Since both types of events are voluntary, they can be linked as in Bagnoli and Khanna (1992), in which the corporate event and the manager's expected profit from trading in his company's stocks are jointly determined. An empirical literature tying corporate transactions in the primary market and the manager's personal payoff in the secondary market has also developed. Examples are Karpoff and Lee (1991) and Lee (1997).

order to examine the profitability of a mimicking strategy in the short-term, and taking explicitly "round-trip" (spread) transaction costs into account.

We report evidence of trading around short-term price changes by corporate insiders over the sample period (October 1986-November 1994), in spite of regulatory arrangements. This provides strong evidence that directors trade to exploit patterns in share prices. Although these patterns are statistically significant, their economic significance is not necessarily a cause of great concern. Once an adjustment is made for transaction costs, potential short-term abnormal returns to outsiders are more or less whittled down to zero.

We also report that some signals dominate others in terms of predictive contents over future returns. Buy trades are followed on average by larger abnormal returns than sell trades. Yet an important difference with earlier work is that clustered trades strongly dominate large ones in terms of signal strength. We find that most of these trades are of medium size, and generally report evidence that medium-sized trades as a whole seem more informative than large ones. This is consistent with the "stealth trading" hypothesis of Barclay and Warner (1993). The most plausible interpretation is that informed traders try to make their trading on short-lived information less conspicuous to both market participants and regulatory bodies by avoiding block trades.

1.1 Related prior research

A long literature has developed examining whether corporate insiders seem to benefit from their trades and whether strategies mimicking these trades may also produce abnormal returns in the medium to long run. Early work in the US by Jaffe (1974) and Finnerty (1976) identified excess returns in the first few months after the director's trade, which suggests that insiders are able to predict and exploit future returns. However, this apparent semi-strong form inefficiency was explained away in a later study by Seyhun (1986) in terms of (estimated) transactions costs of trading. Further work by Bettis, Vickrey, and Vickrey (1997) reports that abnormal profits can be made when focusing only on the insiders' block trades (over 10,000 shares, following the definition of blocks used in US markets) as a signal, using again a measure of estimated transactions costs of mean spreads plus mean commissions. Lakonishok and Lee (1998) examine the information conveyed by corporate insiders's trades to the outsiders and also analyse whether the market seems to interpret this information correctly when it is disclosed. They report that, in spite of the fact that for smaller firms in particular, these signals do seem to predict higher returns, little market reaction to the disclosure of the event is noticeable in the short run. The authors interpret this finding along the lines of market under-reaction, a form of inefficiency. Jeng, Metrick, and Zeckhauser (1999) use portfolio performance measurement techniques to assess the profitability of these trades to the insider herself, and although abnormal returns are detected, they conclude that they are modest and should not be a cause of major concern to regulators.

Empirical work on directors' trading using UK data reports comparable findings. Early work by King and Röell (1988) and Pope, Morris, and Peel (1990) seemed to produce conflicting results: the first study reports positive abnormal returns after director purchases, while the second concludes that significant abnormal returns mostly follow director sales. Further work by Gregory, Matatko, Tonks, and Purkis (1994) and Gregory, Matatko, and Tonks (1997) reconciled those conflicting results by making signal definitions comparable and controlling for size effects. Evidence was found of small pre-transaction costs abnormal returns for some signal definitions. These two studies also identified two puzzling phenomena: in the former, there was no evidence of price reaction in the month of the directors' trade, with the implication that directors do not seem to trade on immediate price-sensitive information. These results, however, were not statistically significant. In the latter study, the authors found that the price reaction in the months after the directors' trades was, surprisingly, inversely related to the strength of the signal. They conjectured that this was because in the case of a strong signal, most of the price reaction occurred within the month of the trade. The current paper will attempt to reconcile these somewhat contradictory findings.

In many European countries, disclosure requirements for directors' trades are less stringent than in the U.K. or the U.S. The study of Eckbo and Smith (1998) for the Oslo stock Exchange reports economically insignificant abnormal performance by insiders. A related study by Kabir and Vermaelen (1996) examines the effect on market liquidity of the introduction on the Amsterdam Stock Exchange of a regulation forbidding corporate insiders to trade two months before an annual earnings announcement.

The next section reviews the insider trading debate and the regulation of the trades of corporate insiders. In section 3 we give more details on the data and methodology used. The following section presents the results. Finally, section 5 provides a summary and conclusion.

2 Insider trading and trade disclosure regulations

2.1 The insider trading debate

Financial economists are divided on the welfare benefits of trading by corporate insiders. These benefits may include alignment of managers' and shareholders' incentives, as well as increased price informativeness. Informed traders generally make markets more efficient, and insiders are just seen as a special kind of informed traders whose information has high precision and is acquired at no cost (see Dennert (1991), Hu and Noe (1997) for surveys, and the formal model by Leland (1992)). On the other hand, insider trading has obvious negative distributional aspects. The microstructure literature also shows how bid-ask spreads increase with the number of informed traders on a market, emphasizing the detrimental effects informed trading may have on market liquidity.

Typically, market authorities regulate against insider trading. An important argument for regulatory bodies is that of unfairness: there is no "victimless crime". Less informed or liquidity traders will pay, and market-wide liquidity could suffer because uninformed participants will tend to withdraw from the market. They therefore require company insiders to disclose their trades in the shares of their own firm.

2.2 Regulatory aspects

In the UK, the 1985 Companies' Act specifies that directors are prohibited from dealing in the securities of their own companies for a period of two months prior to the preliminary announcement of year-end or half-year results, and at other times prior to the announcement of price-sensitive information.[3] The difficulty is to define what "price-

[3]Note that, in the UK as in the US, further obligations with respect to Director's trading are quite often set out in the charters of individual companies, especially larger ones.

sensitive information" consists of: clearly included are dividend, earnings, acquisition or spin-off announcements, board appointments or departures, or security issues. This leaves a large grey area open to interpretation: as the Exchange literature indicates, "there are many events which can trigger significant movements in share prices, such as information on a new product, the fact that sales of a new product are not meeting expectations, or that the company has obtained a large order or embarked into a major redundancy programme", but in general "It is not feasible to define any theoretical percentage movement in a share price which will make a piece of information price-sensitive. Attempts at a precise definition of "price-sensitive" are not possible" (London Stock Exchange (1996), pp. 4 and 2, respectively). The disclosure of business and financial information is necessarily imperfect, and this leaves open the possibility of trading around undisclosed events causing short-term price changes.

The disclosure requirements for directors' trades are as follows: directors must inform their company "as soon as possible after the transaction and no later than the fifth business day" of any transaction carried out for their personal account. In turn, a listed company must inform the Stock Exchange of the transaction "without delay and no later than the end of the business day following receipt of the information by the company" (London Stock Exchange (1998), p. 8). The Stock Exchange disseminates this information immediately to data vendors as well as via its own "Regulatory News Service". (The company should also enter this transaction in the Company Register which is available for public inspection within three days of reporting by the insider, but this way of disseminating the information is nowadays much less important).

There is potential uncertainty regarding the starting date that should be used to compute outsiders' returns: the event date is known for the director's trade itself, but this only becomes an event for outsiders when the trade is disclosed to the market. In our computations we assume that some outsiders are able to mimic the director's trade on the day of the trade itself. This assumption can be seen as justified by Meulbroek (1992) who reports in her study of cases of illegal insider trading that the information about the trades of insiders gets quickly detected and incorporated into stock prices even without any disclosure. She concludes that "both the amounts traded by the insider and additional trade-specific characteristics lead to the market's recognition of the informed trading".

As a comparison of regulatory requirements, US regulators have taken a different approach: the Securities Exchange Act of 1934 requires insiders to refrain from trading on "material" undisclosed information, and to fill in statements of their holdings and in the first ten days of the month following the month in which the trade occurs. Profits made on short-term "swings" in prices (formally, within 6 months) must be surrendered to the company.[4] An important difference with the UK regulatory regime is that in the US, "insiders" are more broadly defined and in particular include large shareholders, who are subject to the same reporting requirements as company officers and directors.

3 Data and methodology

3.1 Data sources and sample selection

The data on the trades of directors for the period 1986-1990 were obtained on microfiches from the London Stock Exchange. For 1991-1994, the data were provided to us by Directus Ltd, a subsidiary of Barra which re-sells these data along with investment advice. For all companies listed, this dataset gives details of the identity of the director, the date of the trade, the quantity and direction of the shares traded. In most cases it also gives the transaction price (option-related trades were removed from the data). The stock price series used are adjusted for stock splits, stock dividends and issues.

