Personal Trading by Employees of Financial Intermediaries

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Abstract

Personal stock market trading by brokers, analysts and fund managers is highly profitable over short windows up to a month. These financial experts earn particularly high abnormal returns for their own account when they trade simultaneously with other experts and when they trade ahead of earnings announcements, revisions of analyst recommendations, and large price changes. They also profit by front-running before the execution of corporate insider trades and block trades of mutual funds, and later, by mimicking these trades before they are publicly disclosed. In sum, financial experts appear to benefit handsomely from their privileged access to material private information.

Key Words: Fiduciary duty, informed trading, information asymmetry, leakage, front-running, tipping, insider trades, block trades, social network analysis, private information, broker, fund manager.

JEL codes: G12, G14, G18.

I. INTRODUCTION

Almost all developed countries require company insiders associated with a listed firm to publicly disclose their personal trades in the stock of their own firm. Advocates of insider trading regulation argue that this public disclosure promotes the fairness and integrity of financial markets by curbing unfair enrichment by those with privileged access to private information. In Finland the regulator has taken this reasoning one step further, to require that employees of financial intermediaries who have access to material private information must also publicly disclose all of their personal trades in any stock listed on the Nasdaq OMX Helsinki Exchange.[1]

In this study we examine the personal trading activity of 1,249 employees of financial institutions in Finland during the 5-year period, 2006 through 2011. These financial experts are employed by 40 different financial intermediaries, which represent XX% of the market share in the Finnish brokerage industry and XX% of the market share in the fund management industry.

We begin our analysis with an examination of the *selection and timing* of the personal stock transactions by these financial experts. We find that the likelihood of an expert trading a given stock increases sharply if there is similar trading on the same day or the previous two days by other experts in the same firm, or the same financial services group, or the same empirical trading network.[2] We also show that an expert is more likely to trade if he or she is more prominent within the network of Finnish financial experts. Finally, we document that these experts are more likely to trade in the days around firm-specific information events. Overall, the

[1] The common theme of the rationales for regulation of insider trading is that the "… self-serving use of principal's information to purchase or sell securities, is in breach of a duty of loyalty and confidentiality, defrauds the principal of the exclusive use of that information," and is not consistent with the fairness and integrity of financial markets (McCord, McCord, and Bailey, 2012, p. 145). See also Bhattacharya (2014), Bhattachary and Douck (2002), Bhattacharya and Spiegel (1991), Easterbrook (1985), Manne (1969, 2005), and Padilla (2011).
[2] The same financial services group refers to other brokerage firms, fund management firms, or asset management firms with the same parent company. An empirical trading network is defined as a community of investors heavily connected by similar trading among themselves, but sparsely connected with others. We follow Ozsoylev et al. (2014) and use the methodology of Clauset, Newman, and Moore (2004) to identify the empirical trading network.

selection and timing of personal trading by financial experts suggests that they seek to benefit from their privileged access to valuable information.

In our second set of tests we analyze the trading *performance* of financial experts. We find that they exhibit superior stock-picking skills on both the buy-side and the sell-side over the days immediately following their personal trades. For example, experts significantly outperform retail investors by an average of 11 basis points (bps) per day based on all purchases made on the previous day, and another 5 bps per day based on earlier purchases made over the past week (but excluding the previous day). On the sell side, we also find that experts significantly outperform by -8 bps based on sales made the previous day, and another -3 bps per day based on earlier sales made during the past week. In contrast, previous purchases and sales made by experts over the past quarter (but excluding the prior month), do not significantly outperform retail trades.

Further analysis shows that this extraordinary short term outperformance is concentrated among brokers, analysts, fund managers, and 'other' experts, while there is no such abnormal performance by the board members of financial intermediaries. We also find that, although stand-alone purchases and sales by individual experts are profitable on the next day, such purchases and sales are significantly more profitable if they are conducted jointly with other financial experts. For example, on the day after similar purchases by 5 to 10 experts, the average stock price increase is 28 bps, and this performance increases to 74 bps if a stock is bought by more than 10 experts on the same day.

Given the short term nature of this trading performance by financial experts, we next examine whether they trade profitably based on privileged access to private firm-specific information that is about to become public. We find that they do. For example, when experts trade on the day before earnings announcements, they generate a mean cumulative abnormal return on days 0 and +1 (i.e., *CAR(0,+1)*) of 0.8 percent. Likewise, when they trade one day ahead of large price changes, financial experts generate an average *CAR(0,+1)* of 2.5 percent. Similarly, when experts trade on the day before analysts revise their stock recommendations, they earn an average *CAR(0,+1)* of 0.4 percent. Furthermore, when we limit this latter sample to trades made one day ahead of revisions that are made by an analyst at the same firm as the expert trading, the mean *CAR(0,+1)* increases significantly to 1.6%. On the other hand, financial experts do not trade profitably before takeover announcements, perhaps out of fear that trading ahead of these uncommon events are more likely to attract the attention of regulators.

One possible explanation for this exceptional trading performance by financial experts is that these knowledgeable investors are able to recognize and exploit profitable trading opportunities by using only publicly available information. An alternative explanation is that financial experts may generate at least some of their profits by trading on privileged access to material private information obtained through their professional network, implying a potential breach of their fiduciary duties.[3] While it is beyond the scope of our study to decisively establish the relative veracity of these two alternative explanations, we shed additional light on this issue by further examining two situations where a unique opportunity exists for a breach of fiduciary duties. Namely, we analyze expert trades made in the days before the execution and public disclosure of corporate insider trades and large block trades by Finnish mutual funds.

First, we find that financial experts front-run corporate insider purchases (executed on day 0), by trading on the previous two days (on days -1 and -2). Furthermore, experts continue to

[3] "A fiduciary duty is a legal duty to act solely in another party's interests. Parties owing this duty are called fiduciaries. The individuals to whom they owe a duty are called principals. Fiduciaries may not profit from their relationship with their principals unless they have the principals' express informed consent. They also have a duty to avoid any conflicts of interest between themselves and their principals or between their principals and the fiduciaries' other clients. A fiduciary duty is the strictest duty of care recognized by the US legal system." Source: Legal Information Institute, Cornell University Law School (http://www.law.cornell.edu/wex/fiduciary_duty)

mimic these insider purchases on days 0 and +1, before such trades are disclosed to the public (after day +3). Some of these front-running and copy-cat trades are made by individuals classified as brokers, but these trades also originate from other types of financial experts, suggesting that this private information quickly spreads through the financial services network. Moreover, this information turns out to be valuable. For the trades by all experts made on the same day as insider trades, the mean signed cumulative abnormal return over the next twenty days, *CAR(+1,+20)*, is 1.7 percent.

Second, we analyze the trading behavior of financial experts around days when Finnish mutual funds buy or sell large blocks of stock. Once again, we document significant abnormal personal trading activity by experts on the days before these block trades are executed and disclosed publicly. This front-running and copy-cat trading is also not limited to brokers and fund managers, but includes other employees of intermediaries. On the other hand, we find no evidence of front-running by employees of the fund management firms involved in the block trades. For all trades made by financial experts over the two days before these block trades are executed, the average performance is a mean signed *CAR(+1,+20)* of 1.4 percent. Together with the trading activity around insider trades, this evidence supports the view that valuable private information is shared and traded on throughout the financial services network.

This analysis of personal trading by the employees of financial intermediaries should be of interest to practitioners and regulators alike. This study also contributes to several strands of academic literature. First, we add to the body of work on insider trading. Most work in this area examines the cross-sectional return forecasting ability of corporate insider trades, and finds that insiders outperform when they buy their own company's stock, but not when they sell.[4] Another

[4] For evidence on the performance of insider trading in the U.S., see Jaffe (1974), Jeng, Metrick, and Zeckhauser (2003), Lakonishok and Lee (2001), Rozeff and Zaman (1988, 1998), Seyhun (1986) and Ravina and Sapienza

general feature of this literature is that the outperformance of insider trades tends to accrue over fairly long periods of six to twelve months (e.g., see Jeng, Metrick, and Zeckhauser (2003)). In contrast, we show that financial experts display exceptional stock picking skills on both the buy side and the sell side, and their profits accrue over short windows of only a few days.

Second, we extend the literature on information leakage in financial markets by providing evidence of front-running and copycat trading by these experts prior to the public disclosure of material private information. Several previous studies document information leakage ahead of information events such as earnings surprises, changes in analyst recommendations, insider trades, and takeover announcements. For example, Christophe, Ferri, and Angel (2004) find increased short selling in the five days ahead of negative earnings surprises. Irvine, Lipson, and Puckett (2007) and Nefedova (2012) find abnormal buying by institutions in the five days before the initial release of analyst buy recommendations, consistent with tipping about the contents of forthcoming analyst reports. Chakrabarty and Shkilko (2013) and Khan and Lu (2013) find an increase in short selling on the days when corporate insiders sell, before the trades are officially reported to the public, and sometimes even before the insiders are done selling.[5] Our study adds to this literature by providing evidence that employees of financial intermediaries directly benefit by front-running and mimicking information-based trades in their own personal accounts.

Finally, we extend recent work which documents that valuable information is diffused through social networks. Ozsoylev et al. (2014) identify 'empirical investor networks' composed of investors with similar trading behavior. Other studies focus on specific predefined social networks. For example, Shiller and Pound (1989) show that the trading decisions by institutional

(2010); for U.K. evidence, see Fidrmuc, Goergen, and Renneboog (2006); for Finnish evidence, see Berkman, Koch and Westerholm (2016); and for other countries, see Clacher, Hillier, and Lhaopadchan (2009).

[5] In contrast to the studies above, Griffin, Shu, and Topaloglu (2012) find little evidence of information leakage from brokerage houses to their favored clients.

investors are influenced by communication within their peer network. Cohen, Frazzini, and Malloy (2008) find that mutual fund managers earn abnormal returns based on information obtained through their educational networks. Berkman, Koch and Westerholm (2016) show that corporate directors outperform when they buy interlock stocks, where a co-board member is an insider. Others attribute the similarity of trades by investors in the same geographic area to word-of-mouth communication within their local network.[6] This study provides evidence of rapid diffusion of valuable short term information through the network composed of employees at financial intermediaries.

II. INSTITUTIONAL BACKGROUND AND DATA

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, the Finnish regulations are modelled after U.S. insider trading laws. The Finnish Financial Supervisory Authority (FSA) regulates financial markets in Finland and seeks to enforce the law by monitoring insider trading. What makes Finland special is that the basic regulations pertaining to public disclosure of personal trading by corporate insiders also extend to the employees of financial institutions who have regular access to material private (i.e., insider) information.

Chapter 5, Section 5 of the Securities Markets Act (26.5.1989/495, July 2009) states that:

> "The holding of shares … subject to public trading … shall be (made) public if the holder of the security is:
> 1) a member … of the Board of Directors of … a securities intermediary … ;
> 2) (or) a broker, a person employed by the securities intermediary whose duties include investment research relating to such securities or another employee who, by virtue of his position or tasks, learns inside information relating to these securities on a regular basis ..."

[6] For example, see Brown et al. (2008), Ellison and Fudenberg (1995), Hong, Kubik, and Stein (2005), and Ivkovic and Weisbenner (2005, 2007).

Inside information is defined in the Securities Market Act (Chapter 5, Section 1) to include any:

> "information of a precise nature relating to a security subject to public trading … which has not been made public … and which is likely to have a material effect on the value of the security."

For each person subject to the duty to declare[7], the person's trading activity in any publicly traded securities must be disclosed in the public Insider Register. The information in the register must include the securities owned by this person and all transactions, it must be maintained for at least five years, and it needs to be accessible without difficulty, which in practice means at the premises of the securities intermediary (Securities Market Act, Chapter 5, Section 7).

Chapter 7, Section 3 of the Act further states that:

> "No … functionary of a … securities intermediary … (who) has learned an unpublished fact of the issuer of a security or of the financial status or private circumstance of another or a business or trade secret may reveal or otherwise disclose it or make use thereof ..."

Standard 1.3 of the Act continues by stating:

> "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 (Section 5.9.3, under 174)."

II.B. Data Sources and Descriptive Statistics for Different Types of Trades

II.B.1 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 the 40 firm-specific public insider trading registers of Finnish financial intermediaries during the five-year

[7] This declaration requirement includes the trades of a spouse, a minor, or an organization under the direct or indirect control of this employee of the financial intermediary.

period, March 2006 through March 2011. These registers document all personal transactions in stocks listed on the Nasdaq OMX Helsinki Stock Exchange made by the employees of these financial intermediaries who have regular access to material private information, as well as the trades of their family members or through companies under their control.

We obtain earnings announcement dates from Bloomberg, merger and acquisition announcement dates are taken from SDC Platinum, and broker recommendations are from S&P Capital IQ. 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.

II.B.2 Descriptive Statistics

We partition the sample of all trades by financial experts according to several classification schemes, into trades made by employees in: (i) the five functional roles (i.e., brokers, analysts, fund managers, board members, or ‘others’), (ii) the three types of financial service firms (i.e., brokerage firms, mutual funds, and asset management firms), and (iii) the three professional networks (i.e., the same firm, same financial services group, and same empirical trading network). We also define ‘network trades’ as similar signed trades made in the same stock on the same day by two or more financial experts.

The top five rows in Panel A of Table 1 present the relative frequencies of the number of experts and their trading activity for employees in each functional role. Column 2 shows that we have this trading information for a total of 1,249 financial experts. Of these individuals, 306 are classified as brokers, 92 as analysts, 99 as fund managers, 157 as board members, and 595 individuals are included in the category, ‘other.’

Columns 4 - 9 of Panel A further document the number and proportion of employees who serve in each functional role at the three types of financial service firms. Our sample includes the employees of 16 different brokerage firms, 15 fund management firms, and 9 asset management firms.[8] Over 60% of all employees in our sample (785 of the 1,249 employees) work at brokerage firms, and 39% (303) of these are brokers themselves. The 15 fund management firms in our sample employ 203 people, with 70 classified as fund managers, 66 as board members, 1 as broker, and 66 as 'other.' Finally, 261 individuals work at asset management firms, with 35 classified as board members, 29 as fund managers, 12 analysts, 2 brokers, and 183 'other.'

