The Other Insiders:

Personal Trading by Analysts, Brokers, and Fund Managers

Almost all developed countries require insiders associated with a listed firm to publicly disclose trades they make in stock of that firm. This public disclosure should prevent insiders from using their private information and help preserve market integrity. In Finland the regulator has gone one step further and also requires employees of financial intermediaries to publicly disclose their individual stock market transactions.[1]

In this paper we examine the trading behavior of these employees at financial intermediaries. We focus on 2 important questions. First, in the tradition of the insider trading literature, we examine whether employees at these financial intermediaries obtain and trade on valuable private information. Second, extending the emerging literature on the impact of social networks on stock market trading, we examine how private information spreads in social networks defined by employees at the same firm, the same financial services group, or the same empirical network.

If the financial experts in our sample are able to obtain valuable firm-specific information, this should affect their stock selection and help them to earn abnormal returns. An alternative view is that these financial experts may be overconfident in their own competence in investing in the stock market and end up trading too often. This alternative view is supported by the evidence in Døskeland and Hvide (2011), who find that individual investors overweight professionally close stocks, defined as firms within the two-digit

[1] The requirement to disclose trades for the employees at financial intermediaries can be justified based on the traditional rationales for insider trading regulation: a fiduciary duty (in this case by employees of financial intermediaries) not make a personal profit or avoid loss by using a company's or client's price sensitive information; to reduce investors' concerns that insiders (in this case by employees of financial intermediaries) can exploit their privileged access to information, which could otherwise reduce their willingness to participate in the stock market; a fairness rationale that all investors should have an equal opportunity to obtain and evaluate information relevant to their trading decisions.

industry of their own employment, and experience mean abnormal returns that are either zero or negative.

We investigate these opposing hypotheses by conducting four sets of tests. First, we examine the timing and choice of stocks by employees of financial intermediaries. We find that the likelihood of financial experts trading a given stock increases sharply if other employees at the same firm, the same financial services group, or the same network trade on the same day or one or two days earlier. We also find that an expert is more likely to trade if (s)he is more central in the network of financial experts. Finally, we document that financial experts are more likely to trade on days with information events. These results are consistent with the view that employees at financial intermediaries select stock-days where they are more likely to benefit from their private information and that this private information is frequently obtained through the network of financial experts.

Second, we analyze the trading performance of employees at financial intermediaries. We find that these financial experts exhibit superior stock-picking skills on both the buy-side and the sell-side over the days immediately following trades. They significantly outperform by an average of 27 basis points (bp) per day based on all trades made one day earlier, by 11 bp per day based on trades one week earlier (but excluding day -1), and 4 bp per day for trades made one month earlier (but excluding day -7 through -1). Trades made one quarter earlier (but excluding trades one month earlier) do not generate a significant return. Among the different categories of employees, the outperformance is concentrated among analysts, fund managers, brokers and 'others', but we find no evidence of outperformance by board members.

Our third set of tests delves deeper into two potential sources of the apparent information advantage of financial experts. We first explore the possibility that the outperformance stems from superior private information that is about to become public.

Consistent with this idea, we find that financial experts perform extremely well when they trade just before major information events. For example, based on their trades on the day before major earnings announcements, these experts generate an average cumulative abnormal return on days 0 and +1 (CAR(0,+1)) of 1.3 percent. Likewise, based on their trades one day ahead of large price changes, financial experts generate an average CAR(0,+1) of 1.8 percent. Financial experts do not display stock picking skills in the days before takeover announcements, but based on their trades on the day before the recommendation announcements by brokers other than their own firm, they generate an average CAR(0,+1) of 0.8%, and this outperformance is 3.4% based on the recommendations announced by their own firm. These results show that a relatively large proportion of trades by employees at financial intermediaries during the few days ahead of major information events is motivated by superior private information that is about to become public.

The second potential source of superior information of individual experts is the information shared through the network of financial experts. We argue that it is likely that trades are motivated by shared and valuable information if two or more members of the community of financial experts trade the same stock, on the same day, and in the same direction. Consistent with this idea, we find that these 'network purchases' significantly outperform 'non-network purchases' by an average of 26 basis points (bp) per day, but we do not find that network sales outperform non-network sales. Also consistent with the idea that network trades are more likely to be motivated by private information than non-network trades, we find that network trades (purchases and sales) tend to be larger and tend to be followed by an offsetting transaction sooner.

Our final set of tests address the concern that some of the trades we classify as network trades might not be the result of social interaction, but simply reflect good trading opportunities simultaneously recognized by several knowledgeable people. For these tests, we investigate two sources of private information that are likely to be exclusive to the employees of brokerage firms and fund management firms, respectively. First, we analyse trades by corporate insiders on day T that are made public after T+2. We find a significant increase in the number of trades by financial experts in the interval [T,T+2] that are in the same stock and have the same sign as the trades by the corporate insiders. This increase is particularly large for employees working at the brokerage firms used by the corporate insider. However, we also document an increase in copy-cat trades by employees at different financial intermediaries which strongly suggests that the private information travels through the network. We also analyse the trading behaviour of employees of financial intermediaries around exceptionally large sales or purchases by fund management firms. We document a significant increase in the number of trades by employees at financial intermediaries in the direction of the block trade in the days before the block trade. This increase is not limited to employees of fund management firms, but includes employees of brokerage firms, again supporting the idea that valuable private information tends to spread through the network.