As mentioned above, a contribution of this study is to adjust estimates of the profitability of mimicking strategies for microstructure-induced costs. The selection of stocks was therefore governed by the availability of daily bid and ask prices for February 1986 to end-November 1994, provided roughly in Datastream for deciles 1 to 4 of the constituents of the FT-All Share index. We chose not to focus on the most liquid stocks (FTSE 100 companies) because previous work by Gregory, Matatko, and Tonks (1997) showed higher gross abnormal returns in less-liquid securities. Our sample is compara-

[4] A recent theoretical literature models the welfare effects of these disclosure obligations. Examples are Fishman and Hagerty (1995), in which the trade reporting is used to manipulate the market, while the mandatory disclosure has in Huddart, Hughes, and Levine (1999) the effect of slowing down price discovery. We do not directly address these issues here.

tively homogeneous in terms of firm size, and we use a benchmark portfolio appropriate to our size distribution of firms.

A survivorship bias is possible in the sense that prices were not available for dead companies over the period, which includes companies taken over. Our aim is to see whether signals, on average, can be profitably exploited, and not to estimate the profitability of risk arbitrage strategies, or around any highly unusual event of the kind. Therefore, whether a small number of (possibly very high) returns made by directors whose companies were acquired would significantly bias estimates upward is an open question.

3.2 Descriptive statistics

Over these eight years and 196 companies, we observe a total of 4,399 trades (2,558 buy and 1,841 sell transactions), which represent the raw signal in our empirical work.[5]

Some descriptive statistics on individual (gross) signals are given in panel A of table 1: over the whole sample, the average buy transaction was worth about £66,000, dwarfed by the average sell of about £343,000. The median buy transaction was £6,650, and the median sell was £32,600. The distributions of both types of trades are clearly skewed to the right, with some very large transactions in both cases: the largest transaction on the buy side was almost £23 million (in 1988), while the largest sell was a staggering £154 million (in 1991). Sell transactions are slightly more infrequent, but much larger. Transactions are distributed fairly evenly over the eight-year period, though there appears to be slightly fewer in the last three years of the sample.

3.3 Returns and signal definitions

The basic signal of a director's trade is the *net* quantity of shares traded on an event day, as is standard in this literature, since on occasions, more than one director traded on the same day (occasionally in opposite directions). Signal filters were then applied

[5] The actual transaction price was missing for about 300 of these trades, in most cases for the first two years of the sample. For these we extracted the (unadjusted) price data from Datastream. This is not consequential since we are not computing the profitability of the trading strategy to the insider herself.

(detailed below). Panel B of table 1 reports descriptive statistics on the distribution of the net buy and sell trades, for every year and for the whole dataset. There were 3,409 event-days in total, 1,887 on which directors were net purchasers, and 1,522 when directors were net sellers. Directors as a whole were clearly net sellers of their companies' shares over the sample period.

To compute daily returns on each stock, semi-annual dividend payments were obtained and added back into prices on the ex-dividend dates to calculate daily returns. This yields observations for 2,091 daily returns for each company. We also computed daily returns on the FT-SE Mid 250 index, which will be used as a benchmark in abnormal returns computations. Descriptive statistics on index returns and company returns and spreads are given in panel C of table 1.

3.4 Methodology

We examine the short-term movements in returns around the event date to investigate the ability of directors to engage in "market-timing" using an event-study methodology. The use of daily data is central to our aims but also an advantage in econometric terms because the joint hypothesis or "bad-model" problem is much less serious in studies that focus on short return windows since daily expected returns are close to zero (as appears in our case in table 1) and therefore have little effect on estimates of abnormal returns. The only caveat in the interpretation of the results is that we are not claiming that the event is directly causing any observed pattern in returns, since the directors' trading process is endogenous with respect to the return series (like all market timing). Here, the event is triggered by a realised or expected change in the market value of the security.[6] In turn, mimicking by outsiders after the event may have the potential to move the market in the short-run.

The notation for the modelling of abnormal returns and testing procedures largely follows Campbell, Lo, and MacKinlay (1997) (chapter 4). Event time (a counter) is denoted by τ, with the event date corresponding to $\tau = 0$. The estimation window is defined as the interval from $\tau = T_0 + 1$, to $\tau = T_1$, followed by the event window ($\tau = T_1 + 1$ to $\tau = T_2$). Also let $L_1 = T_1 - T_0$ and $L_2 = T_2 - T_1$ be the length of

[6] the most famous example of this is the stock splits study by Fama, Fisher, Jensen and Roll (1969).

the estimation and the event windows, respectively. In this paper, the event window comprises 20 trading days around the event, while the estimation window is made up of the 200 trading days before this. Therefore, $T_0 = -221$, $T_1 = -21$, and $T_2 = 20$. We compute excess returns in the most standard way, using a market model in the definition of expected returns: Letting $R_{i\tau}$ be the daily observed return on the stock, the returns-generating process for firm i is deemed well-approximated by:

$$R_{i\tau} = \alpha_i + \beta_i Rmid_\tau + \varepsilon_{i\tau} \tag{1}$$

where we use the FT-SE Mid 250 index (to which a number of our firms actually belong) as a benchmark, since, as mentioned above, a significant size effect was found in Gregory, Matatko, and Tonks (1997).[7] Parameters $\widehat{\alpha}_i$ and $\widehat{\beta}_i$ are estimated by OLS over the estimation window defined above,and excess returns $AR_{i\tau}$ are computed as:

$$AR_{i\tau} = R_{i\tau} - \widehat{\alpha}_i - \widehat{\beta}_i Rmid_\tau \tag{2}$$

They are then averaged across events for every day in the event window, and average excess returns are cumulated to yield the familiar cumulative average abnormal return measure centered around the event date, denoted $\overline{CAR}(\tau_1, \tau_2)$:

$$\overline{CAR}(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \left(\frac{1}{N} \sum_{i=1}^{N} AR_{i\tau} \right) \tag{3}$$

where N is the number of events and $T_1 < \tau_1 \leq \tau_2 \leq T_2$. (This is used to accommodate different sampling intervals within the event window, e.g. the post-event period only).

4 Results

4.1 Full dataset

Using the full dataset[8] a first run through the data yielded the following results: for director buys, abnormal returns are significantly negative in the twenty days before the

[7] We also replicated all of the tests using a two-factor model where the first factor $Rall_t$ was the return on the FT-All share index and the second factor was $(Rmid_t - Rall_t)$. The results were insensitive to this change.

[8] Events occurring in the first year of the data are dropped to leave enough days in the estimation window, leaving 1702 buys and 1268 sells.

net purchase, implying that directors purchase shares on average after a downward run of share price movements (in the order of 3%). Over the second half of the event window, the share price clearly recovers and abnormal returns are positive on most days, so that abnormal returns over the 20 days after the director's trade average a significant 1.9%[9] (figure 1 and table 2). The patterns are symmetrical in the case of director sells, though the magnitude of abnormal returns is lower. Directors typically sell shares after a run of positive price movements over twenty days of about 1.25%, and abnormal returns are predominantly negative after the directors' net sale, so that excess returns have averaged about 1.5% twenty days after the event (figure 1 and table 3).

The striking feature of these patterns is that on average, directors appear to be able to time the market in the short run: there is evidence of trading on short-lived information. In some cases, this is evidence of economically significant insider trading. It can be seen that price reversals start occurring on the day before the directors trade, which implies that the price reversal is not caused by the event. These results are in contrast with those reported in Lakonishok and Lee (1998) for the US market, who state in the conclusion of their paper (p. 25) that "there is very little action around the time when insiders trade. The magnitude of the return observed is typically below 0.5 percent."[10]

The second noticeable fact is that larger stock price changes occur around purchases than around sales. These results, using all trades in the data, are made even more striking given that sell trades are on average more than six times larger than sells. If trades of comparable size are considered, the effect is much more pronounced (see below: signal filters). There is a corresponding finding in other papers on the trades of corporate insiders, such as Lakonishok and Lee (1998), or Jeng et al. (1999)[11] but also in the literature studying the price impact of block trades (e.g. Chan and Lakonishok (1993)). One explanation given is that block purchases convey more information than

[9] There are no significant abnormal returns outside this $[-20, 20]$ window.

[10] Jeng and al (1999) however find that one third of total abnormal returns accrue during the first month (one sixth over the first five days) for insider purchases.

[11] Although the post-event price patterns reported by Jeng et al. are quite different. They conjecture that the negative abnormal returns immediately after a sell transaction are essentially due to a price pressure effect. The patterns we find before the event do not seem consistent with this hypothesis.

block sells. Allen and Gorton (1992) for instance argue that decisions to buy should be more information-based and decisions to sell should be more liquidity-based on average. The interpretation cannot be directly extended to the case of directors' trades, since what we observe is not just a price impact due to the trade itself, unlike block trades.