Columns 10 and 11 of Panel A provide the total number and percent, respectively, of stock trading days that are attributable to experts serving in each functional role.[9] Roughly one third (36%) of all expert trades in our sample are made by brokers. This group is closely followed by experts in the 'other' category, who make 30% of all trades. The group with the third most trades is board members (15%), followed by fund managers (13%) and analysts (6%). On a per expert level, column 12 shows that fund managers are most active in the market, with an average of 50 trades per person over the five-year sample period. These individuals are followed by brokers who trade an average of 44 times, board members who trade 35 times, and analysts who trade 26 times. Experts in the "other" category are least active, trading an average of just 19 times during the 5-year sample period.[10]

Panel B of Table 1 presents more detailed summary statistics for the different groups of trades made by financial experts in each functional role. The first five rows give the trading

[8] Finnish intermediaries are classified by the Finnish authorities into the following three financial services groups: brokerage firms, fund management firms (institutional investment and investment management for private clients) and asset management firms (collective investments such as mutual funds and exchange traded funds).
[9] Trades are aggregated for every individual investor for every stock (i) on each day (t), and we use the daily net change in an investor's position of a given stock as our unit of observation.
[10] We note that most experts in our database are not employed by the same reporting entity for the full 5-year period.

statistics for the days on which each type of employee makes net *purchases*. The second five rows provide analogous details for net *sales*.[11]

Column 2 in Panel B reports the total number of stock trading days for experts in each functional role, for days with net buying or net selling. Columns 3 and 4 similarly provide the average number of shares traded and the average monetary value (in €) of the trades in each category. For each functional role, these experts tend to buy more frequently than they sell, but they buy in smaller transaction amounts of € (except for fund managers, whose average purchases and sales are roughly the same amount).

In column 5 of Panel B, it is noteworthy that almost 50 percent of all purchases by financial experts are classified as 'network trades,' in which two or more experts buy the same stock on the same day. This high proportion of network trades suggests a tight financial community whose members routinely purchase stocks based on common information shared through the financial services network. Network sales are less prevalent, but still range between 21% and 29% of all sales by each category of experts. For both purchases and sales, the tendency to make network trades is greatest for analysts and lowest for board members.

Columns 6 - 12 in Panel B provide information about the characteristics of the stocks traded by each type of investment professional. This evidence shows whether financial experts serving in the different functional roles tend to focus on stocks with certain attributes or follow certain investment styles. The entries in these columns are calculated as follows. First, every day we compute the decile rank values for every firm characteristic across all stocks traded on the Helsinki Stock Exchange, and adjust these ranks to range from -0.5 (for the lowest decile rank) to +0.5 (for the highest decile rank). Next we assign the appropriate adjusted decile rank for

[11] We also identify a smaller number of days in which an expert's purchases and sales in a given stock exactly offset one another (i.e., days with round trip trades). There are too few of these trading days to apply our main analysis.

every firm characteristic to each stock trade by an expert in the sample. The mean values presented in columns 6 - 12 are then obtained by averaging the adjusted decile ranks across all stock trading days by experts within every category. For additional details on the construction of these firm characteristics, we refer the reader to Appendix A.

The results in columns 6 - 12 of Panel B reveal that all five types of experts have a tendency to trade stocks with relatively large size and high betas. In addition, most types of employees tend to buy and sell stocks with high market-to-book ratios. Financial experts also tend to be contrarian, buying after stocks have decreased in value, and selling after they have increased (with the exception of the past one-year time frame).

III. LIKELIHOOD OF TRADING BY FINANCIAL EXPERTS

In this section we estimate the likelihood of a financial expert trading any particular stock on any given day, both unconditionally, and conditional on other experts in the same professional network trading the same stock on the same day. We conjecture that these experts actively seek to benefit from their access to valuable information, which leads us to specify two testable hypotheses. First, we expect financial experts to be more active during the short period around major firm-specific information events, when information asymmetry is likely to be high. Second, we anticipate that experts are more likely to buy (or sell) a given stock if another expert in the same professional network is buying (or selling) the same stock.

We consider three professional networks defined as employees in the same: (i) financial firm, (ii) financial services group (but not the same firm), or (iii) empirical trading network. The first two networks are simple to construct from our data on the employees of Finnish financial intermediaries. The third empirical trading network requires the application of statistical tools commonly used in social network theory. We determine the empirical trading network by applying the procedure of Clauset, Newman, and Moore (2004), using data on all financial expert trades during the first two and a half years of our sample period, March 2005 - August 2008. We then analyze the likelihood of trades by experts within the same empirical network during the final two and half years (September 2008 - March 2011).

III.A. Unconditional and Conditional Probabilities of Trading by Financial Experts

In Panel A of Table 2, we present descriptive statistics that reflect various aspects of the overall probability of an expert trading a certain stock on any given trading day during the period, September 2009 - March 2011. First, the unconditional probability of an expert trading a stock (*i*) on any given day (*t*) during this period is 0.019%. This proportion is calculated as the actual number of days on which a financial expert is a net buyer or seller of a stock (18,003), divided by the total number of trading days on which these experts could have traded a stock (roughly 95 million).[12]

The next three descriptive statistics in Panel A of Table 2 are calculated in the same way, but they reflect conditional probabilities of an expert trading, given that other experts in the same professional network of each type are also active in the market on that day. For example, out of the 18,003 stock trading days by experts during the period September 2008 - March 2011, similar network trades by at least one other expert at the same firm occur on 2,208 stock trading days. We divide this figure by the total number of expert-stock trading days where any colleagues at the same firm were active during 2009 (831,069), to obtain the ratio of 0.27%.[13]

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[12] The latter figure is the total number of experts that trade in the period September 2008 through March 2011 (883) times the number of stocks (152) and trading days (735) excluding, for each director, the days when a stock was not traded by any retail investor (3 million, which is 3,424 stock trading days times the number of directors, 883).

[13] Note that this number (831,069) is much larger than the total number of trades by financial experts in 2009 (18,003) because the larger sample includes all of the employees who could also potentially have traded stock *i* on day *t* (when one of their colleagues at the same firm traded stock *i* on day *t*). For example, a stock traded on day *t* by one employee of a brokerage firm with 25 employees increases the denominator by 24

This ratio reflects the probability of an expert making a firm-network trade, conditional on other experts in the same firm making any trade that day. This conditional probability is more than 10 times higher than the unconditional probability of an expert trading.

Likewise, the conditional probability of network trades being made by experts in the same financial services group (but at different firms) is 0.23%, which is also more than 10 times greater than the unconditional probability of any expert trading. Similarly, the probability of an expert trading a given stock conditional on other experts in the same empirical network being active in the market is 0.13%, which is roughly 5 times greater than the unconditional probability of any expert trading. Finally, the conditional probability of an expert trading, given that a major corporate event occurs on that day, is 0.06%, which is more than three times the unconditional probability of any expert trading. This last probability is higher for analyst recommendations (0.068%) and earnings announcements (0.080), relative to large price change events (0.032%) or takeover announcements (0.027%).

III.B. Logit Analysis: Conditional Probability of Trading by Financial Experts

In this section we apply logit analysis to examine all trades made by these experts during the period September 2008 - March 2011. This approach allows us to examine whether the probability of a given financial expert (*e*) buying or selling a certain stock (*i*) on any given day (*t*) is associated with similar trades made on or before day (*t*), by other experts in the same professional network (i.e., the same firm, financial services group, or empirical trading network). In addition, we account for the presence of major firm-specific events occurring on the surrounding days, and we also control for the centrality of the expert (*e*) in the empirical network, the trading volume in stock *i* on day *t*, and other firm attributes, using the following panel logit model:

$$\text{Log}\{(\text{Buy}_{i,e,t} = 1) / (\text{Buy}_{i,e,t} = 0)\} = a_0 + a_1 \text{Analyst}_e + a_2 \text{FM}_e + a_3 \text{BM}_e + a_4 \text{Other}_e +$$

$$+ \sum_{k=0}^{4} a_{5k} \text{Firm-NW}_{i,e,t-k} + \sum_{k=0}^{4} a_{6k} \text{Group-NW}_{i,e,t-k} + \sum_{k=0}^{4} a_{7k} \text{Emp-NW}_{i,e,t-k} + \sum_{k=-3}^{3} a_{8k} \text{Event}_{i,e,t-k}$$

$$+ a_9 \ln(\text{Volume})_{i,t} + a_{10} \text{Centrality}_e + a_{11} \text{Size}_{i,t} + a_{12} \text{Beta}_{i,t} + a_{13} \text{MB}_{i,y} +$$

$$+ a_{14} \text{RYear}_{i,t} + a_{15} \text{Rmonth}_{i,t} + a_{16} \text{RWeek}_{i,t} + a_{17} \text{RDay}_{i,t}, \qquad (1)$$

where

$\text{Buy}_{i,e,t}$ = 1 if expert *e* is a net buyer of stock *i* on day *t*, or 0 otherwise;

Analyst_e = 1 if expert *e* is an analyst, or 0 otherwise;

FM_e = 1 if expert *e* is a fund manager, or 0 otherwise;

BM_e = 1 if expert *e* is a board member of the intermediary, or 0 otherwise;

Other_e = 1 if expert *e* is in the ‘other’ category of functional roles, or 0 otherwise;

$\text{Firm-NW}_{i,e,t-k}$ = 1 if other experts at the same *firm* as expert *e* combine to be a cumulative net buyer of the same stock (*i*), on the same day or an earlier day (*t-k; k = 0-4*),

or = 0 if no other experts at the same *firm* as *e* make a trade in stock i on day *t-k*,

or = -1 if other experts at the same *firm* as expert *e* are a cumulative net seller of the same stock (*i*), on the same day or an earlier day (*t-k; k = 0-4*);

$\text{Group-NW}_{i,e,t-k}$ = 1 if other experts in the same *financial services group* (but not the same firm) as expert *e* are a cumulative net buyer of the same stock (*i*), on the same day or an earlier day (*t-k; k = 0-4*),

or = 0 if no other experts in the same *group* trade stock *i* on day *t-k*,

or = -1 if other experts in the same *financial services group* as *e* are a cumulative net seller of the same stock (*i*), on the same day or an earlier day (*t-k; k = 0-4*);

$\text{Emp\_NW}_{i,e,t-k}$ = 1 if other experts in the same *empirical network* as *e* are a cumulative net buyer of the same stock (*i*), on the same day or an earlier day (*t-k; k = 0-4*),

or = 0 if no other experts in the same *empirical network* trade stock i on day *t-k*,

or = -1 if other experts in the same *empirical network* as *e* are a cumulative net seller of the same stock (*i*), on the same day or an earlier day (*t-k; k = 0-4*);

$\text{Event}_{i,e,t-k}$ = 1 if the trade occurs on day *t*, while a major event for firm *i* occurs k days earlier or later, on day (*t-k; k = -3 to +3*), or 0 otherwise;

$\ln(\text{Volume})_{i,t}$ = the natural log of the total number of trades in stock *i* on day *t* across all retail investors, including the financial experts in our sample;

$Centrality_e$ = the centrality of director *e* within the empirical trading network.[14]

$Size_{i,t}$ = adjusted decile rank of the market capitalization for stock *i* on day *t*;

$Beta_{i,t}$ = adjusted decile rank of the Dimson beta for stock *i*, estimated on day *t*;

$MB_{i,y}$ = adjusted decile rank of the market-to-book ratio for stock *i* in year *y*;

$RYear_{i,t}$ = adjusted decile rank of return for stock *i* over last year, excluding prior month;

$RMonth_{i,t}$ = adjusted decile rank of return for stock *i* over last month, excluding prior week;

$RWeek_{i,t}$ = adjusted decile rank of return for stock *i* over last week, excluding prior day;

$RDay_{i,t}$ = adjusted decile rank of return for stock *i* on the previous day;

The firm-specific events incorporated in the Event dummy variable include earnings announcements, takeover announcements, revisions of analyst recommendations, and large price changes. We further discuss the selection criteria for these respective samples of firm-specific events in section IV.A below. The other control variables are motivated by the work of Grinblatt, Keloharju, and Linnainma (2012), and are described in Appendix A. We also include dummy variables for the different days of the week.

The results are presented in Panel B of Table 2. The left side of Panel B provides the estimates for Equation (1) based on purchases by financial experts, while the right side gives the analogous results for sales. First consider the coefficients of the dummy variables for the different functional roles of experts in the financial sector. On the left (right) side of Panel B, the probability of *buying* (*selling*) by analysts, fund managers, board members and 'other' experts is significantly lower than that of brokers (the omitted group).

Second, the likelihood of a given expert trading a stock is significantly associated with similar trading activity by other financial experts in each of the three social networks. Consistent

[14] We calculate the centrality of expert *e* as the sum of four common centrality measures from social network theory (degree, betweenness, closeness, and eigenvector centrality), after standardizing each measure by dividing the score for every expert by the standard deviation of that score across all experts. We use data from March 2006 - September 2008 to compute these centrality measures. See Berkman, Koch, and Westerholm (2016) for similar analysis.

with expectations, an expert is significantly more likely to *buy* (*sell*) a stock (*i*) on a given day (*t*), if other experts in any of the three social networks are net buyers (sellers) of the same stock (*i*) on the same day (*t*), or on one or more of the previous four days. In addition, the probability of buying and selling by financial experts increases significantly on the days before or after a firm-specific event.

Consider next the coefficients of the control variables. First, financial experts are more likely to buy or sell stock *i* on day *t* if there is a greater number of trades in that stock on that day among all retail investors. Also, experts who are more prominent (i.e., central) within the empirical trading network are significantly more likely to buy or sell on any given day. In addition, experts are relatively more likely to trade stocks with a lower market-to-book ratio, and they tend to be contrarian. Overall, the results in Table 2 indicate that employees at financial intermediaries actively trade on information shared within their professional social networks, and they tend to be more active around corporate event days, consistent with our expectations.

IV. TRADING PERFORMANCE OF FINANCIAL EXPERTS

In this section we begin by examining the performance of trades by all financial experts, relative to retail investors. Next we consider the relative performance of trades made by experts working in the five functional roles or in the three different financial services groups of firms. We also examine the performance when two or more experts make similar network trades. Finally, we focus on the stock picking skills of experts around information events.

IV.A. Performance of Trades by All Financial Experts

We use a Fama-MacBeth (1973) regression approach similar to the analysis of Grinblatt, Keloharju, and Linnainma (2012) to analyze the investment skills of financial experts. The sample period covers all trading days for which we have information on the trading activity of financial experts during March, 2005 - March, 2011. First, for each day (*t*) in the sample period, we identify all Finnish individual accounts that trade in any stock (*i*) over some recent time frame that spans the period from *x* days earlier to *y* days earlier. This process identifies the recent trades by all (more than half a million) Finnish retail investors, including the 1,249 financial experts. Then we separate these trades into purchases versus sales, resulting in two cross-sections for every day (*t*) that contain the purchases and sales, respectively, across all stocks (*i*) over the recent portfolio formation period covering days (*t-x*, *t-y*).

Next we analyze the return performance on day *t* for this collection of recent trades. Specifically, for every day (*t*) we separately estimate the following cross-sectional regression model for the samples of purchases and sales, respectively:

$$\text{(2)} \qquad \text{Return}_{i,t} = b_0 + b_1\,\text{Expert}_{i,e,t} + b_2\,\text{Size}_{i,t} + b_3\,\text{Beta}_{i,t} + b_4\,\text{MB}_{i,t} + b_5\,\text{RYear}_{i,t} + b_6\,\text{RMonth}_{i,t} + b_7\,\text{RWeek}_{i,t} + b_8\,\text{RDay}_{i,t} + \varepsilon_{i,t}\,,$$

where

$\text{Return}_{i,t}$ = geometric close-to-close return for stock *i* on day *t*;

$\text{Expert}_{i,e,t}$ = 1 for trades in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* is a financial expert, or 0 otherwise,

and the other firm-specific control variables are defined above.