II. INSTITUTIONAL BACKGROUND, DATA, AND SAMPLE CHARACTERISTICS

II.A. Institutional Background

Insider trading laws in Finland were passed in 1989 and first enforced in 1993 (see Bhattacharya and Daouk [2002]). Like most other countries in the EU, these regulations are modelled after U.S. insider trading laws. The Financial Supervisory Authority (FSA) regulates financial markets in Finland, and seeks to enforce the law by monitoring insider trading. In addition to the formal laws, insiders are restricted in their trading by guidelines for insiders issued by the Nasdaq OMX Helsinki Exchange and the Finnish Association of Securities Dealers (FASD). Moreover, most publicly listed companies in Finland have adopted their own internal insider trading guidelines, which are often more strict than those of Nasdaq OMX Helsinki and the FASD.

Standard 5.3 of the …Act, "Declarations of insider holdings and public registers", states that the provisions in the standard are applicable to persons employed by Finnish issuers whose securities are subject to public trading, firms offering investment services and fund management companies.
See standard 1.3 "A supervised entity providing an investment service shall take adequate measures aimed at preventing a relevant person from undertaking personal transactions, if those transactions could give rise to a conflict of interest in relation to a transaction or service in which he is involved on account of his position, if he has access to inside information within the meaning of the Securities Markets Act, or confidential information on the investment firm's customers or their business transactions. The confidentiality of such information must also be otherwise…

The purpose of provisions on personal transactions stipulated in this standard is to manage conflicts of interest arising from the provision of investment services. In addition to this standard, transactions carried out by persons specified here may be restricted by provisions on market abuse in chapter 5 of the Securities Markets Act. The said persons may also be subject to standard 5.3 *Declarations of insider holdings and insider registers*.

Also check: http://www.finlex.fi/en/laki/kaannokset/2012/en20120746.pdf

II.B. Data Sources

This study is concerned with the trading activity of employees at financial intermediaries and the share price performance following their trades. Our main data source is a set of all publicly available transactions made by employees of Finnish financial intermediaries during the period, XXX 2006 through XXX 2011.[2] These data are available as pdf files on the following website ….. and were made available by HS because of …..

We obtain earnings announcement dates from Bloomberg. Merger and acquisition announcement dates are taken from SDC Platinum. Daily share prices and the number of shares outstanding are obtained from Compustat Global. The market-to-book ratios for all Finnish firms are from Worldscope. We only include stock-years if a stock has more than 200 days on which it is traded within a given year.

[2] The public insider register in Finland contains information on trading by insiders during the previous five years.

II.C. Descriptive Statistics for Different Types of Trades

Table 1, panel A provides information about the relative frequency and attributes of the different categories of trades by employees. The first five rows in Table 1 present the descriptive statistics for these categories of trades by official classification of the different functional roles. We have insider trading information on 1275 individuals, where the trades by each individual include trades by family members and through companies controlled by the insider. Of these 1275 individuals, 94 are classified as Analyst, 161 as Board member, 306 as Broker, 101 as Fund manager and 613 individuals are included in the category 'Other'.

Our sample represents the employees of 9 different Asset management firms, 15 brokerage firms, and 15 Fund Management firms. Columns 3-5 document the frequency of the different functional roles across the 3 types of financial intermediaries. More than half of the employees in our sample are from Brokerage firms and almost 50% of their employees are classified as 'broker'. Almost 500 of the people are from fund management firms, and of them are classified as Fund manager or board members. Column 6 documents the total number of stock trading days by each of the functional roles.[3] Most trades are from brokers, making up more than 25% of the total number of trades in our sample, closely followed by the category 'Other'. The Fund managers in our sample are most active. On average, over the 5 year sample period, they trade 90 times per person. People in the Other category are least active with 19 trades per person on average. …could compare with other retail and even corp insiders…

Table 1, panel B reports the total number of stock trading days across days and functional roles for sales, purchases, and for days where purchases and sales offset each other. For each role, we see that the employees tend to buy more frequently than they sell, but

[3] Trades are aggregated for every investor each day, and we use the daily net change in an investor's position of a given stock as our unit of observation.

the average size of their sales is on average XX% larger than the average size of their purchases. It is interesting to note that days where sales and purchases offset each other are concentrated in the group of fund managers (2016), and are rare among other groups.