As a first way of testing for the significance of these patterns, we report t-statistics for individual days and cumulative t-statistics over the whole of the event window in tables 2 and 3 (calculated as in Brown and Warner (1985), p. 7 and 29). In general, the significance of the abnormal returns goes down as we move away from the event. The results for buy trades appear strongly significant for most days taken individually, and the overall significance is also strong. The significance of patterns around sell trades is less pronounced, though a window of at least six days around the event is clearly significant. We examine these significance patterns at length below using alternative testing methodologies.

From these patterns in prices, it is clear why previous work using monthly data found returns in the month containing the trade to be about zero, and with little or no statistical significance: the changes in price before the trade largely cancels out that after the trade on average.

4.2 Robustness checks

4.2.1 Thin/non-synchronous trading

There are a number of zero returns for some securities in the data because of thin trading (stale quotes). Besides the fact that this induces (or increases) autocorrelation, and could pose a problem for significance testing, it might also bias the estimated betas and therefore the abnormal return measures. To adjust for this, the betas were recalculated following the Scholes and Williams (1977) procedure. For securities for which thin trading is an issue, abnormal returns are computed as:

$$AR_{i\tau} = R_{i\tau} - \widehat{\alpha}_i' - \widehat{\beta}_i' Rmid_\tau \tag{4}$$

where consistent estimates of beta and alpha are given as:

$$\widehat{\beta}_i' = (\widehat{\beta}_i^{-1} + \widehat{\beta}_i^{0} + \widehat{\beta}_i^{+1})/(1 + 2\widehat{\rho}_{1m}) \tag{5}$$

$$\widehat{\alpha}_i' = \frac{1}{L_1 - 2} \sum_{\tau=T_0+2}^{T_1-1} R_{i\tau} - \widehat{\beta}_i' \frac{1}{L_1 - 2} \sum_{\tau=T_0+2}^{T_1-1} Rmid_\tau \tag{6}$$

where $\widehat{\beta}_i^{-1}$ and $\widehat{\beta}_i^{+1}$ are the OLS estimation period values of $\frac{cov(R_{i\tau}, Rmid_{\tau-1})}{\sigma(Rmid_\tau)\sigma(Rmid_{\tau-1})}$ and $\frac{cov(R_{i\tau}, Rmid_{\tau+1})}{\sigma(Rmid_\tau)\sigma(Rmid_{\tau+1})}$, respectively, and where $\widehat{\rho}_{1m}$ is the estimated first-order autocorrelation coefficient for the index.

Scholes and Williams show how applying this adjustment to actively traded stocks leads to an overestimation of the Beta coefficients. There is no clear-cut way of determining a cutoff point to decide which securities are thinly traded. We sorted securities according to the number of zero returns in the data. The betas for the first three quartiles of securities in our sample were estimated in the usual way, while the above adjustment was applied to stocks to stocks in the bottom quartile.[12]

Although estimated alphas and betas were somewhat increased for these stocks, abnormal returns estimates were not significantly changed by applying this correction: the results, presented in table 6 are that for buy trades, 20-day cumulative average abnormal returns stand at 1.92% (with cumulative t-stat from day 0 of 9.67) while for sell trades, 20-day average $CARs$ amount to 1.46% (with cumulative t-stat from day 0 of -6.96). Applying the Scholes-Williams adjustment to half of the securities produced very comparable results.

4.2.2 Outlier checks

Very large abnormal returns seemed to appear in a few cases, and we ascertained that our results were not driven by a few influential observations by identifying outliers using the methodology presented in Hadi (1992, 1994). This detected 19 cases of extreme returns after buy trades, and only 3 cases of extreme returns after sell trades. Removing them lowered average $CARs$ after buy transactions to 1.66% and after sell trades to 1.48% (virtually unchanged). Therefore the impact of this correction, while not negligible in the case of buys, did not significantly alter our findings.

[12] Eight securities in the bottom quartile of liquidity displayed a higher occurrence of both zero and missing returns, and a higher-order adjustment was applied (see Fowler and Rorke (1983)) corresponding to: $\widehat{\beta}_i = (\beta_i^{-2} + \beta_i^{-1} + \beta_i^0 + \beta_i^{+1} + \beta_i^{+2})/(1 + 2\rho_{1m} + 2\rho_{2m})$

4.3 Significance issues

Besides the "bad model" problem mentioned above, the other major econometric issue in event studies is that the significance of the results itself can be affected by a number of factors. Standard t-tests may reject the null too often in the absence of abnormal performance, mostly because of biased standard errors, or because t-tests have low power. We now consider in turn which of these issues could be the most relevant for our study.

4.3.1 Variance changes

A first issue is that the variance of returns in the event window may be different from the variance in the estimation period, which violates the assumption of identically distributed excess returns. This is usually dubbed "event-induced change in variance", although the possible problem in our case is unlikely to be a change in variance caused by the event itself but by an underlying company event (creating short term price movements and therefore to an extent triggering the trade).

We use the test suggested by Boehmer, Musumeci, and Poulsen (1991) (BMP) shown to be robust to event-induced heteroskedasticity. Called the "standardized cross-sectional test", this involves computing the standardised residual on an event day as the estimated abnormal returns divided by their estimated standard deviation (assuming no heteroskedasticity), based on the residual variance from the estimation period ($\widehat{s}_i$), and the fact that they are prediction errors:

$$SR_{i\tau} = AR_{i\tau} \Bigg/ \widehat{s}_i \sqrt{1 + \frac{1}{L_1} + \frac{(Rmid_\tau - \overline{Rmid})^2}{\sum_{\tau=T_0+1}^{T_1} (Rmid_\tau - \overline{Rmid})^2}} \tag{7}$$

Then the standard deviation of these standardised excess returns is calculated cross-sectionally in the event period. The significance of the average standardised return is tested using the cross-sectionally estimated standard deviation. The (asymptotically unit normally distributed) test statistic is then, for a given event day τ:

$$Z = \frac{1}{N} \sum_{i=1}^{N} SR_{i\tau} \Bigg/ \sqrt{\frac{1}{N(N-1)} \sum_{i=1}^{N} \left(SR_{i\tau} - \sum_{i=1}^{N} \frac{SR_{i\tau}}{N} \right)^2} \tag{8}$$

The multi-day version of which is simply constructed by summing the average standardised residual in the denominator above over the event window, divided by

$$\sum_{\tau=\tau_1}^{\tau_2} \overline{SR}_\tau \Bigg/ \sqrt{\sum_{\tau=\tau_1}^{\tau_2} \widehat{s}^2(\overline{SR}_\tau)} \tag{9}$$

Day-by-day and multi-day tests are presented in tables 4 and 5. The significance levels found, while generally lower than those produced by the t-tests, remain high and consistent with the standard statistic.[13] Variance changes does not seem to be a major problem in these data.

4.3.2 Event clustering

The second issue we were concerned about is a possible clustering of events in the data. This is a problem for inference because the standard errors are not properly estimated if cross-sectional correlation between events is present in the sample. Previous studies such as Seyhun (1992) find quite strong clustering at the monthly level. More generally, there is almost always some event clustering, in the same way that returns on common stocks are never fully independent, though whether this is worth taking into account if the amount of clustering is not extreme (events common to all firms in the sample) has been debated in the econometric literature (see Campbell, Lo, and MacKinlay (1997), chapter 4, and Binder (1998) for overviews). From the simulation studies of Brown and Warner (1985), and Bernard (1987), the general conclusions that emerge are that using higher-frequency data as mentioned before, should make clustering on a single date much less severe than when using monthly data. A simple examination of the data confirms this: even though the number of days for which two signals are recorded is quite large, it only very rarely goes beyond three signals in a day across firms. Given that there

[13] As an alternative way of testing for this, we redid the abnormal returns calculations and the hypothesis tests using simply market-adjusted returns (as opposed to market model-adjusted returns), therefore using a contemporaneous benchmark instead of pre-event period data to estimate the variance of "normal" returns. This methodology is found in Brown and Warner (1985) to have comparable ability to detect abnormal returns at the daily level. We did this and the significance was not noticeably altered: although detailed results are not reported here, the multi-day t-stats at the end of the event window are -6.76 for buys and 4.6 for sells, respectively.

are 196 companies in the sample, this does not seem large. Bernard (1987) finds that diversification across industries should further mitigate the correlatedness problem. Our sample is highly diversified in this respect, since most industry sectors are present in our data. The nature of the event is another reason to believe that severe clustering should not be a problem: although there may be correlation in companies' fortunes, it is likely that directors' trades are mostly triggered by company-specific events.