We estimate Equation (2) with and without the firm-specific control variables. When the control variables are omitted, the intercept (b_0) in Equation (2) reflects the average (normal) return on day *t* based on purchases or sales made by the benchmark omitted group, which includes all retail investors, over the recent portfolio formation period, (*t-x*, *t-y*). Thus, the coefficient of the Expert dummy variable (b_1) reveals the abnormal return relative to this benchmark (normal, retail) return, for the purchases or sales made by all financial experts.[15]

[15] This regression approach is attractive because it documents the marginal effect of being a financial expert on trading performance, while controlling for other attributes of the investors trading and the firms traded.

Table 3 reports the mean coefficients from estimating the daily cross-sectional regression in Equation (2), averaged across all days in the sample period. In Panel A, we present the results for the performance on day *t* based on trades made on the previous day, *t-1*. The p-values in Table 3 are based on Newey-West adjusted standard errors for the mean coefficients.

We first concentrate on the results for purchases from the model without control variables, in Panel A of Table 3. The mean intercept (b_0) is an insignificant -1.2 basis points (bps) per day (p-value = 0.81). This outcome indicates that, during our sample period, retail investors earn a slightly negative average return on day *t* based on their purchases made one day earlier. The corresponding Expert dummy coefficient (b_1) indicates that the recent purchases of financial experts significantly outperform the recent purchases of retail investors by an average of 13 bps on the next day (p-value = 0.00). This daily outperformance for expert purchases on day *t-1* is economically significant, since it corresponds to an annualized return of 32% per annum (i.e., 250 days per year x .129% per day).

The analogous intercept (b_0) for sales on day *t-1*, in Panel A of Table 3, shows that retail investors earn a negative but insignificant mean return of -5.6 bps on day *t* (p-value = 0.24). Now the Expert dummy coefficient (b_1) is -6.8 bps (p-value = .03), which indicates that recent sales by financial experts significantly outperform recent sales by retail investors. This daily performance for expert sales is again economically significant, at -17% per annum (i.e., 250 x -.068%).

When we include the control variables in Equation (2), the results in Panel A of Table 3 are similar and the conclusions remain the same: financial experts are exceptional stock pickers. The stocks they buy significantly outperform those bought by other retail investors on the following day, while the stocks they sell significantly underperform those sold by other retail investors. This significant outperformance on the sell side contrasts with most prior work on insider sales, which typically finds that insider sales are not informative.[16]

In Panel A of Table 3, the mean coefficients of the control variables from Equation (2) generally conform to expectations. For the sample of purchases, the coefficients of the firm's size and beta are significantly negative, suggesting a larger average return for stocks with smaller size and a lower beta. The return from the previous day (RDay) also has a significant negative coefficient, indicating a tendency for a return reversal after one day. Two other lagged return variables have a significant positive mean coefficient (RYear and RMonth), consistent with momentum for stocks based on the return during the previous year and the previous month. For sales, the only significant control variable is RDay, again indicating a tendency for a reversal in stock prices after one day.

IV.B. Alternative Portfolio Formation Periods

In Panel B of Table 3, we investigate how the trading performance of financial experts depends on the length of the portfolio formation period. Here we provide the results from estimating Equation (2) using alternative formation periods that cover three non-overlapping time frames that include: (i) all trades during the past week excluding the previous day, covering days (*t-7*, *t-2*), (ii) prior trades made over the past month excluding the last week, covering days (*t-30*, *t-8*), and (iii) previous trades made over the past quarter excluding the last month, covering days (*t-91*, *t-31*). Here we only report the coefficient for the *Expert* dummy variable, since the coefficients for the control variables are nearly identical to the estimates in Panel A.

[16] Kraus and Stoll (1972), Cohen, Frazzini, and Malloy (2008), and Grinblatt, Keloharju, and Linnainma (2012) find that purchases are more informative than sales. In contrast, Cohen, Malloy, and Pomorski (2012) find that both (discretionary) purchases and sales by insiders are informative, while Berkman, Koch, and Westerholm (2014) find that both purchases and sales made in the accounts of young investors are informative.

First consider the performance of expert purchases on the left hand side of Panel B in Table 3. As we consider portfolio formation periods in the more distant past, the outperformance of financial experts declines in magnitude and significance. While previous expert purchases made over the past week or the past month still significantly outperform similar retail trades over the same time frames, expert purchases made more than one month ago do not significantly outperform analogous purchases by retail investors. Likewise, on the right side of Panel B, expert sales made in the previous week still significantly underperform retail sales, but expert sales made more than one week ago do not. Overall, the evidence in Table 3 suggests that the entire group of financial experts is able to generate significant abnormal returns, on average, presumably because of their access to valuable short term private information that is about to become public in the next few days or weeks.

IV.C. Different Functional Roles, Financial Service Groups, and Network Trades

IV.C.1. Performance of Trades by Experts in the Five Functional Roles

In this section, we first expand Equation (2) to incorporate additional dummy variables that partition the trades by all experts into the five functional roles, as follows:

$$(3)\quad \text{Return}_{i,t} = c_0 + c_1\,\text{Broker}_{i,e,t} + c_2\,\text{Analyst}_{,i,e,t} + c_3\,\text{Fund\_Mgr}_{i,e,t} + c_4\,\text{Board}_{,i,e,t} + c_5\,\text{Other}_{i,e,,t}$$
$$+ c_6\,\text{Size}_{i,t} + c_7\,\text{Beta}_{i,t} + c_8\,\text{MB}_{i,t} + c_9\,\text{RYear}_{i,t} + c_{10}\,\text{RMonth}_{i,t}$$
$$+ c_{11}\,\text{RWeek}_{i,t} + c_{12}\,\text{RDay}_{i,t} + \varepsilon_{i,t}\,,$$

where:

$\text{Analyst}_{i,e,t}$ = 1 for trades in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* is a financial analyst, or 0 otherwise;

$\text{Broker}_{i,e,t}$ = 1 for trades in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* is a broker, or 0 otherwise;

$\text{Fund\_Mgr}_{i,e,t}$ = 1 for trades in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* is a fund manager, or 0 otherwise;

$\text{Board}_{i,e,t}$ = 1 for trades in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* is a board member of a financial intermediary, or 0 otherwise;

$\text{Other}_{i,e,t}$ = 1 for trades in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* is classified as 'other' experts, or 0 otherwise.

This model replaces the single dummy variable in Equation (2), which identifies the trades of any financial expert, with five dummy variables that identify the five different functional roles for these experts. The intercept of this expanded model (c_0) again reflects the average performance of all retail trades and has the same interpretation as b_0 in Equation (2). Thus, the dummy coefficients (c_1 to c_5) from Equation (3) reveal the abnormal returns for every category of expert trades, relative to retail investors. The remaining variables in Equation (3) also appear in Equation (2), and are defined above.

In Panel A of Table 4, we present the results for purchases based on four different non-overlapping portfolio formation periods, while Panel B provides the analogous results for sales. The only change in the specification of Equation (3) is to partition the single dummy variable for all experts into the five functional roles. Thus, the results for the intercept and all control variables in Equation (3) duplicate those from estimating Equation (2), and are not reported here.

The top row of each Panel A in Table 4 reproduces the evidence for all financial experts from estimating Equation (2) in Table 3. The next five rows present the separate results for the five functional roles of these experts from estimating Equation (3). The following three rows provide the analogous evidence for experts serving in the three financial service groups of firms. Finally, the remaining rows give the results for non-network trades versus several alternative groups of network trades in which two or more experts trade on the same day.

First consider the evidence for purchases by financial experts serving in the different functional roles, in rows two to six of Panel A in Table 4. Using a one-day formation period, fund managers are the best stock pickers, with a mean daily abnormal return of 26 bps (p-value = 0.01). This performance is followed by analysts with a mean daily abnormal return of 20 bps (p-value = 0.01), brokers with a mean abnormal return of 15 bps (p-value = 0.01), and ‘other’ experts at 13 bps (p-value = 0.00). We find no significant abnormal performance for purchases made by board members. When we consider earlier portfolio formation periods, analysts and brokers significantly outperform based on earlier trades made up to one month in the past, while ‘other’ experts significantly outperform over the past week.

On the sell side, Panel B of Table 4 indicates that sales by analysts are most informative for the 1-day window, with a mean daily abnormal return of -26 bps (p-value = 0.02). The one-day sell portfolios of ‘others’ also generate a significant mean abnormal return of -9 bps (p-value = 0.04), while the analogous daily abnormal returns for brokers, fund managers, and board members are negative but insignificant. The other columns in Panel B indicate that sales by all types of experts do not generally continue to outperform beyond one day, when we base the portfolio formation on an earlier horizon.

IV.C.2. Performance of Trades by Experts in the Three Financial Services Groups of Firms

We next estimate an alternative specification of Equation (2), to assess the relative performance of trades made by experts who work in the three financial services groups (i.e., brokerage firms, fund management firms, and asset management firms), as follows:

$$
\begin{aligned}
(4)\quad \text{Return}_{i,t} = {} & d_0 + d_1\,\text{Brokerage}_{i,e,t} + d_2\,\text{Fund\_Mgt}_{i,e,t} + d_3\,\text{Asset\_Mgt}_{i,e,t} \\
& + d_4\,\text{Size}_{i,t} + d_5\,\text{Beta}_{i,t} + d_6\,\text{MB}_{i,t} + d_7\,\text{RYear}_{i,t} + d_8\,\text{RMonth}_{i,t} \\
& + d_9\,\text{RWeek}_{i,t} + d_{10}\,\text{RDay}_{i,t} + \varepsilon_{i,t}\,,
\end{aligned}
$$

where:

$\text{Brokerage}_{i,e,t}$ = 1 for trades in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* works for a brokerage firm, or 0 otherwise;

$\text{Fund\_Mgt}_{i,e,t}$ = 1 for trades in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* works for a fund management firm, or 0 otherwise;

$\text{Asset\_Mgt}_{i,e,t}$ = 1 for trades in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* works for an asset management firm, or 0 otherwise.

This model replaces the single dummy variable in Equation (2) with three dummy variables that identify the three different financial services groups of firms that employ these financial experts.

Once again, the intercept of this expanded model (d_0) reflects the performance of all retail trades, has the same interpretation as b_0 in Equation (2), and is unchanged with this specification. Thus, the dummy coefficients (d_1 to d_3) from Equation (4) reveal the abnormal returns relative to retail investors for experts serving at the three respective financial services groups of firms.

The results are provided in rows 7 to 9 of each Panel in Table 4. On the buy side in Panel A, the mean daily abnormal returns based on a one-day horizon are significant, and similar in magnitude across brokerage firms (12 bps, p-value = 0.00), fund management firms (11 bps, p-value = 0.03), and asset management firms (12 bps, p-value = 0.00). For each group of firms, this buying skill also tends to show up for portfolios constructed over earlier formation periods extending up to one month ago. On the sell side in Panel B, there is a significant mean abnormal return based on expert selling over a one-day horizon at asset management firms (-11 bps, p-value = 0.02), but no significant mean abnormal return at brokerage firms or fund management firms. Sell portfolios based on a longer formation period do not generate significant negative mean abnormal returns across the three groups of firms.

IV.C.3. Performance of Network Trades by Two or More Experts

We also estimate another alternative specification of this model to assess the relative performance of stand-alone trades versus identical network trades made by two or more experts. We conjecture that, relative to stand-alone trades by experts, network trades are less likely to be liquidity-motivated, and more likely to be motivated by private information shared across the network of financial experts. If network trades have a higher probability of being informed, then we expect these trades to outperform non-network trades, on average. We test this conjecture by introducing five new dummy variables into Equation (2) that indicate different groups of trades in which the number of experts taking a similar position in the same stock on the same day ranges from one (for stand-alone trades) to more than ten, as follows:

$$(5)\ \ Return_{i,t} = e_0 + e_1\,Expert\_1_{i,e,t} + e_2\,Expert\_2_{\,i,e,t} + e_3\,Expert\_3\text{-}4_{i,e,t} + e_4\,Expert\_5\text{-}10_{i,e,t} + e_5\,Expert\_{>}10_{i,e,t} + e_6\,Size_{i,t} + e_7\,Beta_{i,t} + e_8\,MB_{i,t} + e_9\,RYear_{i,t} + e_{10}\,RMonth_{i,t} + e_{11}\,RWeek_{i,t} + e_{12}\,RDay_{i,t} + \varepsilon_{i,t}\,,$$

where

$Expert\_1_{i,e,t}$ = 1 for purchases (sales) in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* is an expert and no other expert also buys (sells) stock *i* on the same day, or 0 otherwise;

$Expert\_2_{i,e,t}$ = 1 for purchases (sales) in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* is an expert and 1 *other* expert also buys (sells) stock *i* on the same day, or 0 otherwise;

$Expert\_3\text{-}4_{i,e,t}$ = 1 for purchases (sales) in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* is an expert and 2 or 3 *other* experts also buy (sell) stock *i* on the same day, or 0 otherwise;

$Expert\_5\text{-}10_{i,e,t}$ = 1 for purchases (sales) in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* is an expert and between 4 and 9 *other* experts also buy (sell) stock i on the same day, or 0 otherwise;

$Expert\_{>}10_{i,e,t}$ = 1 for purchases (sales) in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* is an expert and more than 9 *other* experts also buy (sell) stock *i* on the same day, or 0 otherwise.

The results are provided in the last five rows of both Panels in Table 4. First consider network purchases by experts, at the bottom of Panel A. Using a one-day formation period, there is a monotonic increase in mean abnormal returns as we move down across these network dummy coefficients, to consider network trades made by an increasing number of experts buying the same stock on the same day. Purchases of stocks by a single financial expert are followed by a significant mean abnormal return of 6.5 bps (p-value = 0.01) on the next day. This mean abnormal return increases to 13 bps (p-value = 0.01) for stocks bought by 2 financial experts, 19 bps (p-value = 0.01) for stocks bought by 3 or 4 financial experts, 28 bps (p-value = 0.02) for stocks bought by 5 to 10 experts, and this average outperformance increases to a striking 74 bp for network purchases by more than 10 experts (p-value = 0.06).[17] When we consider earlier portfolio formation periods up to one month in the past, in the other columns of Panel A, there is some additional evidence of significant longer term outperformance for network purchases by 2 experts, but there is no longer a monotonic relation between the mean abnormal returns and the number of experts making similar trades.

On the sell side, Panel B of Table 4 suggests that expert sales are followed on the next day by a negative mean abnormal return that tends to grow in magnitude when more experts enter a similar sale. However, the significance of these successive dummy coefficients declines as we consider network sales with more and more experts selling on the same day, due to a decreasing sample size. Further unreported tests show that the mean abnormal returns following multiple-expert sales are never significantly different from the mean abnormal returns following sales by one expert. In addition, when we extend the portfolio formation period further back in time, there is little evidence of substantive abnormal returns for earlier sales by experts.