The next six columns describe the characteristics of the stocks sold and bought for each type of profession. The results help determine whether employees tend to follow certain investment styles or focus on stocks with certain characteristics. The table entries are mean adjusted rank values that range from -0.5 (for the lowest decile) to +0.5 (for the highest decile), obtained by averaging these adjusted ranks across all stock trading days within every trade category.[4]

The results of in columns 4-10 reveal that similar to other retail investors, directors have a tendency to trade stocks with relatively high betas, high market-to-book ratios, and large size. They also tend to be contrarian, selling after stocks have increased in value (with the exception of the past year) and buying after they have decreased. …maybe include comparison with other retail investors and or insiders.

A large number of trades by financial experts occur on the same day for the same stock and have the same sign. The total number of these 'network' trades is 14,215 out of a total of 37,417. This very high proportion of almost 40% suggests a tight community with a substantial flow of information. Figure … shows the network of financial experts where connections are defined as trades on the same day in the same stock with the same sign. The largest number of vertices for any expert is 250+, where a vertice exists if there is at least one connected trade between 2 financial experts.

Out of all networked trades, 3,663 (25.8%) happen between people at the same firm, 881 (6.2%) occur between people in the same financial services group (but not the same firm), and 9,324 (65.6%) occur between people in the same empirical network group or

[4] For a detailed description of the analysis, we refer the reader to Appendix A.

‘community’. [5] In total 10,427 (73.4%) of the networked trades can be traced by to firm, group or empirical network.

III.

This section investigates the likelihood of an employee at a financial intermediary trading any given stock. Our conjecture is that these experts actively seek to benefit from any comparative information advantage they might have, leading to two testable hypotheses. First, we expect financial experts to be relatively more active in the short period around information events, when information asymmetry is likely to be high. Second, we anticipate that the experts swap valuable information through their social networks and are therefore more likely to buy (sell) if a connected expert is buying (selling). As before, we distinguish 3 networks: employees at the same firm; employees at the same financial group (but different firm); and an empirically determined network, based on connections observed in historical trading patterns. In this section we analyze the probability of trading using trading data from 2009, and estimate the empirical network based on data from 2006-2008 using the method developed in Closet, Newman, and Moore (2004).

Table XX, Panel A presents descriptive statistics on the likelihood of an expert trading a stock during a trading day in 2009. The unconditional daily probability of an expert trading is 0.034% this number is calculated as the actual number of days in 2009, on which an expert is a net buyer or seller of a stock (6,434), divided by the total number of stock-

[5] Communities are defined as a set of investors who are heavily connected among themselves, but sparsely connected with other investors Following Ozsoyyev and walden RFS, we use the method developed in Closet, Newman, and Moore (2004) to establish ‘communities in the network’.

expert days on which each expert could have been a net buyer or seller of a stock(18.8 m)[6]. The other probabilities in Panel A are calculated in the same way. For example, out of the total number of stock trading days by experts in 2009, 615 coincided with similar trades by one or more of his colleagues at the same firm (i.e the trades had the same sign and where on the same day and for the same stock). The number stock-days where colleagues at the same firm were active in the full sample of all possible expert-stock days is 110,367. The conditional probability is therefore 615/110,367, which is about 16 times higher than the unconditional probability of an expert trading.

The conditional probability of a trade with the same sign occurring when one or more persons in the same empirical network trades is about 8 times the unconditional probability, whereas if a member of the same financial services group (which excludes the same firm) trades, the conditional probability of a same sign trade in the same stock on the same day is as high as 7.6%. Finally, the conditional probability of trading on a day indicated as a corporate event is almost three times as high as the unconditional probability. The conditional probability is higher for analyst recommendations and earnings announcements relative to large price change events and mergers and takeovers.

We further examine how the attributes of a trade or an expert might affect the probability of buying or selling, by estimating variations of the following panel logit model:

(1) $\text{Log}\{(\text{Trade}_{i,e,d} = 1)/(\text{Trade}_{i,e,d} = 0)\} = a_0 + a_1$ event event, +1 +2+3 and -1 -2 -3
Netfrm -1 -2 -3 net group -1 -2 -3 net network -1 -2 -3
Ln_N (= total number of trades by all individuals in stock i on day t)
Analyst dummy and fund manager dummy and other dummy and board dummy

where

$\text{Trade}_{i,e,d}$ =1 if expert *e* is a net buyer or a net seller of stock *i* on day *d*.
If one or more colleagues at the same firm are trading the same stock in the same direction then net_firm=1; if they are trading in the opposite direction then net_firm=-1

[6] This number is equal to the number of financial experts that trade in 2009 (537) times the number of days (258) and stocks (152), but excludes days when a stock was not traded by any retail investor.

same for net_firm-1 which indicates trades by colleagues 1 day earlier etc. same procedure for net_group and net_network

The results are presented in Table 2, panel B. The first model only includes dummy variables for the 7 days around corporate events, dummy variables for the different functional roles and a measure of centrality of the expert in the expert community.[7] It is clear that the probability of trading by financial experts increases significantly on event days and the days before and after the event. We also find that relative to brokers (the omitted group), board members, fund managers and other employees are less likely to trade, whereas the probability of trading for analysts is not significantly different from the probability of trading for brokers. Finally, the results show clear evidence that financial experts that are more central to the community are more likely to be trade.