For these reasons, and although partial overlap of event windows is present in the data, the problem is not reckoned to be severe. In the next section, we use a testing procedure which should be robust to partial event clustering, as well as non normality and autocorrelation.

4.3.3 Non normality and time dependence

Two more issues to consider are that daily returns are not normally distributed for individual securities, and they display a (generally mild) degree of autocorrelation. In the econometric literature, Brown and Warner (1985) present an autocorrelation adjustment and conclude that "The benefits [from autocorrelation adjustment, in hypothesis testing] appear to be limited", while simulations (e.g. in Campbell and Wasley (1993)) show that daily abnormal returns collapse to normality when aggregated over portfolios of 100 stocks or more. However, the characteristics of sample stocks (not the most liquid securities) and the institutional (dealership) features of the London market may increase non normality and time dependencies: since these are smaller stocks, thin trading and high relative spreads may lead to price adjustment delays and a relatively high incidence of zero returns in the data.

To examine these issues together the possible event-clustering problem, a non-parametric (rank) testing procedure introduced by Corrado (1989), which does not rely on normality assumptions, was used. It is shown in simulations to be much more robust to thin trading problems and clustering of events. Campbell and Wasley (1993) for instance consider the test to be well-adapted to Nasdaq market data, and the trading system of the London Stock Exchange over our sample period was a dealership system, explicitly modelled on Nasdaq in the mid-1980s, such that we would expect the data examined by Campbell and Wasley to share several features with our own.

The idea behind this statistic is to sort the series of abnormal returns over *both* the estimation and event windows and transform each observation into its respective rank: $k_{i\tau} = rank(AR_{i\tau})$, for $\tau = T_0 + 1, ..., T_2$. The rank statistic is the ratio of the mean deviation of the securities' day-0 ranks ($k_{i\tau}$) to the estimated standard deviation of the portfolio mean abnormal rank:

$$Z = \left(\frac{1}{N} \sum_{i=1}^{N} (k_{i\tau} - E(k_i)) \right) / \widehat{s}(k) \tag{10}$$

Where $E(k_i)$ is the expected rank for security i, equal to $(L_1 + L_2 + 1)/2$. The denominator, $\widehat{s}(k)$, is the estimated standard deviation of the portfolio mean abnormal return rank, again over both estimation and event windows.

$$\widehat{s}(k) = \sqrt{\frac{1}{L_1 + L_2} \sum_{\tau = T_0 + 1}^{T_2} \left((1/N) \sum_{i=1}^{N} (k_{i\tau} - E(k_i)) \right)^2}$$

The Corrado statistic is asymptotically unit normally distributed. In the case of multi-day event windows, the following statistic is formed:

$$\sum_{\tau=\tau_1}^{\tau_2} \overline{k}_\tau \Bigg/ \sqrt{\sum_{\tau=\tau_1}^{\tau_2} \widehat{s}^2(\overline{k}_\tau)} \tag{11}$$

Note that this testing procedure and the previous one complement each other as recent work by Cowan and Sergeant (1996) has questioned the robustness of the Corrado test under conditions of changes in variance around the event.

The estimated test statistics, for each day in the event window as well the cumulative version are presented for the buy and sell returns in tables 4 and 5. The patterns of significance are consistent with the previous methodologies though the significance levels found are uniformly lower in the case of buys. While lower, the significance levels shown by the Corrado test still confirms our finding of trading around short-term price movements. We are therefore confident in the robustness of our results.

4.4 Application of signal filters

4.4.1 Signal definitions

When deciding on which signals to consider, we are faced with a trade-off: on the one hand, it is obvious that in practical trading strategies, traders will apply such signals, using any relevant information to assess whether the trade is liquidity or information-motivated. The investment advisory services mentioned in appendix 1 do not just report the trade as quickly as possible, they also claim to help investors interpret the signal. On the other hand, we want to stick to a limited number of signals which appear widely used to avoid the "data snooping" pitfall when testing for the profitability of a number of trading rules which can be defined by the researcher: by examining a large number of such rules we are bound to find that some of them will yield positive abnormal returns in a given sample.

One obvious category of signals is based on the value of the director's trade. To illustrate, the Financial Times reports every week the details of trades of directors exceeding £10,000. Similarly, one of the conditions for a director's transaction to be considered "significant" by the Directus service is that its value exceeds £15,000. We will use this second value as a threshold for this first type of signals, keeping buy and sell trades with a value above it.

Alternatively, "contrarian" signals have been suggested as the ones likely to contain the most information. The US manager of the specialised fund mentioned in Appendix 1 defines a strong signal of share undervaluation as a purchase during otherwise declining markets (or a sale during generally rising markets). This action can be interpreted as a bullish (bearish) signal regarding future stock returns. An additional reason for the contrarian trades to be informative is that in bearish (or agitated) markets, there are "flights to quality" towards blue chip stocks, which depresses the price of smaller companies. Corporate insiders and investors at large may see this as the time to "pick up bargains". Lakonishok and Lee (1998) find that in aggregate, corporate insiders tend to be contrarian investors. We therefore define a second type of signal as a purchase (sell) observed when a moving average of returns in a window of 10 days before the event takes a negative (positive) value.[14]

A third category of signals which is regularly mentioned is based on the observation of repeated (clustered) trades within a short time interval, by (the same or different) insiders. This should provide a clear indication of how bullish a given insider is, or a consensus view among several insiders, in any case an unequivocal signal. We therefore define such a signal as any trade which was preceded by another one in the same stock at most 10 days before.

US studies regularly present abnormal return estimates depending on the type of insider (large shareholders, officers, directors) or his rank within the company, usually reporting that the closer the insider is to the top within the company, the stronger and more reliable the signal is.[15] But compared to US data, which includes various categories of insiders, our dataset is smaller and much more homogeneous, containing only directors' transactions.[16] Therefore, this type of signal is not of central relevance in our study.

In all, we therefore evaluate the profitability of three additional types of signals, besides the results obtained using the full dataset.

4.4.2 Results

It has been found in previous work, looking at longer holding periods, that excess returns were more pronounced when applying signal filters.[17] Our results, focusing entirely on short-term returns, are summarised in tables 7 and 8. Figure 2 plots cumulative abnormal returns from $\tau = -20$ to $\tau = 20$ for the different signals used. The thicker lines show the base results obtained earlier (full dataset). We computed all significance tests statistics introduced before for every one of these signals, and as could be expected since we are now focusing on stronger signals, the significance levels found were (with

[14] We tried other window lengths but this did not change results significantly.

[15] This is also pointed out to outside investors explicitly; as an example, Bloomberg News reported on 13 March 1998 that GM managers had been selling quite heavily, although "None of GM's four top executives had sold shares".

[16] Large shareholders in the UK are required to disclose their holdings when they reach 3 per cent of corporate equity, but not the individual trades.

[17] As opposed to considering different categories of firms according to their size.

the exception of contrarian signals) higher than what was found for the full dataset, although we do not report them in detail as this would require 12 more tables. Only cumulative t-stats on the pre- and post-event window average $CARs$ (including the event day in both cases) are reported.

The main points from tables 7 and 8 and figure 2 are the following: Firstly, the asymmetry between excess returns around buy and sell trades is apparent for all signals. Secondly, the pattern in returns across signal definitions is remarkably similar across signals in the pre-event period (with the exception of clustered buy signals, as explained below) but it is different after the event: for the more profitable signals, the price seems to recover almost completely from the pre-event drop or increase, whereas for most other signals, this reversal is only partial. Thirdly, different signals clearly have different strength or predictive contents over future returns: "contrarian signals" do not generate economically significant returns. Indeed, they deliver lower returns than the base case signal (full dataset). Focusing on trades larger than £15,000 (this means keeping only the top 3 deciles of signals, or 534 of the buys) seems to yield larger excess returns twenty days afterwards (2.8% instead of 1.9%), but the type of signal that clearly stands out (in terms of both pre-event price drop and post-event recovery) is the one based on clusters of buy signals. Here, the pre-event drop in prices reaches almost 6%, while the abnormal returns 20 days after the event are slightly larger than 4.5%. Sell signals, on the other hand, tend to be less clustered than buys, but there were still 174 "clustered" sells in the data (against 264 "clustered" buys.). The same signal definition applied to director sell trades yields abnormal returns that are only marginally larger than those of other sell signals: even though clustered sells are the strongest of sell signals, the asymmetry with the buys is more pronounced than for any other signal (excess returns 20 days after clustered buys are twice those after clustered sells). In the following section, we restrict our analysis to the clustered buy signals only.