The evidence in this section indicates that financial experts possess a significant short-term informational advantage that results in superior stock returns on the days immediately following both their purchases and sales. This information advantage tends to be stronger among experts within the same network of each type, and when more than one expert makes an identical trade. While not being conclusive, this evidence suggests the possibility that financial experts in Finland may be prone to breach their fiduciary duty by sharing and trading on their privileged

[17] For the one-day portfolio formation window, the mean abnormal performance of similar purchases by 3 or 4, 5 to 10, or more than 10 experts (i.e., coefficients e_3, e_4, and e_5) is significantly greater than the performance of purchases by a single expert (e_1), at the 5 percent level.

access to material private information. Given the short-term nature of this apparent information advantage, we conjecture that this superior performance may be concentrated in the period just before major corporate events that are commonly associated with increased information asymmetry. This conjecture is the subject of the next section.

IV.D. Performance of Trades before Firm-Specific Information Events

In this section we apply an event study approach to focus on trades made by financial experts during the three weeks prior to earnings announcements, revisions of analyst recommendations, and takeover announcements. In addition, we examine the trades of experts just before large price changes, which presumably reflect the arrival of substantive value-relevant information. We focus on the mean 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 2,291 quarterly announcements made by Finnish firms over the sample period, March 2005 to March 2011. Our sample of changes in analyst recommendations is from Capital-IQ, and consists of all 2,254 revisions during the sample period, where the analyst changed his or her previous recommendation by at least two steps (e.g., from a strong buy to neutral, or from a moderate buy to a moderate sell recommendation). Data on mergers and acquisitions are obtained from SDC Platinum, and include 55 takeover announcements for our sample of Finnish firms during the same period. We also analyze a sample of 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 such price change events if they occur within five days of an earnings announcement, analyst revision, 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 1,460 large price change events over the sample period.

We first compute the stock's market-adjusted daily abnormal return as the actual return minus the return on the value-weighted average return on all stocks on Helsinki Stock Exchange, where the maximum weight of any one stock is limited to 10% of the total market value of the index.[18] Next we sum this abnormal return on the event day and the next day, and we "sign" this market-adjusted *CAR(0,+1)*, multiplying it by -1 for all expert sales. Then, for each event we calculate the mean signed *CAR(0,+1)* across all expert purchases and sales of the stock on day -1, -2, or -3, or during week -1, -2, or -3, respectively, prior to the event. In the final step, we calculate the average signed *CAR(0,+1)* across all events with expert trades during each of the relevant event windows. The standard error of this mean signed *CAR(0,+1)* across all events is used to construct a *t*-test of the null hypothesis that the mean signed *CAR(0,+1)* is zero.

The results are presented in Table 5. Panel A presents the analysis of expert trades before earnings announcements. Panel B similarly analyzes trades before revisions of analyst recommendations, while Panel C restricts the latter sample to the subset of such trades made by employees from the same firm as the recommending analyst. Panel D presents the results for takeover announcements, and Panel E provides the evidence for large price changes. The left side of every Panel presents results for director trades made on each of the three days before the event, while the right side gives analogous results for trades made during each of the three weeks before the event.

First consider expert trades made in the three days before earnings announcements, on the left side of Panel A in Table 5. There are 343 such announcements where at least one expert

[18] This weight limit mitigates the influence of Nokia, Finland's largest stock, on the value-weighted market index.

traded on the day before the earnings release, with a mean signed *CAR(0,+1)* of 0.8% (p-value = 0.02). For trades made two or three days before earnings announcements, we find no further evidence of significant outperformance by financial experts. The right side of Panel A indicates 742 earnings announcements where at least one expert traded in the week before the event, with a mean signed *CAR(0,+1)* of 0.5% (p-value = 0.02).There is no further evidence of outperformance based on earlier trades made two or three weeks before earnings announcements.

Panel B of Table 5 provides the analysis of expert trades made prior to revisions of analyst recommendations. There are 842 such revisions where at least one employee traded on the day before the revision was announced, with a significant mean signed *CAR(0,+1)* of 0.4% (p-value = 0.01). Similarly, the mean signed *CAR(0,+1)* is also 0.4% (p-value = 0.02) based on trades made two days before the revision. The right side of Panel B indicates 1,468 analyst revisions where at least one expert traded during the week before the event, with a mean signed *CAR(0,+1)* of 0.3% (p-value= 0.00). Earlier trades made two or three weeks before analysts change their recommendations display no significant outperformance.

In Panel C of Table 5, we consider the subsets of these same trades from Panel B that are made by experts who work at the same firm as the analyst who revises the recommendation. For example, there are 134 such events where at least one employee traded on the day before a revision by an analyst at the same firm, with a mean signed *CAR(0,+1)* of 1.6% (p-value = 0.00). There are fewer events where an expert traded two or three days before a revision by an analyst at the same firm, and they yield no significant mean abnormal return. When we focus on analogous trades during the first or second week before a revision by an analyst at the same firm, we find a mean signed *CAR(0,+1)* of 0.6% (p-value = 0.04 and 0.06, respectively).[19]

[19] When we consider the alternative subsets of expert trades that are made by experts at a *different firm* than the revising analyst, from the total samples of expert trades in every cell of Panel B, we still find significant

For the sample of Finnish takeover targets analyzed in Panel D of Table 5, there are too few trades by financial experts in the three days before the M&A announcements to conduct a meaningful analysis. On the right side of Panel D, we find somewhat larger samples of roughly 25 such events where at least one expert traded in each of the three weeks before the takeover announcement. While the mean signed *CAR(0,+1)* is 2.6% based on the trades during the week before takeover announcements, the paucity of trades and the lack of precision in their average performance suggests that financial experts do not reliably profit from trading on information about upcoming mergers and acquisitions.

Finally, consider the evidence for trades made in the three days before large price changes, on the left side of Panel E in Table 5. There are 128 events where at least one employee traded on the day before a large price change, with a mean signed *CAR(0,+1)* of 2.5% (p-value = 0.01). The mean signed *CAR(0,+1)* is also marginally significant when it is based on trades made three days before the price change (*CAR(0,+1)* = 2.0%, p-value= 0.07), and is significant based on trades made during the first or second week before these events (*CAR(0,+1)* = 1.5% and 1.2%, with p-values = 0.02 and 0.05, respectively).[20]

This event study analysis provides strong evidence that financial experts outperform when they trade just before major firm-specific information events. We conclude that these trades are motivated by privileged access to superior private information that is about to become public.

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outperformance based on trades made on the two days preceding the event, as well as based on trades made during the week before the event. However, these alternative mean signed *CAR(0,+1)* are consistently smaller (TRUE?) than the analogous measures provided in Panel C for expert trades made by experts at the same firm as the revising analyst, and they are significantly smaller for trades made one day before the analyst revision (mean difference t-test = x.x, p-value = 0.yy).

[20] When we split the trades by experts into sales and purchases prior to each type of event, the abnormal returns that are significant in Table 5 also tend to be significant for both the samples of sales and purchases separately. The exceptions are earnings announcements, where the CARs are significant for sales but not for purchases, and large price change events, where the significant abnormal returns in Table 5 are significant for purchases but not for sales.

V. FRONT-RUNNING AND INFORMATION LEAKAGE BY FINANCIAL EXPERTS

In this section we further explore the possibility of a breach of fiduciary duty, by testing for the presence of front-running and information leakage by financial experts. In particular, we investigate the timing and performance of trades made by experts in the days before the execution and public disclosure of corporate insider trades and large block trades by Finnish mutual funds. Similar to the U.S., in Finland these information-based trades must be publicly disclosed three to seven days after their execution (i.e., from day +3 to day +7). Brokers and fund managers have early access to this value-relevant information, and may be tempted to front-run these trades prior to their execution (on day 0), or to share this information with other experts who could then mimic these trades after their execution, but prior to their public disclosure.

We apply the event study methodology described above, and assign 'day 0' to the day on which a corporate insider trade is executed, or the day on which one of the major mutual funds in our sample buys or sells a large block of stock. We then examine the timing and performance of trading by financial experts in the days around these events.

V.A. Trading and Performance by Financial Experts around Corporate Insider Trades

During our sample period, there are a total of 2,513 trades by Finnish corporate insiders at all listed firms on the Helsinki OMX Exchange. We exclude insider trades that occur within three days after another insider trade for the same firm. We also exclude trades by corporate insiders who appear in our sample of financial experts as an employee or a board member of a Finnish financial intermediary. These screens leave 1,541 corporate insider trades in the sample.

We define event day 0 as the day on which the insider trade is executed. For each such insider trade event (i), we consider all expert trades made during the 31-day window that extends from five weeks before the insider trade to one week after the trade, covering days $t = (-25, +5)$.

The first four weeks of this window, covering days *t = (-25,-6)*, represent the pre-event period that we use to establish 'normal' trading behavior by each group of financial experts, while the remaining 11 days, *t = (-5,+5)*, represent the event window.

V.A.1. Abnormal Trading Activity by Financial Experts around Insider Trades

For each group of trades by financial experts, for every day in the event window (*t*), and for each event (*i*), we define abnormal trading activity as the difference between the actual number of expert trades on day *t* and the daily average number of expert trades for event *i* during the pre-event window, *t = (-25,-6)*. Next, we calculate the mean abnormal trading activity for each group of expert trades across all events, and we use the standard error of this mean to test the null hypothesis that the mean abnormal trading activity on day *t* is zero. We separately analyze purchases and sales by corporate insiders, because we anticipate divergent stock price reactions following these two groups of trades which may lead to divergent trading activity among financial experts.[21]

Panel A of Table 6 presents the results for abnormal trading activity by experts around insider purchases. The first row provides the analysis of all trades across all financial experts. The next five rows present the analogous evidence for the five functional roles of experts, followed by the results for experts serving in the three financial services groups of firms. Finally, the last two rows analyze non-network trades versus network trades.

Several findings stand out. The first row of Panel A in Table 6 indicates that experts were active at least once in the window, (*t-25*, *t+5*) for 605 events (i.e., purchases by corporate insiders). There is significant abnormal trading activity by all experts beginning two days before

[21] Consistent with most studies in this area, Berkman et al. (2016) find that purchases by corporate insiders in Finland are followed by significant positive abnormal returns, whereas abnormal returns after sales are insignificant. See also Jeng, Metrick, and Zeckhauser (2003) and Lakonishok and Lee (2001) and Ravina and Sapienza (2010).

the insider purchase and persisting through the day after the purchase. This abnormal trading peaks on day 0, with an average of 0.29 additional expert trades per event (p-value = 0.00). The earlier abnormal trading activity by experts on day -2 and day -1 suggests that corporate insiders sometimes consult with a broker about their intention to trade, or perhaps submit limit orders with their brokers that are not executed on the same trading day.

Rows 2 to 6 of Panel A in Table 6 show that this abnormal trading around insider trades is not limited to brokers. For example, the mean abnormal trades on day 0 is largest for the last category of ‘other’ experts, which is closely followed by brokers, and then board members and analysts. Similarly, rows 7 to 9 reveal that this significant mean abnormal trading activity is not limited to employees of brokerage firms, but is also significant for asset management firms, while being only marginally significant for fund management firms on day -1.

Finally, the last two rows of Panel A indicate a particularly sharp increase in abnormal trading by financial experts around day 0 for event days when more than one expert trades. The average abnormal number of such network trades on day 0 is 0.50 (p-value = 0.01), which is significantly greater than the mean number of abnormal trades of 0.07 (p-value = 0.00) for stand-alone, non-network trades. This outcome indicates that information about insider purchases is quickly shared and acted upon by participants across the network of financial experts.

Panel B of Table 6 reveals substantially less abnormal trading by experts around insider sales, with only 294 events where experts are active at least once in the window (*t-25*, *t+5*). Moreover, the top row indicates that abnormal selling by financial experts is significantly different from zero only on day 0, where the mean number of abnormal trades is 0.17 (p-value = 0.00). This increased selling activity on day 0 is concentrated among experts who serve as brokers or who work for brokerage firms. In addition, consistent with Panel A, Panel B reveals a particularly sharp increase in abnormal trading by financial experts around day 0 for event days when more than one expert trades, at 0.38 abnormal trades per event (p-value = 0.03).[22]

V.A.2. Performance of Expert Trading Activity around Insider Trades

We next investigate whether financial experts profit from this abnormal trading activity around corporate insider trades. Based on the results in Table 6, we separately examine the cumulative abnormal returns earned by two subsets of trades by financial experts. First we consider expert trades made on the same day that the insiders buy or sell (i.e., on day 0). Second, we consider expert trades made immediately before or after insider purchases (i.e., on days -2, -1, and +1).[23] We present the results for expert trades on day 0 on the left side of Table 7, while the results for expert purchases on days -2, -1, and +1 are provided on the right side.

Similar to the event study analysis in Table 5, we begin by computing the market-adjusted daily abnormal return for each stock (*i*). We then cumulate these daily abnormal returns over the ten or twenty trading days following every expert trade, for each group of expert trades. This procedure generates two measures of performance, *CAR(+1,+10)* and *CAR(+1,+20)*, following each group of expert trades. We consider both a ten-day and a twenty-day window, to ensure that the *CAR* includes the performance that is realized after the insider trade becomes public knowledge (which happens at the earliest 4 days after the trade, and at the latest 7 days after the trade). Once again, we multiply the *CAR* by -1 for expert sales and then calculate the mean signed *CAR* across each group of expert trades for each event. Finally we compute the average of these mean signed *CARs* across all events, and use the standard error of this mean to construct a t-test of the null hypothesis that the mean signed *CAR* is zero.

[22] This mean abnormal network trading is also significantly larger than abnormal trading for stand-alone expert trades (mean difference t-test = x.x, p-value = 0.yy).
[23] In the latter analysis, we do not consider expert trading on days -2, -1, and +1 around insider *sales*, because there is less evidence of abnormal expert trading on these days in Panel B of Table 6.

First consider the evidence for all expert trades made on the same day (0) as insider purchases or sales, on the left side of the top row in Table 7. The 10-day mean signed *CAR(+1,+10)* is 1.25% (p-value = 0.00), while the 20-day mean signed *CAR(+1,+20)* is 1.69% (p-value = 0.00). The next five rows reveal that these mean signed *CARs* are particularly high for analysts, brokers and 'other' experts, ranging from 1.3% for the 10-day analysis to 2.4% for the 20-day analysis. The mean signed *CARs* are positive but insignificant for analysts, fund managers and board members. In the following three rows, when we split the expert trades across the financial service groups of firms, we find *CARs* of a similar magnitude for the employees of brokerage firms, fund management firms, and asset management firms. However, they are significant only for the employees of brokerage and asset management firms. Finally, stand-alone trades and network trades are followed by abnormal returns of a similar magnitude. However, only the *CARs* of stand-alone trades are significant at the .05 level, partly due to the relatively small numbers of network trades around these insider trading events.