The second model in table 2, Panel B includes the log of the number of retail investors that trade stock *i* on day *d*. Not surprisingly, the probability by experts is significantly associated with the trading activity by other retail investors. We also find that relative to other retail investors experts are not significantly more likely to trade on the days around events, with the exception of the event day itself, which still has a significantly higher probability of trading by experts. The third model introduces the network variables. We find strong support for network effects for each of the specified networks: firm, group and empirical network. These effects are not limited to same-day trades, but expert trading is also significantly more likely in stocks that have been trades by other traders in their firm network or empirical network in the previous days.

[7] We calculate centrality as the sum of 4 standardized centrality measures (degree, betweenness, closeness and eigenvector centrality). Each of the four centrality measures is standardized by dividing the score for every expert by its cross sectional standard deviation across all experts. We use data from the 2006-2008 period to calculate our centrality measures.

Overall, the results in Table 2 indicate that employees at financial intermediaries are more active on corporate event days and actively trade on information shared within their networks.

(Model including fixed effects for each of the experts and each of the stocks shows same results …but an't include analysts etc and centrality. Not sure what it adds as Ln(trades) is similar to 'firm fixed effects but better).)

IV. INVESTMENT SKILLS OF EMPLOYEES OF FINANCIAL INTERMEDIARIES

In this section we examine the relative investment skills of financial experts. We first analyze this performance using a calendar-time portfolio approach and then focus on their stock picking skills around particular information events. Finally, we test the conjecture that relative to individual trades, networked trades are less likely to be liquidity trades and more likely to be motivated by private information.

III.A. Calendar Time Portfolio Approach: Analysis of Trades by Employees of FIs

The calendar time portfolios used in this section are designed to mimic a trading strategy based on trades by employees of financial intermediaries. We report results for portfolios based on trades by different groups of employees and different groups of stocks. For example, the '1-day buy portfolio for broker trades', reports the 1-day performance of a portfolio that includes all stocks where the number of brokers who were net buyers over the previous day exceeds the number of brokers who were net sellers over the previous day. Similarly, the '1-quarter sell portfolio for analyst trades', reports the 1-day performance of a portfolio that includes all stocks where the number of analysts who were net buyers over the previous quarter is smaller the number of analysts who were net sellers over the previous quarter.

More specifically, our portfolio design proceeds as follows. First, for each trading day (t) in the sample period, we identify all accounts (e) that trade in any given stock (i) during the preceding period, covering calendar days, t-x to t-y. Second, for each account (e), we aggregate the trading activity across all trades in the stock (i) during this period, to determine whether that account was a net buyer or net seller of the stock. Third, on each day (t) we allocate a given stock (i) into the 'buy portfolio' if more accounts are net buyers than net sellers of that stock, or into the 'sell portfolio' if more accounts are net sellers. This allocation results in buy and sell portfolios based on trades by the employees in our sample over calendar days, t-x to t-y that are updated each trading day t. Finally, we compute the equally weighted portfolio return on day t ($R_{p,t}$) for each of the portfolios.

We then analyze the 1-day return performance of these portfolios ($R_{p,t}$), using the Fama-French 3-factor model, as follows:[8]

(4) $$R_{p,t} - R_{f,t} = \alpha_p + \beta_1 (R_{m,t} - R_{f,t}) + \beta_2 HML_t + \beta_3 SMB_t + \varepsilon_{p,t}.$$

The dependent variable is the excess return on day t for each portfolio, p. We emphasize that the Fama-French alpha from this model (α_p) represents the risk-adjusted 1-*day* performance of the buy or sell portfolio, based on trades by certain groups of employees at financial intermediaries over calendar days, t-x to t-y.

The regression results are provided in Panels A and B of Table 3 for the sell portfolios and the buy portfolios, respectively. In all Panels of Table 3, the t-statistics for the alpha's from the Fama-French regressions are constructed from Newey-West robust standard errors.

The first row in Panel A of Table 2 reports the daily alpha for the sell portfolio across all employees for portfolio formation windows: 1 day, 1 week (excluding day -1), 1 month (excluding last week), and last quarter (excluding last month). The sell portfolio based on the 1-day formation period has a significantly negative alpha of -11 bp per day (t-ratio = -3.1),

[8] We follow the procedures in Fama and French (1993) to calculate their three factors, using daily data for all Finnish stocks.

whereas for the other formation periods none of the alphas are significant. The buy portfolios in Panel B have significant positive 1-day alphas for portfolio formation windows up to 1 month, which are largest in magnitude and significance for the 1-day portfolio formation period at 15 basis points (bp) per day (t-ratio = 5.2).