4.5 Abnormal returns and trade size after directors' buy signals

Given the magnitude of the price movements around the directors' clustered buy signals, we investigated the pattern around this signal in more detail. In particular, we examined the distribution of individual event CARs according to trade value. In the previous section, we used the Directus definition (over £15,000) of a "significant" trade, though it is difficult to define small, medium-sized or large trades by just looking at the distribution of signals given its strong skewness. We somewhat arbitrarily define a small trade (for an individual investor) as belonging in the [0, £5000) interval, a medium-sized trade in turn being comprised in the [£5000, £70000) interval (£70000 being the 90th percentile), and classify all trades above this value as "large". The average $CARs$ for each category are as follows (table 9): the 20-day average CAR for the small director trades (607 events) is 1%. For the medium-sized ones (936 events), the same CAR is 2.6%, while for the large trades (159 events) it is only 1.6%. (Further focusing on the larger trades in the medium-sized category (156 events between £20,000 and £70,000) yields an average CAR of 3.7%!).

If directors trade in medium sizes and these are the most significant as signals of positive future abnormal returns, we should find, going back to the results of the previous section, that the clustered trades we found to be the most informative are generally medium-sized. Indeed, looking at the distribution by value of these clustered trades, this is exactly the case. Comparing those clustered trades to the ones in the [£5000, £70000] interval, we find that although their means appear quite different, the mean of the clustered trades is pulled up by a handful of large transactions. Once these (the top decile of trades by value, or 27 of them out of 254) are excluded, the means (£13,000 vs £17,000), medians (£7,700 vs £12,000) and standard deviations (15,600 vs 13,300) of the two data subsets become very similar (and much smaller than those of the full dataset).

Therefore medium-sized trades as a whole seem to predict higher returns than large ones. This evidence is consistent with the "stealth trading" hypothesis and findings of Barclay and Warner (1993) who report that the trades which seem to cause most of the total price changes in the price run-ups occurring before a takeover is disclosed to the market are concentrated in the medium-sized category. Our results cannot strictly be interpreted in the same way as it is not clear whether the post-event patterns in prices were or not partly caused by the mimicking by outsiders of the insider's trade, but one interpretation is that directors avoid trading in very large amounts around upcoming events which they expect will be accompanied by sizeable changes in the security's price. This would be revealing to the market that they are informed (especially in a dealership system such as the London Exchange where trading is not anonymous) as well as calling for regulatory scrutiny. Directors can make their trading less conspicuous by using one or several medium-sized trades.

4.6 Inclusion of transaction costs

As a final step, we assess the profitability of the mimicking strategies after correcting for microstructure (spread) transactions costs. Unlike previous research, we do not use mean estimates for spreads but more accurate daily data for each security. These estimates of transactions costs may be seen as relatively conservative, since they are closing prices and research on patterns in the bid-ask spreads in the London Exchange has documented that they decline at the end of the trading day (presumably for inventory management reasons by market makers). In the case of a small number of very large trades, the mid-point to mid-point returns calculation is arguably preferable, since there is evidence that the execution prices of a sizeable proportion of block trades in London are negotiated and occur somewhere within the quotes or even at the mid-point (Reiss and Werner (1994)). But the average director trade in our data is not very large by London Exchange standards, traditionally geared towards institutional investors, such that most of these trades would actually occur at or near the bid and ask quotes.

Whereas returns have so far been computed from midpoint price to midpoint price, we now remove from the previously estimated cumulative abnormal returns (from $\tau_1 = 0$ to $\tau_2 = 20$) for each event the two half-spreads that would have been incurred at the time of purchase or sale:

$$Net\ CAR_i(\tau_1, \tau_2) = CAR_i(\tau_1, \tau_2) - (S_{i,\tau_1}/2P_{i,\tau_1} + S_{i,\tau_2}/2P_{i,\tau_2}) \tag{12}$$

The results, presented in tables 10 and 11, are that signals followed by higher returns are compensated by higher spreads, such that profitability seems on average wiped out by round-trip costs. Net returns are slightly negative except for three types of signals, and even then the highest average net return is 1.32% (as expected, for clustered buy trades). It is striking to see how close to zero these net returns are, as they should in an efficient market.

In this study, as well as in the previous ones using lower frequency data, the magnitude of *net* abnormal returns found after most signals is consistent with market efficiency. It remains to be seen how the excess returns found in the current paper could change the conclusions of previous studies which were using monthly data and were not able to statistically identify short-term excess returns. We leave this for future research but our results generally highlight the need to study events which may constitute market timing in the short as well as in the longer run and at different frequencies.

5 Summary and conclusion

Previous work examining the profitability of the trades of corporate insiders and of strategies mimicking these trades reported mixed evidence on long-run abnormal returns following these trades. Returns during the month (or even the two weeks) containing the trade, however, were found to be not significantly different from zero. This paper examined the patterns of security returns immediately around the trades of corporate insiders in the shares of their own company, with two aims. One was to examine price movements around directors' trades, and a second was to look at the returns to strategies mimicking-directors' trades in the days immediately following the trade and after taking transactions costs into account.

With respect to the first aim, we find patterns in abnormal returns in the days around a director's trade that are consistent with trading on short-lived information by directors. This could be interpreted as evidence that the insider trading rules in place in London were not fully serving their intended purposes or, alternatively, as a reflection of the impossibility to prevent trading around all events in the life of a public company that are susceptible of influencing its share price in the short run but do not have to be disclosed to the market.

With respect to the second aim, we find positive gross, but not net, abnormal returns to imitating some of the trades of directors once "round-trip" costs are taken into account. Therefore, although these patterns are statistically significant, their economic significance should not necessarily be a cause of great regulatory concern.

We also report that some types of trades predict higher future returns. In line with previous work on this topic but also on the price effects of block trades, buy trades are followed by larger abnormal returns than sells. We also report that, with respect to short-term returns, the strongest signals are the clustered ones, most of which are of medium size. More generally, medium-sized trades seem more informative than large ones, consistently with Barclay and Warner's (1993) "stealth trading" hypothesis. An obvious interpretation is that informed traders try to conceal their information by avoiding to trade in blocks, while transactions costs rule out a series of small trades as a strategy for accumulating a significant position.

The lack of profitability reported here does not preclude a possible impact on results contained in earlier work. Generally, this points to the need to study the profitability of events which may constitute market timing at different frequencies to pick up both short- and long-term effects. The standard event methodology is not best-adapted for that.

References

Admati, A., and P. Pfleiderer, 1988, "Selling and Trading on Information in Financial Markets," *American Economic Review*, 78(2), 96–103.

Allen, F., and G. Gorton, 1992, "Stock Price Manipulation, Market Microstructure and Asymmetric Information," *European Economic Review*, 36, 624–630.

Bagnoli, M., and N. Khanna, 1992, "Insider Trading in Financial Signaling Models," *Journal of Finance*, 47, 1905–1934.

Barclay, M., and J. Warner, 1993, "Stealth Trading and Volatility (Which Trades Move Prices?)," *Journal of Financial Economics*, 34, 281–305.

Bernard, V., 1987, "Cross-Sectional Dependence and Problems in Inference in Market-Based Accounting Research," *Journal of Accounting Research*, 25, 1–48.

Bettis, C., D. Vickrey, and D. W. Vickrey, 1997, "Mimickers of Corporate Insiders Who Make Large Volume Trades," *Financial Analysts Journal*, 53, 57–66.

Binder, J. J., 1998, "The Event Study Methodology Since 1969," *Review of Quantitative Finance and Accounting*, 11, 111–137.

Boehmer, E., J. Musumeci, and A. Poulsen, 1991, "Event-Study Methodology under Conditions of Event-Induced Variance," *Journal of Financial Economics*, 30, 253–272.

Brown, S., and J. Warner, 1985, "Using Daily Stock Returns (The Case of Event Studies)," *Journal of Financial Economics*, 14, 3–31.

Campbell, C., and C. Wasley, 1993, "Measuring Security Price Performance Using Daily NASDAQ Returns," *Journal of Financial Economics*, 33, 73–92.

Campbell, J. Y., A. Lo, and A. C. MacKinlay, 1997, *The Econometrics of Financial Markets*. Princeton University Press, Princeton, N.J.

Chan, K., and J. Lakonishok, 1993, "Institutional Trades and Intraday Stock Price Behavior," *Journal of Financial Economics*, 33, 173–199.

Corrado, C., 1989, "A Nonparametric Test for Abnormal Security Price Performance in Event Studies," *Journal of Financial Economics*, 23, 395–395.