On the right side of Table 7, we report the mean signed *CARs* following expert trades on days -2,-1, and +1 around the purchases of corporate insiders. The top row indicates that only the twenty-day *CAR* is significant for these trades by all experts. The analogous results in the next five rows show that only the trades of brokers and analysts have mean signed *CARs* that are marginally significant. The following three rows reveal that the magnitudes of these mean signed *CARs* are similar for employees of the three types of firms, but they are only marginally significant for employees of brokerage firms.

Overall, we conclude that financial experts profit from significant abnormal trading activity in the short period around the trades of corporate insiders. There is evidence of front-running by experts in the two days before insider purchases are executed, as well as on the same day that insider sales are executed. There is also significant abnormal copycat trading that continues on the day of and the day after the execution of insider purchases, which is still several days prior to public disclosure of these trades (after day +3). This evidence indicates that private information about forthcoming insider purchases spreads quickly across the community of financial experts, and this front-running, information leakage, and copycat trading is not limited to the activities of brokers or brokerage firms.

V.B. Trading and Performance by Financial Experts around Block Trades

In this subsection we investigate expert trading around the days on which mutual funds make unusually large block purchases or sales in a given stock. We identify these 'large block trading days' as follows. First, we identify the Euroclear accounts of the six largest mutual funds for which we have data on their employees' trading activity.[24] These funds comprise more than 90 percent of the domestic market share (i.e., total asset value) of all mutual funds in Finland. Second, on each day (*t*) and for every stock (*i*), we aggregate the market value of the net order flow (i.e., shares bought minus shares sold multiplied by the closing price) for each mutual fund. Third, we compute the standard deviation of these daily time series of aggregate net order flows, for each mutual fund, for every stock (*i*) and across all days (*t*) during each year of our sample period, March 2006 - March 2011. Finally, for each mutual fund we select the stock-days every year for which the fund's order imbalance is more than two standard deviations away from zero. We exclude any such block trading days that occur within three days after another block trading day for the same stock and fund. This procedure identifies 1,808 'large block trading days' by mutual funds across all Finnish stocks over the sample period.

[24] We match the holdings of Finnish public mutual funds as reported in Bloomberg with the holdings of mutual funds in Euroclear. We find almost exact matches on all holdings for each of the fifteen funds in our sample, which indicates that we have identified the correct accounts of these mutual funds in the Euroclear database.

We then use the similar research design as in our previous tests of expert trading around insider trades, and assign event day 0 to the block trading day. For each group of expert trades, for every day in the event window, *t = (-5,+5)*, and for each event (*i*), we then define abnormal expert trading activity as the difference between the actual number of expert trades on day *t* and the daily mean number of expert trades for that event during the pre-event window, *t = (-25,-6)*.

V.B.1. Abnormal Trading Activity by Financial Experts around Block Trades

Panel A of Table 8 presents the abnormal trading by experts around the days with block purchases by one of the six largest mutual funds in Finland. The top row indicates significant mean abnormal trading activity by all financial experts in the days around block purchases. This abnormal expert trading becomes significant beginning four days before the block purchase is executed (on day 0), and persists through the following week (until day +5). This activity is high on day 0 with an average of 0.30 additional expert trades per event (p-value = 0.00), and it peaks on day +3 with an average of 0.47 additional expert trades per event (p-value = 0.00).

The significant abnormal trading by financial experts from day -4 through day -1 suggests front-running prior to the execution of block purchases on day 0. Much of the continued abnormal copycat trading activity from day 0 through day 3 likely occurs before the public disclosure of OTC purchases (which happens at the end of trading on day +3), although we cannot conclusively verify that this is the case.[25]

Rows 2 to 6 of Panel A in Table 8 show that this front-running ahead of block purchases is significant across all functional roles, although it is relatively small for fund managers where it

[25] If a mutual fund trades on the Helsinki OMX Exchange, its trades are reported immediately. If a mutual fund trades off-market through 'limit order books …, then public disclosure of the trade occurs within 90 seconds and this rule also applies to most trades on dark limit markets ... ." In contrast, for trades in the over-the-counter (OTC) market, trade reporting can be as late as three days after the trade. We cannot separate OTC trades from other trades, and our main focus is on expert trading in the days before large block trading days. Some of the largest block trades by mutual funds are likely to be OTC trades that are typically not disclosed publicly until three trading days later.

is only significant on day -4. Brokers and ‘other’ employees are most active in the periods both before and after the block purchase. Rows 7 to 9 reveal that employees at brokerage firms and asset management firms are most active around these large block purchase days. In contrast, there is little evidence of elevated trading activity by employees of the fund management firms that actually conduct the block purchases (where it is only significant on days +2 and +3). This evidence suggests that, while employees at fund management firms are reticent to trade in their own personal accounts around their own firms’ block purchases, this information quickly spreads through the rest of the network of financial experts who do trade in their own accounts. Finally, consistent with the above discussion, the last two rows in Panel A show that both front-running and copycat trading are particularly high in the form of network trades by two or more experts.

Panel B of Table 8 also reveals evidence of abnormal trading by financial experts around days with block sales by mutual funds. Front-running activity appears one day before the block sales are executed (on day -1), for the full sample of experts, as well as for brokers, employees of brokerage firms and network trades. In addition, copycat trading continues on the following days for employees in most functional roles, as well as across all three financial services groups of firms, and it is particularly large for network trades.

V.B.2. Performance of Expert Trading Activity around Block Trades

Table 9 replicates the analysis in Table 7 for days with large block purchases or sales by mutual funds, by computing the mean signed *CAR(+1,+10)* and *CAR(+1,+20)* after these events. We focus our discussion on the mean cumulative abnormal returns that apply to ‘front-running’ trades by financial experts, on day -2 and day -1.

The results in Table 9 reveal that ‘front-running’ trades on days -2 and -1 generate significant abnormal returns across all experts, with a mean signed 10-day *CAR* of 0.87% (p-value = 0.00) and a mean signed 20-day *CAR* of 1.37% (p-value = 0.00). This abnormal *performance* is highest for analysts and fund managers, and is also significant for board members. This significant abnormal performance extends to the trading activity by experts at all three financial services groups of firms. On the other hand, these mean *CARs* are significant only for the group of stand-alone trades by financial experts, whereas they are insignificant for network trades, partly due to the smaller number of events with such trades.

Based on the evidence in this section, we conclude that Finnish financial experts profit from trading on private and confidential information for their own personal accounts, and they share this valuable information with others in the financial services network who also trade on this information. This evidence of front-running and copycat trading prior to the execution or public disclosure of these information-based trades suggests a potential breach of fiduciary duty.

VI. SUMMARY AND CONCLUSIONS

This study examines the personal trading activity of employees at Finnish financial institutions, including brokers, analysts, fund managers, board members, and other financial experts. This analysis is made possible because of Finnish insider trading laws, which extend the usual obligation for company insiders to disclose personal trades in their own firm's stock to a broader obligation by a larger group of 'insiders' who have access to private value-relevant information. In particular, Finnish regulations also require that all employees of financial institutions who have such access to material private information must disclose all of their personal trading in any listed stock.

We find that these financial experts reveal a significant propensity for abnormal trading activity in their own personal accounts, based on valuable private information obtained through their professional networks, prior to the time that this information is publicly available. We also show that they generate significant short term abnormal returns from this trading activity. For example, these experts outperform when they trade ahead of major firm-specific information events such as earnings announcements, revisions of analyst recommendations, and large price changes. Furthermore, we provide evidence suggesting that valuable private information is regularly shared and acted upon throughout the financial services network. For example, we document a penchant for these experts to trade for their own personal accounts in the days before corporate insider trades are executed, as well as the days before Finnish mutual funds trade large blocks of stock. Furthermore, we find significant copycat trading by financial experts in the days following these two types of information-based trades, before they are disclosed to the public. This personal trading activity generates mean abnormal returns that are economically and statistically significant. This evidence indicates that (i) these financial experts engage in front-running in their own accounts ahead of such information-based trades, (ii) they leak this information to other financial experts in the network who mimic these trades, and (iii) they profit handsomely from this behavior.

Taken together, this body of evidence makes a strong case for a possible breach of fiduciary duty by the employees of Finnish financial institutions. This evidence is even more remarkable given that it is gleaned from readily available data on all of the personal trades of these experts, who are required to publicly disclose their trading activity in any listed stocks. This analysis calls for further discussion of the costs and benefits of establishing and enforcing similar regulation in the U.S. and elsewhere, which would compel public disclosure of all trading activity by employees of financial institutions who have access to material private information. Of course, such regulation should be accompanied by adequate monitoring to guard against the potential breach of fiduciary duty that is suggested by our analysis. Such transparency and enforcement activity may serve to enhance the fairness and integrity of financial markets.

References

Anderson, Anders, and Jose Martinez, “Brokerage-Firm Trading and Profits around Recommendation Revision Dates,” (2012), Working Paper.

Barber, Brad, Reuven Lehavy, Maureen McNichols, and Brett Trueman, “Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns,” *Journal of Finance* 56 (No. 2, 2001), 531-563.

Barber, Brad, Reuven Lehave, and Brett Trueman, “Comparing the Stock Return Performance of Investment Banks and Independent Research Firms,” *Journal of Financial Economics* 85 (2007), 490-517.

Berkman, Henk, Paul D. Koch, and Joakim Westerholm, “Informed Trading through the Accounts of Children,” *Journal of Finance*, 69 (2014), 363-404.

_________, “Inside the Network: When Insiders Trade Outside Stocks,” Working Paper, 2016.

Bhattachary, Uptal, “Insider Trading Controversies: A Literature Review,” *Annual Review of Financial Economics* 6 (2014), 385-403.

Bhattacharya, Utpal, and Hazem Daouk, “The World Price of Insider Trading,” *Journal of Finance*, 4 (2002), 75–108.

Bhattacharya, Utpal, and Matthew Spiegel, “Insiders, Outsiders, and Market Breakdowns,” *Review of Financial Studies*, 4 (1991, No. 2), 255–282.

Blau, Benjamin, and Chip Wade, “Informed or Speculative Short Selling Analyst Recommendations,” 2011, Working Paper.

Brown, Jeffrey R., Zoran Ivkovic, Paul A. Smith, and Scott Weisbenner, “Neighbors Matter: Causal Community Effects and Stock Market Participation,” *Journal of Finance*, 63 (3) (2008), 1509–1531.

Chakrabarty, Bidisha, and Andriy Shkilko, “Information Transfers and Learning in Financial Markets: Evidence from Short Selling around Insider Sales,” *Journal of Banking and Finance* 37 (No. 5, 2013), 1560-1572.

Christophe, Stephen, Michael Ferri, and James Angel, “Short-Selling Prior to Earnings Announcements,” *Journal of Finance* 59 (No. 4, 2004), 1845-1875.

Christophe, Stephen, Michael Ferri, and Jim Hsieh, “Informed Trading before Analyst Downgrades: Evidence from Short Sales,” *Journal of Financial Economics* 95 (2010), 85-106.

Chung, Kee, and Seong-Yeon Cho, “Security Analysis and Market Making,” *Journal of Financial Intermediation* 14 (2005), 114-141.

Clauset, Aaron, Mark Newman, and Christopher Moore, “Finding Community Structure in Very Large Networks,” *Physical Review E* 70, (Issue 6, 2004), 066111.

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, “The Small World of Investing: Board Connections and Mutual Fund Returns,” *Journal of Political Economy*, 116 (2008), 951–979.

Cohen, Lauren, Christopher Malloy, and Lukasz Pomorski, “Decoding Inside Information,” *Journal of Finance* 67 (Issue 3, 2012), 1009-1043.

Døskeland, Trond M., and Hans K. Hvide, “Do Individual Investors have Asymmetric Information Based on Work Experience?” *Journal of Finance*, 66 (2011), 1011–1041.

Dugar, Amitabh, and Siva Nathan, “The Effect of Investment Banking Relationships on Financial Analysts’ Earnings Forecasts and Investment Recommendations,” *Contemporary Accounting Review* 12 (No. 1, 1995), 131-160.

Easterbrook, Frank, "Insider Trading as an Agency Problem," In John. W. Pratt and Richard J. Zeckhauser, eds., *Principals and Agents: The Structure of Business*, Boston, MA: Harvard Business School Press, 1985, 81-99.

Ellis, Katrina, Roni Michaely, and Maureen O'Hara, "When the Underwriter Is the Market Maker: An Examination of Trading in the IPO Aftermarket," *Journal of Finance* 55 (No. 3, 2000), 1039-1074.

Ellison, Glenn, and Drew Fudenberg, "Word-of-Mouth Communication and Social Learning," *Quarterly Journal of Economics* 110 (No. 1, 1995), 93-125.

Fama, Eugene F., and Kenneth R. French, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics*, 33 (1993), 3–56.

Fidrmuc, Jana P., Marc Goergen, and Luc Renneboog, "Insider Trading, News Releases, and Ownership Concentration," *The Journal of Finance*, 61 (6) (2006), 2931–2973.???

Fracassi, Cesare, "Corporate Finance Policies and Social Networks," University of Texas, Working Paper, 2012.

Geczy, Christopher, and Jinghua Yan, "Who Are the Beneficiaries when Insiders Trade? An Examination of Piggybacking in the Brokerage Industry," 2006, Working Paper.

Green, Clifton, "The Value of Client Access to Analyst Recommendations," *Journal of Financial and Quantitative Analysis* 41 (No. 1, 2006), 1-24.

Griffin, John, Tao Shu, and Selim Topaloglu, "Examining the Dark Side of Financial Markets: Do Institutions Trade on Information from Investment Bank Connections?" *Review of Financial Studies* 25 (2012), 2155-2188.

Grinblatt, Mark, and Matti Keloharju, "The Investment Behavior and Performance of Various Investor Types: A Study of Finland's Unique Data Set," *Journal of Financial Economics*, 55 (2000), 43–67.

Grinblatt, Mark, Matti Keloharju, and Juhani Linnainma, "IQ and Stock Market Participation," *Journal of Finance*, 66 (2011), 2121–2164.

__________, "IQ, Trading Behavior, and Performance," *Journal of Financial Economics*, 104 (2012), 339–362.

Heidle, Hans, and Xi Li, "Information Leakages and Opportunistic Behavior before Analyst Recommendations: An Analysis of the Quoting Behavior of Nasdaq Market Makers," 2004, Working Paper.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, "Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers," *The Journal of Finance*, 60 (2005), 2801–2824.

Irvine, Paul, "Do Analysts Generate Trade for their Firms? Evidence from the Toronto Stock Exchange," *Journal of Accounting and Economics* 30 (2001), 209-226.

__________"The Incremental Impact of Analyst Initiation of Coverage," *Journal of Corporate Finance* 9, (No. 4, 2003), 431-451.

__________, "Analysts' Forecasts and Brokerage-Firm Trading," *The Accounting Review* 79 (No. 1, 2004), 125-150.

Irvine, Paul, Marc Lipson, and Andy Puckett, "Tipping," *Review of Financial Studies* 20 (2007), 741-768.