These results in the first row in Panel A and B clearly show that employees of financial intermediaries are good stock pickers. The results are also economically significant. With daily rebalancing, the excess return on the sell portfolio accumulates to a hypothetical excess return of around -27.5% on an annual basis, and the excess return on the buy portfolio accumulates to more than 35% on an annual basis. Both results suggest a relatively high proportion of trades by employees at financial intermediaries is likely to be informed. In this light the exceptional stock picking skills on the sell side are noteworthy. This result contrasts with prior evidence in several studies which find that purchases are more informative than sales and suggests that sales are less likely to be triggered by liquidity shocks.[9]

Rows 2 to 6 in both panels present the results for the different functional roles. The results in panel A indicate that sales by analysts are most informative with the daily alphas equalling -33 bp (t-ratio = -2.6), whereas the daily alphas of the board sell portfolio and the fund manager sell portfolios are close to zero and insignificant. On the buy-side, in panel B, we see that fund managers are the best stock pickers. The daily alpha of their buy portfolio based on a 1-day formation period is 35 bp (t-ratio=4.7). The second best performing category are analysts with 25 bp (t-ratio=2.4). Similar to the results on the sell side, we do not find any evidence that board members trade on private information (alpha is 4 bp, t-ratio=0.6).

[9] Kraus and Stoll (1972), Cohen, Frazzini, and Malloy (2008), and Grinblatt, Keloharju, and Linnainma (2012) find that buys are more informative than sales. In contrast, Cohen, Malloy, and Pomorski (2012) find both purchases and sales by insiders are informative, and Berkman, Koch and Westerholm (2014) find both purchases and sales by young investors are informative.

Rows 7 to 9 show the 1-day alphas based on portfolios formed for the three firm types in our sample of financial intermediaries. The daily alphas of the buy and sell portfolios are fairly close across brokers, fund management firms and asset management firms and suggest that stock picking skills are not concentrated in any particular financial intermediary.

Finally, we split the sample in Finnish stocks with and without an ADR (rows 10 and 11). The results in Panel A show that the daily alpha of the sell portfolio is only significant for the non-ADR stocks (-21 bp, t-ratio=-4.2). The results in panel B show that the buy portfolio has significant alphas for both ADR and non-ADR stocks that are similar in magnitude (e.g. based on the 1-day formation period the alpha of ADR stocks is 10 bp (t-ratio=3.1) and 14 bp (t-ratio=3.1) for non-ADR stocks).

Overall, the results in this section strongly suggest that employees at financial intermediaries possess significant short-term informational advantages that result in superior stock returns on the days immediately following their trades. Given the short-term nature of this apparent information advantage, we expect this superior performance to manifest itself more profoundly around large price changes or major corporate events that are commonly associated with increased information asymmetry, such as takeover, broker recommendations and earnings announcements. This conjecture is the subject of the next section.

III.B. Performance of Trades around major information events

This section uses an event study approach to focus on trades made by employees at financial intermediaries during the three weeks prior to takeover announcement, earnings announcements and broker recommedations. In addition, we examine financial expert trades before large price changes, which presumably reflect the arrival of substantive value-relevant information. We focus on the mean size-adjusted cumulative abnormal return on the day of and the day after each type of event (*CAR(0,+1)*).

Our sample of earnings announcements is obtained from Bloomberg and consists of XXX quarterly announcements made by Finnish firms over the period, 2006 to 2011. Data on mergers and acquisitions are obtained from SDC Platinum, and include YYY merger announcements for our sample of Finnish firms. Our sample of broker recommendations is from factset….note we need to acquire these data…..Our final sample includes large price changes, which we generate by selecting the two days each year with the largest and smallest market-adjusted abnormal returns for every stock. We exclude all such major price change events if they occur within five days of an earnings or acquisition announcement, or if they occur within one month of another large price change event for the same stock with the opposite sign. This sample contains XXX large price change events.

For each event, we first compute the stock's size-adjusted cumulative abnormal return on the event day and the next day, *CAR(0,+1)*. We then "sign" this *CAR* for each stock for every expert, depending on whether that expert was a net buyer or seller in the first (or second or third) week before the event. If an expert was a net buyer (i.e., shares bought exceed shares sold during the week), then the event period return for that expert equals the stock's *CAR(0,+1)*. Alternatively, if an expert was a net seller (i.e., shares sold exceed shares bought), then the event period return for that expert equals the stock's *CAR(0,+1)* multiplied by -1.

For each event, and for every category of trades, we then calculate the mean signed *CAR(0,+1)* across all experts that were net buyers or sellers of the stock during day -1, -2 or -3, or week -1, -2, or -3. We then average these mean signed *CARs* across all events. The standard error of this mean signed *CAR* across all events is used to construct a t-test of the null hypothesis that the mean *CAR(0,+1)* is zero.