Cowan, A., and A. Sergeant, 1996, "Trading Frequency and Event Study Test Specification," *Journal of Banking and Finance*, 20, 1731–1757.

Dennert, J., 1991, "Insider Trading," *Kyklos*, 44(2), 181–202.

Eckbo, B., and D. Smith, 1998, "The Conditional Performance of Insider Trades," *Journal of Finance*, 53(2), 467–498.

Finnerty, J., 1976, "Insiders and Market Efficiency," *Journal of Finance*, 31, 1141–48.

Fishman, M., and K. Hagerty, 1995, "The Mandatory Disclosure of Trades and Market Liquidity," *Review of Financial Studies*, 8(3), 637–676.

Fowler, D., and H. Rorke, 1983, "Risk Measurement When Shares Are Subject to Infrequent Trading: Comment," *Journal of Financial Economics*, 12(2), 279–283.

Gregory, A., J. Matatko, and I. Tonks, 1997, "Detecting Information from Directors' Trades: Signal Definition and Variable Size Effects," *Journal of Business Finance and Accounting*, 24(3-4), 309–342.

Gregory, A., J. Matatko, I. Tonks, and R. Purkis, 1994, "UK Directors' Trading: The Impact of Dealings in Smaller Firms," *Economic Journal*, 104, 37–53.

Hadi, A., 1992, "Identifying Multiple Outliers in Multivariate Data," *Journal of the Royal Statistical Society*, 54, 761–771.

———, 1994, "A Modification of a Method or the Detection of Outliers in Multivariate Samples," *Journal of the Royal Statistical Society*, 56, 393–396.

Hu, J., and T. Noe, 1997, "The Insider Trading Debate," *FRB Atlanta Economic Review*, 83(4), 34–45.

Huddart, S., J. Hughes, and C. Levine, 1999, "Public Disclosure of Insider Trades, Trading Costs, and Price Discovery," Duke University Fuqua School of Business Working Paper.

Jaffe, J., 1974, "Special Information and Insider Trading," *Journal of Business.*, 47(3), 410–28.

Jeng, L., A. Metrick, and R. Zeckhauser, 1999, "The Profits to Insider Trading: A Performance-Evaluation Perspective," *NBER Working Paper*, No 6913.

Kabir, R., and T. Vermaelen, 1996, "Insider Trading Restrictions and the Stock Market: Evidence from the Amsterdam Stock Exchange," *European Economic Review*, 40, 1591–1603.

Karpoff, J., and D. Lee, 1991, "Insider Trading Before New Issue Announcements," *Financial Management*, 20, 1947–1961.

King, M., and A. Röell, 1988, "Insider Trading," *Economic Policy*, 7, 163–193.

Lakonishok, J., and I. Lee, 1998, "Are Insiders' Trades Informative?," NBER Working Paper No. 6656.

Lee, I., 1997, "Do Firms Knowingly Sell Overvalued Equity?," *Journal of Finance*, 52, 1439–1466.

Leland, H., 1992, "Should Insider Trading Be Prohibited?," *Journal of Political Economy*, 100(4), 859–887.

London Stock Exchange, 1996, "Guidance on the Dissemination of Price Sensitive Information," (Stock Exchange Publication).

——— , 1998, "Continuing Obligations Guide," (Stock Exchange Publication).

Meulbroek, L., 1992, "An Empirical Analysis of Illegal Insider Trading," *Journal of Finance*, 47(5), 1661–1699.

Pope, P., R. Morris, and D. Peel, 1990, "Insider Trading: Some Evidence on Market Efficiency and Directors' Share Dealings in Great Britain," *Journal of Business Finance and Accounting*, 17(3), 359–80.

Reiss, P., and I. Werner, 1994, "Transactions Costs in Dealer Markets: Evidence from the London Stock Exchange," in Andrew Lo, ed., Industrial Organization and Regulation of the Securities Industry (NBER-University of Chicago Press).

Scholes, M., and J. Williams, 1977, "Estimating Betas from Nonsynchronous Data," *Journal of Financial Economics*, 5, 309–327.

Seyhun, H., 1986, "Insiders' Profits, Costs of Trading and Market Efficiency," *Journal of Financial Economics*, 16, 189–212.

Seyhun, N., 1992, "Why Does Aggregate Insider Trading Predict Future Stock Returns?," *Quarterly Journal of Economics*, 107, 1303–1331.

6 Appendix

This appendix gives some evidence on the amount of interest surrounding the signals sent by-directors' trades. The question traditionally asked by the-directors' trading literature is whether there is a way to consistently generate abnormal profits by mimicking-directors' trades. Data on these trades, though much closer to private information than, say, basic earnings data, and (at least until recently) reserved to the professional investment community for costs reasons, are still formally considered public information, since their availability is known to all market participants, and access is only a matter of the cost of information acquisition. The most detailed level of data on-director's trades is, as just mentioned, what is available to the financial services industry, and available from the London Exchange's own "Regulatory News Service" or from portfolio management/data vending companies such as Barra's Directus subsidiary, which supplied part of the data for this study. Individual investors now have more and more means of accessing these data directly or indirectly: investment newsletters tracking the trading of corporate insiders are available, and recently a US investment fund the strategy of which is entirely based on such signals has been launched. The Financial Times presents a summary of-director's trades made during the past week (in the "Money" section of the week-end edition). More recently still, some of this information has become freely available on the Internet -at least for US stocks (see, e.g., the Bloomberg website, "Insider Focus" section). To give an anecdotal illustration of how closely followed they have become, it was reported at some point in 1997[18] that the selling activity of top executives at the Chrysler corporation had been unusually heavy for several weeks. Chrysler had to issue a public statement explaining why this was not to be interpreted as a bearish signal.

[18] CNN financial news, 09/09/1997

Table 1

Descriptive statistics

	N	**p10**	**Median**	**p90**	**Mean**	**St. Dev.**	**Skew**	**Kurtosis**
				Panel A: Raw Signals				
Buys	2,558		6,650		66,068.4	652,503.5	27.54	859.64
Sells	1,841		32,600		343,068.9	3,833,629	35.89	1419.04
				Panel B: Net signals				
Buys								
1986	38	1,125	11,625	695,600	156,999	433,530		
1987	211	1,470	8,600	140,040	82,303	289,228		
1988	233	1,568	6,500	100,800	195,764	1,569,983		
1989	238	1,756	8,600	74,400	32,525	94,201		
1990	258	2,060	9,369	69,550	78,430	695,286		
1991	218	1,740	6,680	65,000	114,496	1,272,066		
1992	296	2,020	7,323	40,750	57,061	402,183		
1993	170	2,333	8,806	52,400	42,241	230,441		
1994	225	1,330	7,488	32,250	22,627	93,567		
Overall	1,887	1,750	7,950	70,000	80,044	776,710	23	605
Sells								
1986	33	5,400	48,000	553,500	257,049	750,182		
1987	241	5,742	33,500	673,460	343,950	1,230,274		
1988	226	4,622	27,150	325,440	166,815	465,732		
1989	206	6,160	37,860	373,500	958,938	10,753,229		
1990	169	6,440	48,200	647,500	424,028	2,168,552		
1991	217	6,440	28,176	742,500	577,511	3,019,809		
1992	164	5,396	27,593	391,500	222,227	717,038		
1993	180	7,504	30,419	490,000	263,963	845,109		
1994	86	6,844	20,865	148,750	70,632	167,798		
Overall	1,522	6,150	30,675	475,517	403,173	4,229,704	32	1157
				Panel C: Returns and spreads				
R_i	404328		0		0.00041	0.0196	-0.88	0.5
$Rmid$	2090		0.000725		0.00036	0.0086	-0.11	0.074
spread	404817		0.0185		0.0232	0.018		0.67

The table reports descriptive statistics on signals and sample stock returns. “p10" and “p90" are the tenth and ninetieth percentiles, respectively.