Ivkovic, Zoran, and Scott Weisbenner, "Local Does as Local Is: Information Content of the Geography of Individual Investors' Common Stock Investments," *Journal of Finance*, 60 (2005), 267-306.

__________, "Information Diffusion Effects in Individual Investors' Common Stock Purchases: Covet Thy Neighbors' Investment Choices," *Review of Financial Studies*, 20 (2007), 1327–1357.

Jackson, Andrew, "Trade Generation, Reputation, and Sell-Side Analysts," *Journal of Finance* 60 (No. 2, 2005), 673-717.

Jaffe, Jeffrey F., "Special Information and Insider Trading," *Journal of Business*, 47 (No. 3, 1974), 410–428.

Jegadeesh, Narasimhan, and Yue Tang, "Institutional Trades around Takeover Announcements: Skill vs. Inside Information," 2010, Working Paper.

Jeng, Leslie A., Andrew Metrick, and Richard Zeckhauser, "Estimating the Returns to Insider Trading: A Performance-Evaluation Perspective," *Review of Economics and Statistics* 85 (No. 2, 2003), 453-471.

Juergens, Jennifer, and Laura Lindsey, "Getting Out Early: An Analysis of Market Making Activity at the Recommending Analyst's Firm," *Journal of Finance* 64 (2009), 2327-2359.

Khan, Mozaffar, and Hai Lu, "Do Short Sellers Front-Run Insider Sales?" *The Accounting Review* 88 (No. 5, 2013), 1743-1768.

Kim, Sok Tae, Ji-Chai Lin, and Myron Slovin, "Market Structure, Informed Trading, and Analysts' Recommendations," *Journal of Financial and Quantitative Analysis* 32 (1997), 507-524.

Lakonishok, Josef, and Inmoo Lee, "Are Insider Trades Informative?" *Review of Financial Studies*, 14 (1, Spring) (2001), 79–111.

Larcker, David F., Eric C. So, and Charles C. Y. Wang, "Boardroom Centrality and Firm Performance," *Journal of Accounting and Economics*, 55 (2013), 225–250.

Madureira, Leonardo, and Shane Underwood, "Information, Sell-Side Research, and Market Making," *Journal of Financial Economics* 90 (2008), 105-126.

Malmendier, Ulrike, and Devin Shanthikumar, "Do Security Analysts Speak in Two Tongues?" forthcoming, *Review of Financial Studies* (2014).

Manne, Henry, *Insider Trading and the Stock Market*, New York, NY: Free Press, 1969.

__________, "Insider Trading: Hayek, Virtual Markets, and the Dog that Did Not Bark," *Journal of Corporation Law* 31 (1) (2005), 167-185.

Michaely, R., and Kent Womack, "Conflict of Interest and the Credibility of Underwriter Analyst Recommendations," *Review of Financial Studies* 12 (1999), 653-686.

McCord, J. W. H., S. L. McCord, and C. S. Bailey, *Criminal Law and Procedure for the Paralegal: A Systems Approach*, 2012, Clifton Park, NY: Delmar, 4th Edition.

Nefedova, Tamara, "Tippers and Tippees: Brokers' Pre-release of Price-sensitive Information to their VIP Clients," 2012, Working Paper.

Ozsoylev, Han N., Johan Walden, M. Deniz Yavuz, and Recep Bildik, "Investor Networks in the Stock Market," *Review of Financial Studies* 27, (No. 5, 2014), 1323-1366.

Padilla, Alexandre, "Should the Government Regulate Insider Trading?" *Journal of Libertarian Studies*, 22, (2011), 379-398.

Ravina, Enrichetta, and Paola Sapienza, "What do Independent Directors Know? Evidence from Their Trading," *Review of Financial Studies*, 23 (3) (2010), 962–1003.

Seyhun, H. Nejat, “Insiders’ Profits, Costs of Trading, and Market Efficiency,” *Journal of Financial Economics*, 16 (1986), 189–212.

Shiller, Robert J., and John Pound, “Survey Evidence on the Diffusion of Interest and Information Among Investors,” *Journal of Economic Behavior*, 12 (1989), 47–66.

Womack, Kent, “Do Brokerage Analysts’ Recommendations have Investment Value?” *Journal of Finance* 51 (1996), 137-167.

Appendix A. Measurement of Firm Characteristics

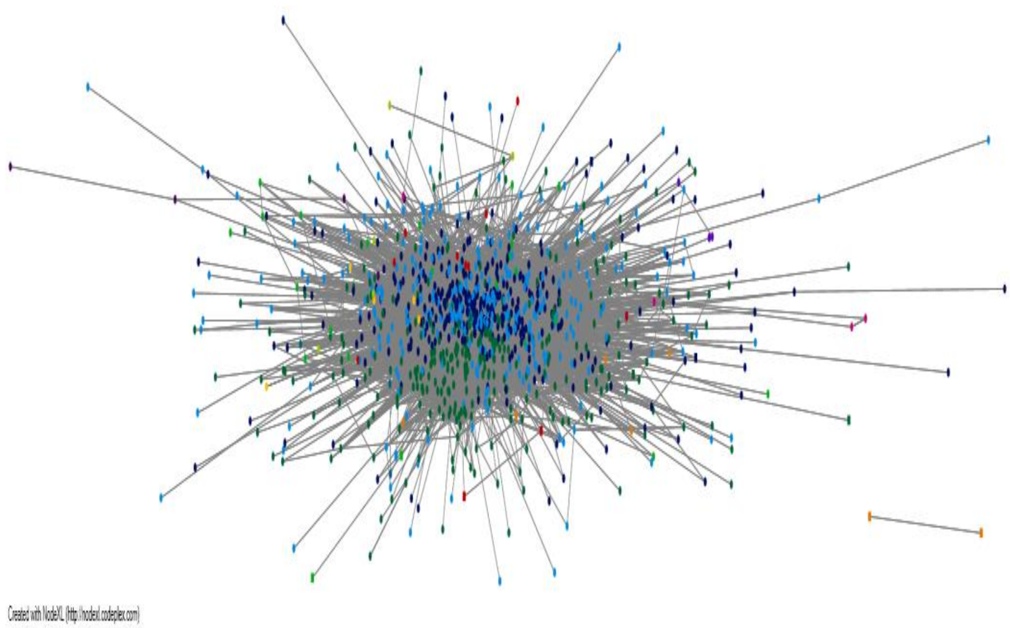
For each day in the sample period, we obtain every stock's adjusted decile rank values for several firm characteristics using a two-step procedure. First we construct each variable. For example, we construct the Dimson beta (*BETA*) for each stock (*i*) traded on day *t*, by regressing the stock's daily return on the value-weighted market return, along with three leads and lags of the market return, over the 250-day period ending one day before the trade date (*t-1*). Market capitalization (*Size*) is the number of shares outstanding multiplied by the daily closing price. For trade date *t*, we use the median market capitalization over the 21-day period ending 20 trading days earlier. The market-to-book ratio (*MB*) is the market value of equity divided by the book value of equity at the end of the prior fiscal year. Finally, we measure the past return for each stock over four non-overlapping windows: the last year excluding the most recent month (*RYear*), the last month excluding the most recent week (*RMonth*), the last week excluding the most recent day (*RWeek*), and the last day (*RDay*).

Second, we transform each control variable into decile ranks by first sorting the cross section of stocks each day into 10 groups. Next, we assign a value to the stocks in each decile, where the values are adjusted to range from -0.5 (for the lowest decile) to +0.5 (for the highest decile). This adjustment serves to attenuate the influence of outliers.[26] The mean adjusted rank values in Panel B of Table 1 are then obtained by averaging these adjusted ranks across all stock trading days within every trade category.

[26] See Grinblatt, Keloharju and Linnainma (2012) and Berkman, Koch and Westerholm (2014) for similar analysis.

Figure 1. Network of Financial Experts

Figure 1 displays the network connecting all financial experts who make network trades, which are defined as identical trades made in the same stock (i) on the same day (t) by two or more employees in the financial services industry. In this Figure, each node represents a different financial expert who engages in at least one network trade sometime over the five-year sample period.[27] The individual with the largest number of such connections makes over 250 network trades during our sample period. Out of the roughly 14,200 network trades in our sample, 3,663 (25.8%) occur between people at the same firm, 881 (6.2%) occur between people in the same financial services group (but at different firms), and 9,324 (65.6%) occur between people in the same empirical trading network. In total, 73.4% (10,427) of all network trades can be traced to people either at the same firm, financial services group, or empirical trading network.



[27] Note that Figure 1 displays connections among all experts who engage in at least one 'network trade' during the five-year sample period. The network in this Figure is not the 'empirical trading network' that is defined elsewhere.

Table 1. Summary of Trading Activity by Employees in the Financial Services Network

This Table presents summary statistics for the five categories of financial experts (brokers, analysts, fund managers, board members, and 'others') who work at the three types of financial intermediaries (brokerage houses, mutual fund management firms, and asset management firms). Panel A provides the relative frequencies of the five categories of experts in our sample who work at the three types of firms. In addition, Panel A summarizes the total number of trades made by each type of expert.

Panel B presents additional information about the attributes of the purchases and sales made by these five categories of financial experts. For each category of experts, this information includes the total number of trades in our sample, the average number of shares traded, the average value (in €) of each trade, and the percentage of trades that constitute network trades. Network trades are identified as similar trades made in the same stock and the same direction on the same day by more than one expert in our sample. All remaining trades are classified as non-network trades.

In addition, Panel B provides the attributes of the average firm traded by each type of financial expert. These attributes include the firm's market capitalization, beta, market-to-book ratio, and past returns measured over several non-overlapping time frames, including the past year (excluding the prior month), the past month (excluding the last week), the past week (excluding the last day), and the previous day. For every firm attribute, we first compute the decile ranks across each category of trades every year, and then adjust these decile ranks to range between -0.5 (for the lowest decile) to +0.5 (for the highest decile). The mean values are then obtained by averaging these adjusted ranks across all stock trading days by experts within every category.

Panel A. Summary Statistics for Different Categories of Financial Experts at Different Types of Financial Firms

	Relative Frequency of the Five Categories of Financial Experts								Relative Frequency of Trades		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Type of Expert	Frequency (%)		Brokerage (%)		Fund Mgt (%)		Asset Mgt (%)		# Trades (%)		# Trades / Person
Broker	306	24%	303	39%	1	0%	2	1%	13,377	36%	44
Analyst	92	7%	80	10%	0	0%	12	5%	2,389	6%	26
Fund Mgr	99	8%		0%	70	34%	29	11%	4,963	13%	50
Board	157	13%	56	7%	66	33%	35	13%	5,461	15%	35
Other	595	48%	346	44%	66	33%	183	70%	11,119	30%	19
Total	1,249	100%	785	100%	203	100%	261	100%	37,309	100%	30
# Firms			16		15		9				

Table 1, continued

Panel B. Summary Statistics for Purchases and Sales by Different Categories of Financial Experts

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Attributes of Trades				Attributes of Firms Traded						
Type of Expert	# Trades	# Shares per Trade	Value (€) per Trade	% Network Trades	Size	Beta	MB	RYear	RMonth	RWeek	RDay
Purchases											
Broker	7,911	1,270	5,398	47%	.25	.20	.02	-.07	-.09	-.05	-.04
Analyst	1,445	796	4,831	50%	.24	.20	.00	-.05	-.06	-.03	-.03
Fund Mgr	2,343	12,280	34,676	42%	.22	.18	.03	-.04	-.07	-.05	-.02
Board	3,131	6,644	51,389	41%	.29	.23	.03	-.01	-.04	-.02	-.03
Other	7,062	1,689	8,698	48%	.29	.22	.03	-.07	-.08	-.04	-.03
Sales											
Broker	5,397	-1,781	-9,414	24%	.21	.19	-.01	-.04	.06	.04	.03
Analyst	938	-1,998	-7,659	29%	.14	.15	-.04	-.02	.08	.01	.02
Fund Mgr	1,958	-3,884	-30,589	23%	.19	.17	.01	-.01	.04	.02	.03
Board	2,112	-9,998	-77,177	21%	.25	.20	.02	.02	.03	.03	.05
Other	4,051	-4,414	-20,227	26%	.24	.19	.02	-.02	.05	.03	.02
Total Trades	36,348										

Table 2. Likelihood of Financial Experts Trading on Any Given Day

This Table presents our analysis of the likelihood that financial experts will trade certain stocks. First we construct the empirical trading network using data on the trades of financial experts for the first two and one half years of our sample period, March 2005 through August 2008. Then we use this information to compute the measures of trading probability for the remaining two and one half years, September 2008 through March 2011. Panel A provides descriptive stastics that reflect the probability of an expert trading, both unconditionally, and conditional on similar trades being made by other experts in the same professional network of each type, as well as conditional on a major firm event occurring on the same day. Panel B presents the results from estimating the following panel logit model:

$$\text{Log}\{(\text{Trade}_{i,e,t} = 1)/(\text{Trade}_{i,e,t} = 0)\} = a_0 + a_1\,\text{Analyst}_e + a_2\,\text{FM}_e + a_3\,\text{BM}_e + a_4\,\text{Other}_e + \sum_{k=0}^{4} a_{5k}\,\text{Firm-NW}_{i,e,t\text{-}k} + \sum_{k=0}^{4} a_{6k}\,\text{Group-NW}_{i,e,t\text{-}k} + \sum_{k=0}^{4} a_{7k}\,\text{Emp-NW}_{i,e,t\text{-}k} + \sum_{k=-3}^{3} a_{8k}\,\text{Event}_{i,e,t\text{-}k} + a_9\,\ln(\text{Volume})_{i,t} + a_{10}\,\text{Centrality}_e + \text{Other Controls.} \quad (1)$$

The variables in this model are described in the text.

Panel A. Descriptive Statistics for the Probability of Experts Trading

	# of Trades of Interest N_1	# of Trades Possible N_2	Probability of Trading (N_1/N_2)
1. Unconditional Probability of an Expert Trading:			
N_1 = # Trades by All Experts;	18,003	95,288,621	0.019%
N_2 = # Trading Days on which these experts could have traded.			
2. Conditional on Similar Trades by Another Expert at the Same Firm on the Same Day:	2,208	831,069	0.266%
N_1 = # Trading Days where More Than One Expert at the Same Firm Made Similar Trades;			
N_2 = # Trading Days where Any Colleagues at the Same Firm Traded.			
3. Conditional on Similar Trades by Another Expert in the Same Financial Services Group:	846	376,405	0.225%
N_1 = # Trading Days where More Than One Expert in the Same Group Made Similar Trades;			
N_2 = # Trading Days where Any Experts in the Same Group Traded.			
4. Conditional on Similar Trades by Another Expert in the Same Empirical Trading Network:	4,243	3,250,262	0.131%
N_1 = # Trading Days where > 1 Expert in the Same Empirical Trading Network Traded;			
N_2 = # Trading Days where Any Expert in the Same Empirical Trading Network Traded.			
5. Conditional on A Major Firm-Specific Event Occurring on the day that an Expert Trades:	1,266	1,981,763	0.064%
N_1 = # Trading Days where an Expert Traded on the Same Day as a Firm-Specific Event;			
N_2 = # Trading Days where Any Major Corporate Event Occurred.			