The results are presented in Table 3. The analysis of earnings announcements appears in Panel A, merger and acquisition announcements are presented in Panel B, large price changes are in Panel C and broker recommendations are in panel D. Every Panel provides results for the director trades made during each of the 3 days before the event date on the left hand side of the panel, and each of the 3 weeks before the event date on the right hand side of the panel. Each set of results presents the analysis for the all trades by employees, and for trades in ADR and non-ADR stocks.

First consider the analysis of earnings announcements in Panel A of Table 3. There are 317 earnings announcements where at least one employee traded on day before the earnings announcement. The average signed CAR(0,+1) is 1.1% (t-ratio = 3.0). For the 172 events for non-ADR stocks, the average CAR is more than twice as large as the average CAR for the 145 earnings announcements for ADR stocks. For trades two and three days before earnings announcements, we find no evidence that employees outperform on the announcement. The results on the right hand side of Panel A show that there are 727 earnings announcements where at least one employee traded in the week before earnings announcements. The average signed CAR(0,+1) is 0.5% (t-ratio = 2.2). For the 436 events for non-ADR stocks the average CAR 0.91% (t-ratio=2.9). For non-ADR stocks the CAR is not significant. There is no evidence of significant outperformance around earnings announcements based on trades by employees in two or three weeks before earnings announcements.

Second, the results for merger and acquisition announcements in Panel B of Table 3 do not provide convincing evidence that employees exploit private information about upcoming events. While the mean signed CAR is positive 4.8% (t-ratio=1.9) for the 21 events where at least one employee trades in the week before a takeover announcement, the mean CAR is negative and of similar magnitude for the 23 events where at least one employee trades two weeks before a takeover announcement.

Panel C of Table 8 presents the analysis of large price change events. There are 169 events where at least one employee traded on day before the large price change. The average signed CAR(0,+1) is 1.6% (t-ratio = 2.5) and the average CAR is larger for ADR stocks than for non-ADR stocks. The results on the right hand provide evidence of significant outperformance around large price changes based on trades by employees in each of the three weeks before large price change events.

Finally, panel D of Table 3 gives the results around broker recommendations. Our sample only includes broker recommendations where the broker revision is at least two steps (e.g. from neutral to strong buy or strong sell). There are 731 recommendations where at least one employee traded on day before the recommendation was announced. The average signed CAR(0,+1) for these events is 0.7% (t-ratio = 4.1). Similar to earnings announcements, we find that the average CAR is more than twice as large for non-ADR stocks as for ADR stocks. Also similar to earnings announcements, we find that the profitable trades are limited to trades in the week before the recommendations change.

Together, this analysis provides strong evidence that employees at financial intermediaries outperform when they trade just before major information events. We conclude that a relatively large proportion of these trades during the few days ahead of both major information events is motivated by superior private information that is about to become public.

III.C. Network Trades vs Individual Trades

This section tests the hypothesis that relative to individual trades, networked trades are less likely to be liquidity trades and more likely to be motivated by private information that is shared across two or more people in the sample. We introduce a dummy $Network_{i,d}$ that equals 1 if stock *i,* on day *d* is traded in the same direction by two or more financial experts, and no financial expert is trading in the opposite direction. If networked trades have a higher probability of being information motivated, then we expect these trades to outperform and we expect financial experts to take relatively large positions. We employ two panel regression models to test these hypotheses:

$$AR1_{i,d+1} = a + b \text{ Network }_{i,d}$$

$$Log\_Value_{i,d} = c + d \text{ Network }_{i,d}$$

Where $AR_{i,d+1}$ is size-adjusted abnormal return on the day after a trade on day *d*, and $Log\_Value_{i,d}$ is the natural of the transaction value of the trade in stock *i* on day *d*.

We separately estimate these models for purchases and sales and with and without stock and expert fixed effects. The results for abnormal returns are reported in Panel A and the results for the value of the trades are reported in Panel B. Both Panels have the results for purchases on the left hand side and the results for sales on the right hand side. T-statistics are calculated using standard errors clustered on day and stock.

All results for the first 2 models in panel A, indicate significant outperformance on the buy side. This first model shows that the outperformance of network-purchases equals 25 bp (t-ratio= 2.9) on average. The inclusion of stock fixed effects and expert fixed effects does not change this result, which indicates that, on average, the same expert, trading the same stock generates a higher abnormal return if at least 1 other expert is also buying the same stock on the same day. The results for sales are not consistent with our hypothesis. While the results in column 3 indicate that abnormal returns on average are significantly negative the day after a sale by an expert, the network dummy is insignificant whether or not we include stock and expert fixed effects.

Turning to the value of the trade in Panel B, we see that network-purchases and sales tend to be significantly larger than non network purchases and sales. However, after inclusion of stock and expert fixed effects, network purchases are not significantly different in terms of their transaction value.