Table 2

Abnormal returns and significance tests (Buy trades)

Days around event	$\overline{AR}$	t	$\overline{CAR}(-20,20)$	$cumul.\ t$	$\overline{CAR}(0,20)$
-20	-0.000932	-2.092	-0.00093	-2.092	
-15	-0.001168	-2.619	-0.00484	-4.433	
-10	-0.000919	-2.062	-0.01004	-6.794	
-8	-0.001026	-2.303	-0.01262	-7.851	
-6	-0.002484	-5.573	-0.01638	-9.488	
-4	-0.003491	-7.832	-0.02166	-11.787	
-3	-0.002080	-4.666	-0.02374	-12.555	
-2	-0.002496	-5.599	-0.02624	-13.504	
-1	-0.002317	-5.199	-0.02855	-14.325	
0	0.001514	3.397	-0.02704	-13.238	0.00151
1	0.002747	6.163	-0.02429	-11.620	0.00426
2	0.001999	4.485	-0.02229	-10.430	0.00626
3	0.001729	3.878	-0.02056	-7.206	0.00799
4	0.000884	1.983	-0.01968	-9.418	0.00887
6	0.001022	2.292	-0.01724	-7.445	0.01131
8	0.001279	2.869	-0.01539	-6.412	0.01316
10	0.000400	0.897	-0.01392	-5.609	0.01463
15	0.000351	0.787	-0.01049	-3.924	0.01806
20	0.000868	1.947	-0.00892	-3.126	0.01963

The table reports abnormal returns on selected days around a director's buy trade. Column 2 lists average daily abnormal returns computed from equation 2. Column 4 lists average cumulative abnormal returns from equation 3 from the beginning of the event window. T-statistics on individual days' average abnormal returns (column 3) and on average CARs (column 5) are computed as in Brown and Warner (1985), p.7 and 29, respectively. The last column reports average CARs computed from the event day.

Table 3

Abnormal returns and significance tests (Sell trades)

Days around event	$\overline{AR}$	t	$\overline{CAR}(-20,20)$	*cumul. t*	$\overline{CAR}(0,20)$
-20	0.000561	1.215	0.00056	1.215	
-15	-0.000296	-0.640	0.00040	0.352	
-10	0.000485	1.050	0.00312	2.040	
-8	0.000467	1.011	0.00394	2.363	
-6	0.000970	2.100	0.00591	3.305	
-4	0.001321	2.860	0.00812	4.267	
-3	0.001327	2.873	0.00945	4.824	
-2	0.001124	2.433	0.01057	5.253	
-1	0.001755	3.800	0.01233	5.970	
0	-0.000099	-0.214	0.01223	5.779	-0.000099
1	-0.001653	-3.580	0.01058	4.883	-0.001752
2	-0.001585	-3.432	0.00899	4.060	-0.003337
3	-0.001140	-2.469	0.00785	3.471	-0.004477
4	-0.000183	-0.395	0.00767	3.322	-0.004660
6	-0.001447	-3.134	0.00497	2.071	-0.007361
8	-0.001110	-2.404	0.00331	1.332	-0.009017
10	-0.000887	-1.921	0.00163	0.634	-0.010700
15	-0.000101	-0.219	0.00078	0.280	-0.011553
20	-0.000541	-1.172	-0.00232	-0.786	-0.014654

The table reports abnormal returns on selected days around a director's sell trade. Column 2 lists average daily abnormal returns computed from equation 2. Column 4 lists average CARs from equation 3 from T_1, the first day in the event window. T-statistics on individual days' average abnormal returns (column 3) and on cumulative abnormal returns (column 5) are computed as in Brown and Warner (1985), p.7 and 29, respectively. The last column reports average CARs computed from the event day.

Table 4

Additional significance tests (buy trades)

Days around event	BMP	Cumul. BMP	Corrado	Cumul. Corrado
-20	-1.978	-1.978	-0.889	-0.889
-15	-2.287	-4.166	-1.857	-2.35
-10	-1.928	-6.437	-2.424	-3.929
-8	-1.770	-6.340	-1.652	-4.691
-6	-3.877	-6.750	-0.628	-4.900
-4	-5.439	-8.428	-3.569	-5.913
-3	-3.223	-9.450	-2.979	-6.448
-2	-4.201	-9.880	-2.379	-6.822
-1	-2.614	-7.504	-0.682	-6.802
0	1.904	-7.424	2.106	-6.178
1	5.010	-9.310	3.272	-5.339
2	3.981	-9.272	2.751	-4.648
3	3.278	-8.130	2.139	-4.113
4	1.890	-8.708	1.850	-3.660
6	2.206	-7.430	1.829	-2.817
8	2.396	-5.623	1.420	-2.397
10	0.661	-5.922	1.643	-1.698
15	0.568	-3.510	0.376	-0.554
20	1.793	-2.992	1.567	-0.299

The table presents additional significance tests on selected days around a director's buy trade. These additional test methodologies provide confirmation of the significance of the results in table 2. Column 2 presents the Boehmer, Musumeci and Poulsen test (computed from equation 8). Column 3 reports the same statistic on the cumulative abnormal returns computed (as in 9). Column 4 reports the non-parametric test statistic of Corrado from equation 10 while the last column gives the multi-day version of the same statistic (from equation 11).

Table 5

Additional significance tests (sell trades)

Days around event	BMP	Cumul. BMP	Corrado	Cumul. Corrado
-20	1.917	1.917	0.971	0.971
-15	-0.895	0.491	0.827	1.656
-10	1.681	3.264	1.364	3.201
-8	1.609	3.763	0.369	3.364
-6	2.971	4.676	1.994	4.131
-4	3.961	5.909	2.366	4.851
-3	4.198	7.048	2.663	5.342
-2	3.770	8.140	2.403	5.751
-1	5.122	8.048	2.717	6.213
0	-0.273	7.345	-0.689	5.912
1	-5.739	7.828	-3.296	5.074
2	-5.437	6.433	-3.373	4.259
3	-4.197	5.900	-1.191	3.926
4	-0.704	5.915	0.355	3.918
6	-5.267	3.480	-2.156	3.095
8	-4.014	2.224	-2.098	2.353
10	-2.656	0.876	-0.891	1.898
15	-0.399	0.511	0.885	2.051
20	-2.067	-1.388	-0.540	1.342

The table presents additional significance tests on selected days around a director's buy trade. These additional test methodologies provide confirmation of the significance of the results in table 3. Column 2 presents the Boehmer, Musumeci and Poulsen test (computed from equation 8). Column 3 reports the same statistic on the cumulative abnormal returns computed as 9. Column 4 reports the non-parametric test statistic of Corrado from equation 10, while the last column gives the multi-day version of the same statistic (from equation 11)

Table 6

Average CARs after thin trading adjustment

Signal definition	No obs	$\overline{CAR}(-20,0)$	t cumul.	$\overline{CAR}(0,20)$	t cumul.
Buys	1702	-2.63%	-13.26	1.92%	9.67
Sells	534	1%	5.87	-1.46%	-6.96

The table reports cumulative average abnormal returns when market model coefficients are adjusted for thin trading using the Scholes and Williams (1977) procedure (equations 5 and 6).

Table 7

20-day average CARs after 4 types of buy signals

Signal definition	No obs	$\overline{CAR}(-20,0)$	t cumul.	$\overline{CAR}(0,20)$	t cumul.
All Buys	1702	-2.85%	-14.32	1.96%	9.84
Large Buy	534	-3.03%	-8.42	2.8%	7.79
"Contrarian" Buy	835	-3.27	-12.21	1.01%	3.79
Clustered Buy	264	-5.46%	-10.25	4.52%	8.47

The table reports cumulative average abnormal returns prior to and after directors' buy trades. The first row reports the results for the full dataset. Large buys are defined as exceeding £15,000 in value. "Contrarian" buys occur in bearish markets. A clustered buy is a share purchase which was preceded by another buy in the ten days or less before.

Table 8

20-day average CARs after 4 types of sell signals

Signal definition	No obs	$\overline{CAR}(-20,0)$	t cumul.	$\overline{CAR}(0,20)$	t cumul.
All Sells	1268	1.22%	5.92	-1.46%	-7.09
Large Sell	1042	1.09%	4.85	-1.66%	-7.37
"Contrarian Sell"	716	1.65%	6.15	-1.11%	-4.14
Clustered Sell	174	1.04%	2.1	-2.41%	-4.85

The table reports cumulative average abnormal returns prior to and after directors' sell trades. The first row reports the results for the full dataset. Large sells are defined as exceeding £15,000 in value. "Contrarian" sells occur in bullish markets. A clustered sell is defined as a sell trade which was preceded by another sell in the ten days or less before.

Table 9

Average CARs and trade size

Signal definition	No obs	$\overline{CAR}(-20,0)$	t cumul.	$\overline{CAR}(0,20)$	t cumul.
Small buy	607	-2.35%	-6.9	0.98%	12.86
Medium-sized buy	936	-2.79%	-10.46	2.59%	9.72
Large buy	159	-4.55%	-7.85	1.57%	2.71

The table reports cumulative average abnormal returns after directors' buy trades. Small buys are defined as the ones having value of less than £5,000. Medium-sized trades belong in the [£5000, £70000) interval while any trade of more than £70,000 is a large one.