Table 2, continued

Panel B. Estimation of Logit Model in Equation (1)[a]

	Purchases		Sales	
	Coeff	p-value	Coeff	p-value
Intercept	**-12.172**	.05	**-12.037**	.00
Analyst	**-.118**	.00	**-.430**	.00
Fund Manager	**-.152**	.00	**-.386**	.00
Board Member	**-.120**	.00	**-.601**	.00
Other	**-.280**	.00	**-.651**	.00
$\text{Firm-NW}_{i,e,t}$	**.940**	.00	**-.803**	.00
$\text{Firm-NW}_{i,e,t-1}$	**.406**	.00	**-.320**	.00
$\text{Firm-NW}_{i,e,t-2}$	**.271**	.00	**-.264**	.00
$\text{Firm-NW}_{i,e,t-3}$	**.155**	.00	**-.161**	.02
$\text{Firm-NW}_{i,e,t-4}$	**.263**	.00	-.047	.50
$\text{Group-NW}_{i,e,t}$	**.720**	.00	**-.405**	.00
$\text{Group-NW}_{i,e,t-1}$	**.180**	.00	-.004	.97
$\text{Group-NW}_{i,e,t-2}$	-.054	.37	**-.335**	.00
$\text{Group-NW}_{i,e,t-3}$	**.193**	.00	-.036	.73
$\text{Group-NW}_{i,e,t-4}$	.028	.65	**-.203**	.05
$\text{Emp-NW}_{i,e,t}$	**.297**	.00	**-.173**	.00
$\text{Emp-NW}_{i,e,t-1}$	**.082**	.00	**-.169**	.00
$\text{Emp-NW}_{i,e,t-2}$	**.108**	.00	**-.121**	.00
$\text{Emp-NW}_{i,e,t-3}$	**.053**	.04	**-.123**	.00
$\text{Emp-NW}_{i,e,t-4}$	**.089**	.00	**-.078**	.04
$\text{Event}_{i,e,t+1}$	**.309**	.00	**.266**	.00
$\text{Event}_{i,e,t+2}$	.056	.19	**.133**	.02
$\text{Event}_{i,e,t+3}$	**.108**	.02	**.184**	.00
$\text{Event}_{i,e,t}$	.063	.19	.078	.22
$\text{Event}_{i,e,t-1}$	**.146**	.00	.054	.38
$\text{Event}_{i,e,t-2}$	-.035	.53	**.111**	.09
$\text{Event}_{i,e,t-3}$	.030	.59	.084	.22
ln(# Trades)	**.766**	.00	**.674**	.00
Centrality	**.136**	.00	**.153**	.00
Size	-.023	.70	-.068	.32
Beta	-.046	.35	**.098**	.09
MB	**-.237**	.00	**-.247**	.00
RYear	.001	.99	**-.081**	.03
RMonth	**-.312**	.00	**.535**	.00
RWeek	**-.256**	.00	**.347**	.00
RDay	**-.171**	.00	**.300**	.00
Monday	**-.078**	.01	**.138**	.00
Tuesday	-.047	.13	**.125**	.00
Wednesday	-.018	.55	**.089**	.02
Thursday	.012	.69	**.139**	.00

[a] Coefficients highlighted in **bold** are significant at the .10 level or better.

Table 3. Performance of Trades by All Financial Experts made One Day Earlier

This Table presents the mean daily coefficients from estimating the cross sectional regression model in Equation (2), as follows:

$$Return_{i,t} = b_0 + b_1 Expert_{i,e,t} + b_2 Size_{i,t} + b_3 Beta_{i,t} + b_4 MB_{i,t} + b_5 RYear_{i,t} + b_6 RMonth_{i,t} + b_7 RWeek_{i,t} + b_8 RDay_{i,t} + \varepsilon_{i,t}. \quad (2)$$

The model is estimated separately for the cross sections of purchases and sales made on day *t-1* by all retail accounts in Finland. When the control variables are excluded, the intercept b_0 represents the average one-day return (in percent) across the benchmark (omitted) group of retail trades made one day earlier, while the coefficient b_1 indicates the abnormal return for similar trades made by the group of all financial experts, relative to this benchmark return. Panel A presents the results for purchases or sales made one day earlier, while Panel B provides analogous results for earlier trades made over several non-overlapping portfolio formation windows. The left side of each Panel presents the evidence for purchases, while the right side gives the results for sales, with and without the control variables in Equation (2). The p-values are based on Newey-West adjusted standard errors for the mean daily coefficients. Coefficients highlighted in **bold** are significant at the .10 level.

Panel A. All Trades based on a 1-day Portfolio Formation Window

Variable		Purchases				Sales			
		Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Intercept	b_0	-.012%	.81	-.008%	.85	-.056%	.24	-.010%	.80
Expert	b_1	**.129%**	.00	**.110%**	.00	**-.068%**	.03	**-.077%**	.00
Size	b_2			**-.123%**	.09			-.082%	.23
Beta	b_3			**-.078%**	.09			-.056%	.17
MB	b_4			.016%	.80			.039%	.50
RYear	b_5			**.107%**	.05			.015%	.76
RMonth	b_6			**.116%**	.02			.011%	.79
RWeek	b_7			-.050%	.28			-.041%	.33
RDay	b_8			**-.485%**	.00			**-.566%**	.00

Panel B. Coefficient of the Expert Dummy Variable for Trades based on Different Formation Windows

Formation Window		Purchases				Sales			
days (*t-x* , *t-y*)		Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
(*t-7* , *t-2*)	b_1	**.050%**	.00	**.047%**	.00	**-.029%**	.06	**-.029%**	.04
(*t-30* , *t-8*)	b_1	**.018%**	.03	**.022%**	.00	-.005%	.65	-.005%	.57
(*t-90* , *t-31*)	b_1	.001%	.85	.001%	.85	.004%	.58	.004%	.58
Controls:		no		yes		no		yes	

Table 4. Performance of Trades by Different Types of Financial Experts

This Table presents the relevant results from estimating Equations (2), (3), (4), and (5), to analyze the relative performance of different groups of trades by financial experts: (i) in the five functional roles of the financial services industry, (ii) at the three financial services groups of firms, and (iii) that comprise non-network trades versus network trades by two or more financial experts.

Panel A. One-Day Alphas for Buy Portfolios using Different Formation Periods[a]

Dependent Variable: Return on Portfolio of		Portfolio Formation Period Covering Days (*t-x* , *t-y*)			
		(*t-1*)	(*t-7, t-2*)	(*t-31, t-8*)	(*t-90* , *t-32*)
		Equation (2): All Experts			
1. All Expert Trades	b_1	**.110%**	**.047%**	**.022%**	.001%
p-value		0.01	0.01	0.00	0.85
		Equation (3): Experts in the Five Functional Roles			
2. Brokers	c_1	**.147%**	**.028%**	**.023%**	.001%
p-value		0.01	0.06	0.01	0.89
3. Analysts	c_2	**.196%**	**.062%**	**.087%**	-.004%
p-value		0.01	0.10	0.01	0.74
4. Fund Managers	c_3	**.256%**	.055%	.025%	.018%
p-value		0.01	0.12	0.15	0.14
5. Board Members	c_4	-.025%	.034%	.016%	-.004%
p-value		0.56	0.15	0.31	0.70
6. Others	c_5	**.128%**	**.040%**	.011%	.000%
p-value		0.00	0.02	0.30	0.96
		Equation (4): Experts in the Three Financial Services Groups			
7. Brokerage Firms	d_1	**.120%**	**.043%**	**.023%**	-.003%
p-value		0.00	0.00	0.00	0.63
8. Fund Mgt Firms	d_2	**.106%**	**.064%**	.011%	.014%
p-value		0.03	0.01	0.45	0.17
9. Asset Mgt Firms	d_3	**.120%**	**.040%**	**.026%**	-.003%
p-value		0.00	0.05	0.04	0.68
		Equation (5): Non-Network Trades versus Network Trades			
10. 1 Expert	e_1	**.065%**	**.052%**	**.027%**	.002%
p-value		0.01	0.01	0.00	0.72
11. 2 Experts	e_2	**.132%**	**.059%**	**.027%**	.003%
p-value		0.01	0.02	0.05	0.74
12. 3 or 4 Experts	e_3	**.194%**	.046%	.012%	-.006%
p-value		0.01	0.16	0.48	0.65
13. 5 to 10 Experts	e_4	**.277%**	-.021%	.000%	.006%
p-value		0.02	0.67	1.00	0.78
14. > 10 Experts	e_5	**.742%**	.194%	-.104%	-.045%
p-value		0.06	0.21	0.13	0.48

Table 4, continued

Panel B. One-Day Alphas for Sell Portfolios using Different Formation Periods[a]

Dependent Variable: Return on Portfolio of		Portfolio Formation Period Covering Days (*t-x* , *t-y*) (*t-1*)	(*t-7, t-2*)	(*t-31, t-8*)	(*t-90* , *t-32*)
		Equation (2): All Experts			
1. All Expert trades	b_1	**-.077%**	**-.029%**	-.005%	.004%
p-value		0.00	0.04	0.57	0.58
		Equation (3): Experts in the Five Functional Roles			
2. Brokers	c_1	-.061%	.000%	.010%	.009%
p-value		0.13	0.99	0.51	0.30
3. Analysts	c_2	**-.256%**	.007%	-.033%	-.002%
p-value		0.02	0.88	0.19	0.91
4. Fund Managers	c_3	-.026%	-.061%	-.023%	.000%
p-value		0.70	0.12	0.29	0.99
5. Board Members	c_4	-.070%	-.012%	-.023%	-.001%
p-value		0.24	0.77	0.26	0.95
6. Others	c_5	**-.088%**	**-.051%**	.007%	.000%
p-value		0.04	0.09	0.53	0.99
		Equation (4): Experts in the Three Financial Services Groups			
7. Brokerage Firms	d_1	-.052%	-.025%	.004%	.006%
p-value		0.12	0.11	0.71	0.45
8. Fund Mgt Firms	d_2	.049%	-.009%	-.019%	.025%
p-value		0.46	0.85	0.48	0.13
9. Asset Mgt Firms	d_3	**-.111%**	-.043%	-.014%	-.009%
p-value		0.02	0.15	0.26	0.33
		Equation (5): Non-Network Trades versus Network Trades			
10. 1 Expert	e_1	**-.055%**	-.009%	-.005%	.005%
p-value		0.04	0.51	0.60	0.49
11. 2 Experts	e_2	**-.116%**	-.074%	.002%	.013%
p-value		0.08	0.11	0.93	0.28
12. 3 or 4 Experts	e_3	-.106%	-.041%	-.034%	.011%
p-value		0.46	0.50	0.43	0.73
13. 5 to 10 Experts	e_4	-.234%	-.125%	-.057%	-.073%
p-value		0.41	0.36	0.42	0.33
14. > 10 Experts	e_5	-.163%	-.252%	.122%	.017%
p-value		0.13	0.08	0.28	0.85

[a] Alphas highlighted in **bold** are significant at the .10 level or better.

Table 5. Performance of Trades By Financial Experts Prior To Major Firm Events

Panels A - E of this Table present event study analysis of the performance of trades made by financial experts in the three weeks prior to four kinds of firm events: earnings announcements, analyst revisions, merger announcements, and large price changes. We consider all events where at least one expert trades during one of the three days or weeks before the event. In the text we further discuss the criteria for selecting the sample for each kind of event. We consider the mean 'signed' cumulative abnormal return on the day of and the day after each type of event *CAR(0,+1).* For net purchasers, we use the *CAR(0,+1)*. For net sellers, we 'sign' the *CAR(0,+1)* by multiplying it by -1. We then present the mean 'signed' *CAR(0,+1)*, for the groups of trades made by financial experts in each of the three days or weeks before each type of event.

	Mean Signed CAR(0,+1)	p-value	# Events with ≥ 1 trade	# of trades		Mean Signed CAR(0,+1)	p-value	# Events with ≥ 1 trade	# of trades
Panel A. Earnings Announcements									
1 Day Before	**0.83%**	0.02	343		1 Week Before	**0.50%**	0.02	742	
2 Days Before	0.18%	0.65	283		2 Weeks Before	-0.09%	0.70	652	
3 Days Before	0.28%	0.50	299		3 Weeks Before	0.02%	0.93	680	
Panel B. Revisions of Recommendations by Analysts									
1 Day Before	**0.36%**	0.01	842		1 Week Before	**0.29%**	0.00	1468	
2 Days Before	**0.38%**	0.02	687		2 Weeks Before	-0.05%	0.62	1322	
3 Days Before	-0.02%	0.92	630		3 Weeks Before	0.13%	0.19	1289	
Panel C. Revisions of Recommendations by Analysts at the Same Firm as the Financial Expert Trading									
1 Day Before	**1.58%**	0.00	134		1 Week Before	**0.60%**	0.04	305	
2 Days Before	-0.51%	0.48	68		2 Weeks Before	**0.59%**	0.06	234	
3 Days Before	-0.26%	0.70	79		3 Weeks Before	0.04%	0.88	252	
Panel D. Merger and Acquisition Announcements									
1 Day Before	--		--		1 Week Before	2.64%	0.29	24	
2 Days Before	--		--		2 Weeks Before	-1.42%	0.50	23	
3 Days Before	--		--		3 Weeks Before	-1.06%	0.76	26	
Panel E. Large Price Changes									
1 Day Before	**2.46%**	0.01	128		1 Week Before	**1.47%**	0.02	293	
2 Days Before	1.06%	0.26	112		2 Weeks Before	**1.22%**	0.05	302	
3 Days Before	**2.04%**	0.07	117		3 Weeks Before	0.37%	0.59	312	

[a] Mean CARs highlighted in **bold** are significant at the .10 level or better.

Table 6. Timing of Trades by Financial Experts around Corporate Insider Trades

This Table presents the average abnormal frequency of trades that are made by different groups of financial experts around insider trades. For each group of expert trades, for every day in the event window, *t = (-5,+5)*, and for each event (*i*), we define abnormal expert trading activity as the difference between the actual number of expert trades on day *t* and the daily average number of expert trades for event *i* in the pre-event window, *t = (-25,-6)*. Next, we compute the mean abnormal trading activity for each day (*t*) across all events and use the standard error of this mean to test the null hypothesis that the mean abnormal trading activity on day *t* is zero. Panel A provides the mean abnormal number of expert trades for each day in the event window around insider purchases, while Panel B presents the analogous results around insider sales.