Overall, we conclude that network trades are more likely to be motivated by private information than non-network trades. Purchases by financial experts based on shared information tend to generate larger abnormal returns. Sales based on shared information generate significant negative abnormal returns, and are significantly larger in terms of value that non-network sales.

buy	level	N_trades	# shares	Value avg	rbeta	rbm	rsize	rretyr	rretm	rretw	rretd
-1	ANALYST	948	-1985	-7602	0.149	-0.041	0.144	-0.023	0.078	0.013	0.021
-1	BOARD	1883	-11410	-87055	0.180	0.017	0.232	0.008	0.022	0.020	0.033
-1	BROKER	5423	-1812	-9504	0.188	-0.013	0.208	-0.044	0.062	0.038	0.033
-1	FUND MANAGER	3386	-3879	-40506	0.153	0.008	0.179	-0.034	0.010	0.008	0.008
-1	OTHER	4313	-4829	-21985	0.190	0.022	0.236	-0.026	0.051	0.031	0.020
0	ANALYST	6	0	0	0.296	-0.111	0.407	-0.130	0.093	-0.185	-0.111
0	BOARD	180	0	0	0.310	0.155	0.419	-0.032	-0.026	-0.001	0.042
0	BROKER	72	0	0	0.075	-0.011	0.081	-0.154	-0.063	-0.025	-0.084
0	FUND MANAGER	2016	0	0	0.153	0.042	0.265	-0.058	-0.004	0.004	-0.019
0	OTHER	7	0	0	0.241	0.087	0.373	-0.037	0.103	-0.087	-0.103
1	ANALYST	1463	799	4832	0.198	-0.001	0.235	-0.048	-0.066	-0.030	-0.035
1	BOARD	2736	14486	67320	0.210	0.025	0.281	-0.042	-0.070	-0.040	-0.028
1	BROKER	8042	1262	5393	0.204	0.023	0.254	-0.067	-0.090	-0.050	-0.037
1	FUND MANAGER	3737	9397	41029	0.154	0.029	0.203	-0.038	-0.046	-0.034	-0.005
1	OTHER	7495	2071	10923	0.222	0.026	0.290	-0.074	-0.079	-0.040	-0.027
		41707									

Total People

job	Frequency	Asset Mgt	Broker	Fund Mgt	#trades	trades/pp
ANALYST	94	12	82	0	2417	26
BOARD	161	36	54	71	4799	30
BROKER	306	2	303	1	13537	44
FUND MANAGER	101	29	0	72	9139	90
OTHER	613	194	350	69	11815	19
	1275	273	789	213	41707	33
# firms		9	15	15		

Table 2

Panel A. One-Day Alphas for the Sell Portfolios using Different Formation Periods

1-day Alphas (%)

Dependent Variable: Return on Portfolio of	Portfolio Formation Period (number of calendar days)			
	-1	(-7,-2)	(-31,-8)	(-90,-32)
All trades	-.11	-.03	.00	.00
t-ratio	-3.1	-1.4	-0.9	0.3
Analyst	-.33	-.08	-.02	.02
t-ratio	-2.6	-1.4	-0.8	0.8
Board	-.01	-.03	.02	.03
	-0.8	-0.7	0.6	0.1
Broker	-.13	.00	.00	.02
	-2.2	0.1	-0.1	0.9
Fund Manager	-.01	-.37	-.02	.01
	-0.5	-0.8	-0.6	0.5
Other	-.15	-.66	-.01	.01
	-2.6	-2.3	-0.6	0.6
Asset Management Firms	-.11	-.06	-.04	-.02
	-1.7	-1.5	-1.7	-1.3
Brokerage Firms	-.08	-.04	-.02	.03
	-1.6	-1.5	-0.9	1.6
Fund Management Firm	.00	.00	-.14	.03
	0.1	-0.1	-0.4	1.2
ADR stocks	.40	-.03	-.27	.02
	0.9	-1.2	-1.1	0.7
No ADR stocks	-.21	-.04	.02	.02
	-4.2	-1.2	0.8	1.0

Panel B. One-Day Alphas for the Buy Portfolios using Different Formation Periods

1-day Alphas (%)

Dependent Variable: Return on Portfolio of	Portfolio Formation Period (number of calendar days) -1	(-7,-2)	(-31,-8)	(-90,-32)
All trades	.15	.08	.04	.00
t-ratio	5.2	5.0	2.5	0.3
Analyst	.25	.10	.09	.00
t-ratio	2.4	2.2	3.8	0.0
Board	.04	.04	.02	.00
	0.6	1.3	1.1	0.0
Broker	.18	.06	.03	.00
	4.1	3.0	1.6	0.3
Fund Manager	.35	.07	.04	.03
	4.7	1.8	2.0	1.5
Other	.15	.07	.03	.01
	3.3	3.0	1.3	0.7
Asset Management Firms	.18	.07	.06	.01
	3.6	2.4	3.3	0.7
Brokerage Firms	.16	.08	.02	.00
	4.7	4.1	1.5	0.1
Fund Management Firm	.14	.09	.03	.01
	2.2	3.3	1.5	0.5
ADR stocks	.10	.05	.03	.03
	3.1	3.0	2.3	2.0
No ADR stocks	.14	.11	.04	.00
	3.1	4.2	1.8	-0.3

Table 8. Event Study: The Performance of Different Types of Trades by Directors Prior To Major Information Events

Panels A - C of this Table present event study analysis of the performance of trades made by directors during the three weeks prior to three kinds of events: earnings announcements, takeover announcements, and large price changes. We consider all events where at least one director trades during one of the three weeks before the event. In the text we further discuss the criteria for selecting the sample for each kind of event. We give the mean size-adjusted cumulative abnormal return on the day of and the day after each type of event, CAR(0,+1), for three types of trades by directors: insider trades, interlock trades, and all unconnected trades. If an account is a net seller then the CAR(0,+1) for that account equals the stock's CAR(0,+1) multiplied by -1.