Table 10

Average buy CARs after inclusion of transactions costs

Signal definition	$Net\ \overline{CAR}(0,20)$
All Buys	-0.66%
Large Buy	0.285%
Contrarian Buy	-1.68%
Clustered Buy	1.32%

The table reports CAARs after removing “round-trip" transaction costs (the half-spreads incurred at the time of trading) as in equation 12.

Table 11

Average sell CARs after inclusion of transactions costs

Signal definition	$Net\ \overline{CAR}(0,20)$
All Sells	-0.55%
Large Sell	-0.23%
Contrarian Sell	-0.86%
Clustered Sell	0.366%

The table reports CAARs after removing “round-trip" transaction costs (the half-spreads incurred at the time of trading) as in equation 12.

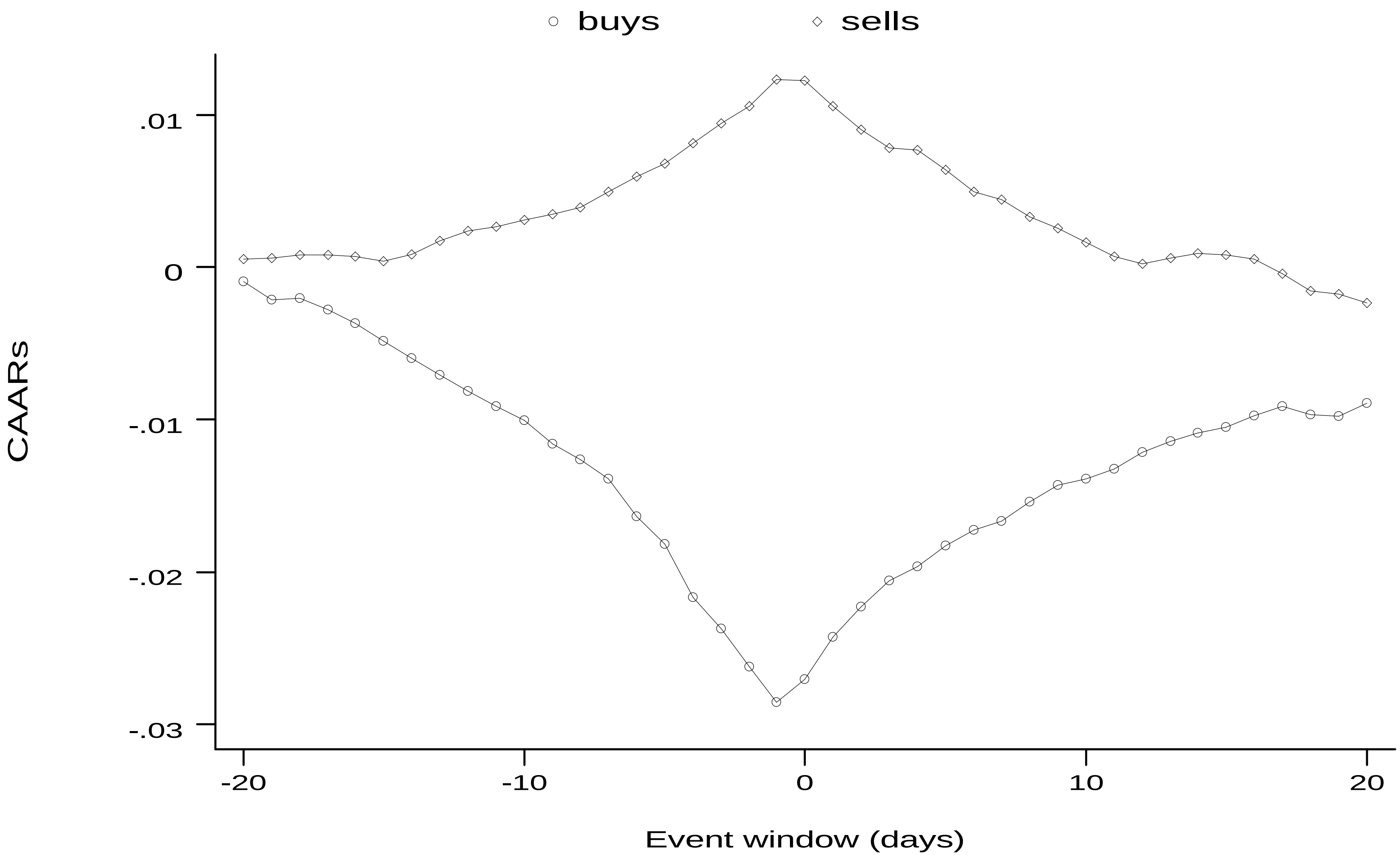

Fig 1: Returns around Directors' buy and sell signals (full sample)

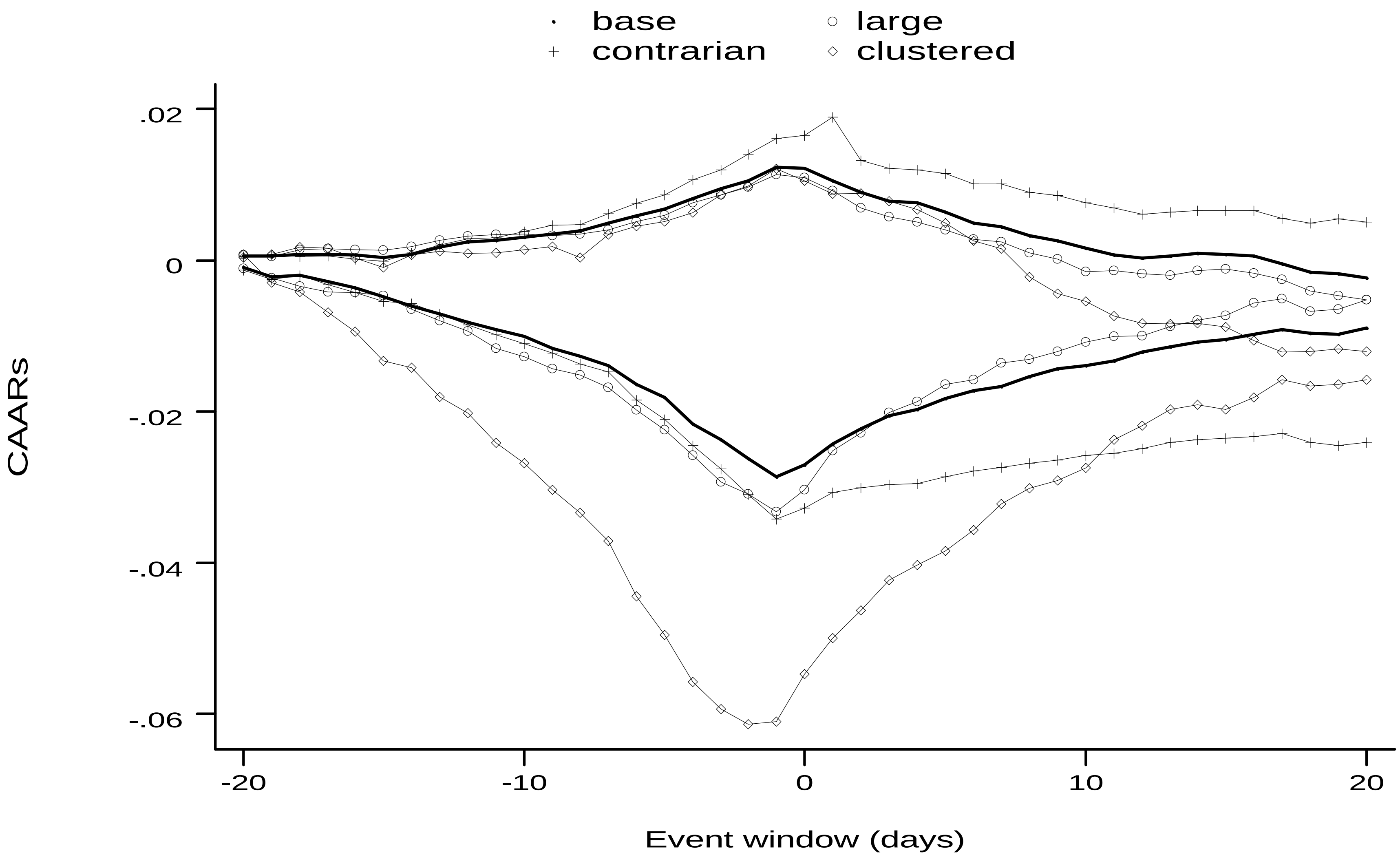

Fig 2: Returns around different signals