Panel A. Mean Abnormal Number of Trades by Financial Experts on the Days Around Insider Purchases

	#Events	day-5	day-4	day-3	day-2	day-1	day 0	day 1	day 2	day 3	day 4	day 5
1. All trades	605	-.01	.01	.01	**.12**	**.22**	**.29**	**.16**	.02	.01	.02	.05
p-value		.82	.75	.74	.00	.00	.00	.01	.59	.70	.48	.21
2. Brokers	490	-.01	-.01	.00	**.06**	**.10**	**.12**	**.05**	.00	.02	.02	.02
p-value		.45	.50	.99	.02	.00	.00	.05	.99	.43	.27	.35
3. Analysts	221	.00	.03	.02	**.06**	**.06**	**.06**	.04	.04	-.01	.01	.03
p-value		.93	.09	.37	.01	.01	.04	.15	.07	.69	.66	.24
4. Fund Managers	226	.01	-.01	-.03	.04	**.09**	.01	.04	.01	.01	.00	.00
p-value		.65	.58	.08	.10	.01	.76	.16	.80	.64	.96	.96
5. Board Members	269	-.02	**-.03**	.01	.02	.03	**.11**	.04	.00	-.01	-.01	.01
p-value		.28	.05	.76	.29	.16	.00	.14	.92	.48	.62	.76
6. Others	422	.02	.04	.02	.04	**.11**	**.17**	**.11**	.00	.00	.00	.02
p-value		.42	.10	.34	.15	.00	.00	.02	.99	.92	.92	.34
7. Brokerage Firms	551	-.03	.03	.02	**.10**	**.16**	**.21**	**.10**	.03	.01	.03	.04
p-value		.21	.17	.56	.00	.00	.00	.01	.32	.72	.22	.15
8. Fund Mgt Firms	287	.00	-.02	-.02	.03	.05	.06	.05	-.02	.00	.01	.01
p-value		.87	.35	.28	.20	.06	.18	.10	.33	.89	.52	.74
9. Asset Mgt Firms	366	.03	-.02	.01	.03	**.08**	**.11**	**.08**	.00	.00	-.02	.01
p-value		.16	.26	.58	.24	.00	.00	.03	.89	.89	.17	.72
10. 1 Expert trading	602	.02	.02	-.01	**.05**	**.08**	**.07**	**.05**	.03	.03	.01	.03
p-value		.24	.22	.68	.01	.00	.00	.01	.06	.14	.52	.10
11. >1 Expert trading	270	-.06	-.03	.04	.16	**.33**	**.50**	.26	-.04	-.03	.02	.04
p-value		.32	.58	.57	.08	.00	.01	.06	.53	.60	.73	.60

Table 6, continued

Panel B. Mean Abnormal Number of Trades by Financial Experts on the Days Around Insider Sales

	# Events	day-5	day-4	day-3	day-2	day-1	day 0	day 1	day 2	day 3	day 4	day 5
1. All trades	294	-.03	.04	.05	.07	.02	**.17**	-.01	-.05	-.03	-.01	-.02
p-value		.23	.18	.09	.08	.53	.00	.80	.06	.27	.82	.46
2. Brokers	198	.01	-.03	.05	**.07**	.01	**.12**	-.01	**-.04**	-.04	.00	-.03
p-value		.58	.11	.06	.02	.53	.00	.81	.04	.09	.86	.17
3. Analysts	91	-.03	.01	.02	.02	.00	.02	.03	-.03	-.03	.01	.00
p-value		.12	.78	.52	.53	.85	.53	.44	.13	.13	.79	.87
4. Fund Managers	98	**-.06**	.03	.01	.00	.02	.04	.03	**-.06**	.00	-.04	-.02
p-value		.02	.36	.69	.92	.50	.33	.39	.03	.92	.22	.63
5. Board Members	95	-.02	.05	.00	.01	-.02	.06	-.02	.02	.00	-.01	.03
p-value		.43	.16	.96	.79	.46	.19	.51	.58	.96	.71	.42
6. Others	206	-.01	.04	.02	.02	.02	.07	-.02	.00	.00	.01	-.01
p-value		.49	.09	.55	.52	.54	.06	.19	.82	.84	.81	.64
7. Brokerage Firms	250	-.01	.02	**.05**	.06	.02	**.12**	-.01	-.03	**-.05**	.00	-.04
p-value		.59	.35	.05	.06	.36	.00	.82	.30	.04	.95	.08
8. Fund Mgt Firms	108	**-.05**	.03	-.01	-.02	.00	.07	.00	**-.07**	.00	-.03	-.02
p-value		.02	.38	.84	.35	.93	.26	.92	.00	.92	.25	.44
9. Asset Mgt Firms	165	-.01	.02	.02	.04	.00	.07	-.01	-.01	.01	.01	.04
p-value		.80	.53	.51	.17	.98	.06	.80	.79	.71	.67	.25
10. 1 Expert trading	291	-.01	**.05**	**.05**	**.06**	.04	.05	.01	-.02	-.03	.00	.02
p-value		.82	.04	.03	.02	.15	.06	.73	.27	.11	.83	.54
11. >1 Expert trading	97	-.09	-.03	.00	.01	-.05	**.38**	-.05	-.09	-.01	-.04	**-.11**
p-value		.10	.66	.95	.87	.45	.03	.42	.11	.94	.61	.01

[a] Figures highlighted in **bold** are significant at the .05 level or better.

Table 7. Performance of Trades by Financial Experts around Corporate Insider Trades

This Table presents the mean signed *CARs* over the 10 or 20 days following trades that are made by groups of financial experts on the days around insider trades. For net purchasers we use the *CAR*. For net sellers we 'sign' the *CAR* by multiplying it by -1. On the left side of Table 7, we present the mean 'signed' *CARs* for the groups of trades made by financial experts on the same day as the insider trades. On the right side we provide the analogous results for expert trades made on the days before or after insider purchases.

CARs following Expert Trades:	on Day of Insider Purchases or Sales (Day 0)			on Days (-2, -1, +1) around Insider Purchases		
	CAR(1,10)	*CAR(1,20)*	n	*CAR(1,10)*	*CAR(1,20)*	n
1. All trades	**1.25%**	**1.69%**	353	.35%	**.74%**	369
p-value	.00	.00		.26	.05	
2. Brokers	**1.30%**	**1.36%**	186	.67%	**1.05%**	221
p-value	.01	.04		.19	.07	
3. Analysts	2.39%	2.42%	28	**2.17%**	**2.38%**	52
p-value	.15	.23		.09	.10	
4. Fund Managers	.66%	1.30%	54	-.02%	.46%	86
p-value	.41	.31		.97	.60	
5. Board Members	.64%	1.04%	67	-.36%	.80%	79
p-value	.49	.37		.56	.30	
6. Others	**1.67%**	**2.34%**	126	.46%	.59%	171
p-value	.09	.02		.31	.30	
7. Brokerage Firms	**1.41%**	**1.53%**	258	.43%	**.84%**	287
p-value	.01	.01		.24	.06	
8. Fund Mgt Firms	.36%	1.60%	73	.34%	.99%	102
p-value	.62	.16		.50	.20	
9. Asset Mgt Firms	**1.49%**	**1.96%**	91	.50%	.50%	136
p-value	.08	.06		.38	.45	
10. 1 Expert	**1.27%**	**1.57%**	298	.30%	.56%	339
p-value	.01	.01		.36	.16	
11. 2 Experts%	.98%	**1.98%**	69	.54%	1.05%	103
p-value	.27	.10		.46	.19	

[a] Figures highlighted in **bold** are significant at the .10 level or better.

Table 8. Timing of Trades by Financial Experts around Large Block Trades by Mutual Funds

This Table presents the average abnormal frequency of trades that are made by different groups of financial experts around block trades. For each group of expert trades, for every day in the event window, *t = (-5,+5)*, and for each event (*i*), we define abnormal expert trading activity as the difference between the actual number of expert trades on day *t* and the daily average number of expert trades for event *i* in the pre-event window, *t = (-25,-6)*. Next, we compute the mean abnormal trading activity for each day (*t*) across all events and use the standard error of this mean to test the null hypothesis that the mean abnormal trading activity on day *t* is zero. Panel A provides the mean abnormal number of expert trades for each day in the event window around block purchases, while Panel B presents the analogous results around block sales.

Panel A. Mean Abnormal Number of Trades by Financial Experts on the Days around Block Purchases

	#Events	day-5	day-4	day-3	day-2	day-1	day 0	day 1	day 2	day 3	day 4	day 5
1. All trades	706	.04	**.14**	**.10**	**.20**	**.21**	**.30**	**.21**	**.22**	**.47**	**.15**	**.10**
p-value		.24	.00	.07	.00	.00	.00	.00	.00	.00	.00	.02
2. Brokers	652	.00	**.07**	.00	**.10**	**.08**	**.13**	**.09**	**.09**	**.18**	**.06**	**.04**
p-value		.94	.01	.83	.00	.00	.00	.00	.00	.00	.02	.04
3. Analysts	353	.01	.00	**.04**	.01	**.03**	**.06**	**.05**	**.03**	**.05**	.02	.00
p-value		.68	.87	.07	.35	.06	.00	.02	.07	.02	.14	.85
4. Fund Managers	423	.03	**.03**	.00	.01	.02	**.05**	**.03**	**.06**	**.08**	.01	.00
p-value		.12	**.05**	.78	.70	.29	.02	.09	.00	.01	.61	.99
5. Board Members	506	.02	.02	**.03**	**.05**	.03	**.05**	.01	**.03**	**.09**	**.04**	-.01
p-value		.38	.25	.06	.01	.12	.02	.51	.10	.00	.03	.59
6. Others	650	.02	**.04**	**.06**	**.06**	**.09**	**.09**	**.08**	**.07**	**.19**	**.05**	**.07**
p-value		.39	.05	.06	.04	.01	.00	.01	.00	.00	.06	.01
7. Brokerage Firms	689	.00	**.09**	**.07**	**.14**	**.16**	**.21**	**.12**	**.13**	**.30**	**.10**	**.08**
p-value		.87	.01	.05	.00	.00	.00	.00	.00	.00	.00	.02
8. Fund Mgt Firms	448	.02	.01	.01	.00	-.01	.01	.01	**.06**	**.08**	.02	.02
p-value		.40	.53	.65	.84	.46	.53	.51	.00	.02	.47	.41
9. Asset Mgt Firms	611	**.03**	**.05**	.03	**.07**	**.07**	**.10**	**.09**	**.07**	**.15**	**.05**	.02
p-value		.07	.01	.26	.01	.01	.00	.00	.00	.00	.03	.43
10. 1 Expert trading	705	.01	.01	.01	**.05**	**.03**	**.05**	.01	.03	.02	.02	-.02
p-value		.46	.66	.54	.02	.10	.02	.56	.11	.22	.22	.28
11. >1 Expert trading	520	.04	**.18**	**.12**	**.21**	**.24**	**.34**	**.26**	**.26**	**.61**	**.17**	**.16**
p-value		.41	.00	.10	.02	.00	.00	.00	.00	.00	.01	.00

Table 8, continued

Panel B. Mean Abnormal Number of Trades by Financial Experts on the Days around Block Sales

	#Events	day-5	day-4	day-3	day-2	day-1	day 0	day 1	day 2	day 3	day 4	day 5
1. All trades	756	-.02	.01	-.01	.00	**.14**	**.33**	**.22**	**.19**	**.19**	**.12**	.02
p-value		.73	.80	.73	.94	.03	.00	.00	.00	.00	.00	.49
2. Brokers	657	.01	-.01	-.01	.00	**.11**	**.16**	**.11**	**.07**	**.10**	**.08**	.02
p-value		.65	.61	.79	.85	.00	.00	.00	.01	.00	.00	.25
3. Analysts	379	.01	.02	-.01	.01	-.01	.02	.02	.02	.02	.00	.01
p-value		.58	.36	.53	.46	.32	.27	.29	.15	.24	.89	.66
4. Fund Managers	455	.02	-.01	.01	.01	.01	**.05**	.02	**.04**	.02	.03	-.02
p-value		.50	.85	.57	.70	.73	.01	.31	.07	.21	.11	.06
5. Board Members	508	-.03	.02	.01	.01	.02	**.05**	.02	**.03**	**.04**	.03	.01
p-value		.06	.20	.73	.65	.25	.01	.38	.06	.04	.12	.56
6. Others	681	-.03	.00	-.01	-.02	.04	**.12**	**.11**	**.08**	**.06**	.02	.01
p-value		.17	.99	.48	.18	.20	.00	.00	.00	.00	.27	.60
7. Brokerage Firms	718	.00	.00	-.01	.01	**.14**	**.25**	**.15**	**.12**	**.14**	**.08**	.02
p-value		.97	.95	.80	.73	.00	.00	.00	.00	.00	.01	.49
8. Fund Mgt Firms	475	**-.02**	**-.03**	.00	.00	.00	**.07**	.05	**.04**	**.05**	**.05**	.00
p-value		.08	.01	.92	.88	.82	.00	.13	.05	.01	.02	.82
9. Asset Mgt Firms	641	.00	.04	-.01	-.01	.01	**.05**	**.06**	**.06**	**.03**	.02	.00
p-value		.91	.23	.67	.46	.54	.06	.02	.01	.10	.28	.81
10. 1 Expert trading	754	**-.03**	-.02	.01	-.01	.02	.00	.02	.03	**.04**	.02	.01
p-value		.09	.24	.65	.67	.33	.85	.38	.14	.02	.19	.70
11. >1 Expert trading	510	.02	.05	-.03	.01	**.19**	**.49**	**.31**	**.24**	**.22**	**.14**	.02
p-value		.78	.47	.49	.87	.05	.00	.00	.00	.00	.01	.60

[a] Figures highlighted in **bold** are significant at the .05 level or better.

Table 9. Performance of Trades by Experts around Block Trades

This Table presents the mean signed *CARs* over the 10 or 20 days following trades that are made by groups of financial experts on the two days before Finnish mutual funds buy or sell large blocks of stock. For net purchases by experts we use the *CAR*. For net sales by experts we 'sign' the *CAR* by multiplying it by -1. We then present the mean 'signed' *CARs* for the groups of trades made by financial experts on days -2 and -1 before the block trades. We also provide the number of events (n) in which at least one financial expert in each group trades the stock on the two days before the block trade.

CARs around Expert Trades:	on Days (-2,-1) before Block Trades		
	CAR(1,10)	*CAR(1,20)*	n
1. All trades	**.87%**	**1.37%**	844
p-value	.00	.00	
2. Brokers	.19%	.60%	467
p-value	.63	.26	
3. Analysts	.54%	**1.87%**	85
p-value	.58	.10	
4. Fund Managers	**1.14%**	**1.83%**	159
p-value	.03	.02	
5. Board Members	**.92%**	**1.04%**	244
p-value	.05	.07	
6. Others	.61%	.41%	345
p-value	.12	.41	
7. Brokerage Firms	.42%	**.83%**	631
p-value	.17	.05	
8. Fund Mgt Firms	**.92%**	**1.56%**	200
p-value	.05	.02	
9. Asset Mgt Firms	**1.38%**	**1.34%**	291
p-value	.00	.01	
9. 1 Expert	**.90%**	**1.54%**	728
p-value	.00	.00	
10. 2 Experts	.23%	.12%	259
p-value	.64	.84	

[a] Figures highlighted in **bold** are significant at the .10 level or better.