Panel A. Earnings Announcements

		Mean CAR(0,+	statist	# of Events with ≥ 1 trade			Mean CAR(0,	-statisti	# of Events ith ≥ 1 trad
1 Day Before	All Trades	1.06%	3.0	317	1 Week Before	All Trades	0.50%	2.2	727
	no ADR	1.37%	2.8	172		no ADR	0.91%	2.9	436
	ADR	0.68%	1.3	145		ADR	-0.12%	-0.4	291
2 Days Before	All Trades	-0.12%	-0.2	200	2 Weeks Before	All Trades	-0.02%	-0.1	634
	no ADR	0.27%	0.3	103		no ADR	0.01%	0.0	369
	ADR	-0.53%	-0.9	97		ADR	-0.07%	-0.2	265
3 Days Before	All Trades	0.32%	0.5	172	3 Weeks Before	All Trades	-0.03%	-0.1	658
	no ADR	1.13%	1.3	93		no ADR	0.14%	0.5	389
	ADR	-0.62%	-0.8	79		ADR	-0.28%	-0.8	269

Panel B. Merger and Acquisition Announcements

1 Day Before					1 Week Before	All Trades	4.77%	1.9	21
						no ADR	4.88%	1.7	12
						ADR	4.61%	1.0	9
2 Days Before					2 Weeks Before	All Trades	-3.22%	-1.1	23
						no ADR	-8.80%	-1.4	10
						ADR	1.06%	1.1	13
3 Days Before					3 Weeks Before	All Trades	1.03%	0.2	22
						no ADR	-0.76%	-0.1	13
						ADR	3.61%	0.8	9

Panel C. Large price Changes

1 Day Before	All Trades	1.61%	2.5	169	1 Week Before	All Trades	1.15%	3.3	508
	no ADR	1.11%	1.2	101		no ADR	1.16%	2.5	333
	ADR	2.35%	2.5	68		ADR	1.12%	2.2	175
2 Days Before	All Trades	1.22%	1.6	115	2 Weeks Before	All Trades	0.74%	2.1	513
	no ADR	1.55%	1.5	66		no ADR	0.84%	1.8	332
	ADR	0.76%	0.7	49		ADR	0.57%	1.1	181
3 Days Before	All Trades	1.52%	1.9	109	3 Weeks Before	All Trades	0.67%	1.8	511
	no ADR	1.87%	1.6	63		no ADR	0.84%	1.7	337
	ADR	1.05%	0.9	46		ADR	0.34%	0.7	174

Panel D. Broker Recommendations price Changes

1 Day Before	All Trades	0.71%	4.1	731	1 Week Before	All Trades	0.40%	3.7	1850
	no ADR	1.32%	3.2	199		no ADR	0.64%	2.7	602
	ADR	0.49%	2.7	532		ADR	0.29%	2.6	1248
2 Days Before	All Trades	0.24%	1.1	510	2 Weeks Before	All Trades	0.11%	1.2	1782
	no ADR	0.08%	0.2	145		no ADR	0.02%	0.1	586
	ADR	0.30%	1.2	365		ADR	0.16%	1.5	1196
3 Days Before	All Trades	0.08%	0.5	506	3 Weeks Before	All Trades	0.04%	0.4	1730
	no ADR	0.51%	1.2	114		no ADR	-0.16%	-0.9	532
	ADR	-0.04%	-0.2	392		ADR	0.13%	1.1	1198

Panel A: Return on day T=1 after a trade on day t										
BUY						*SELL*				
Intercept	0.0007	1.8	0.0075	0.8		Intercept	-0.0005	-2.1	-0.0094	-1.2
network	0.0025	2.9	0.0028	3.0		network	-0.0008	-0.6	-0.0006	-0.6
FE stock		no		yes		FE stock		no		yes
FE account		no		yes		FE account		no		yes

Panel B: Value of Trade on day t										
BUY						*SELL*				
Intercept	7.884	128.0	8.62	73.230		Intercept	8.440	149.8	8.071	17.2
network	0.17	2.6	0.01	0.37		network	0.14	2.9	0.09	3.8
FE stock		no		yes		FE stock		no		yes
FE account		no		yes		FE account		no		yes

Network of Financial Experts