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 engage in profitable front-running ahead of corporate insider trades and ahead of institutional buying or selling pressure. 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 theory.

JEL codes: G12, G14, G18.

"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."

Legal Information Institute, Cornell University Law School (http://www.law.cornell.edu/wex/fiduciary_duty)

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 access to private information. In Finland the regulator has taken this reasoning one step further, to also require that employees of financial intermediaries publicly disclose all of their personal trades in any stock listed on the Nasdaq OMX Helsinki Exchange.[1]

In this study we investigate the possibility of informed trading, and the potential breach of fiduciary duty, by analyzing the personal trading activity of these Finnish financial experts. We begin by showing that financial experts tend to trade in a way that suggests that they seek to benefit from their access to valuable information. They are more active around major firm specific information events and they tend to buy (sell) a given stocks when other experts are buying (selling) the same stock. We then document that they earn exceptional abnormal short term returns in general, and that this outperformance is enhanced when they trade simultaneously with other experts, or when they trade ahead of company-specific news. Finally, we show that

[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).

experts are also abnormally active and profit from trading in the days before the execution or public disclosure of trades by corporate insiders, or days with substantial buying or selling pressure by Finnish mutual funds.

We begin our analysis with an examination of the *selection and timing* of personal stock transactions by the employees of financial intermediaries. We find that the likelihood of financial experts 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, 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 is more central within the network of financial experts. Finally, we document that these experts are more likely to trade in the days around firm-specific information events.

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 generate significant risk-adjusted returns that average 11 basis points (bp) per day based on all purchases made on the previous day, and 5 bp per day based on earlier purchases made over the past week (but excluding day -1). Similarly, we find that risk-adjusted returns average -8 bp on the day after a sale, and -3 bp per day after sales made during the previous week. In contrast, purchases and sales made earlier over the past quarter (but excluding the prior month), generate insignificant abnormal returns. Further analysis shows that this extraordinary short term outperformance is concentrated among brokers, analysts, fund managers, and 'other' experts, while there is no such outperformance by the board members of financial intermediaries. We also show that, although

[2] The same financial services group refers to other brokerage firms, fund management firms, or asset management firms that have the same parent company. An empirical trading network is defined as a community of investors heavily connected through similar trading activity among themselves, but sparsely connected with others. We follow Ozsoylev et al. (2014), and use the methodology of Clauset, Newman, and Moore (2004) to determine the empirical trading network each year.

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 others financial experts. For example, the day after a purchase by 5 to 10 experts the average stock price increase is 0.3 percent, and if a stock is bought by more than 10 experts the average return is as high as 0.7 percent.

Given the short term nature of this outperformance by financial experts, we next examine whether they profitably trade on superior private firm-specific information that is about to become public. We find that they do. For example, when experts trade on the day before major earnings announcements, they generate a mean cumulative abnormal return on days 0 and +1 (*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 made by analysts at the same firm as the expert trading, the mean *CAR(0,+1)* increases 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 could attract the attention of regulators.

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

First, we find that financial experts front-run corporate insider purchases (made on day 0), by trading in the previous two days (on days -1 and -2). Furthermore, experts continue to mimic these insider purchases on days 0, +1, and +2, before such trades are disclosed to the public (after day +4). Some of these front-running and copy-cat insider trades are made by people classified as brokers, but a large number of these copy-cat trades come from other experts suggesting this private information quickly spreads through the network. Moreover, this information turns out to be valuable. For the trades by 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 with exceptional net buying or selling by Finnish mutual funds. Once again, we document significant abnormal personal trading by experts in the same direction as the block trade, on the days before these large trades are executed and disclosed publicly. Once again, this front-running and copy-cat trading is not limited to brokers and fund managers, but also includes the employees of other intermediaries. For all trades made by experts over the two days before increased mutual fund trading, the average performance is a mean signed *CAR(+1,+20)* of 1.0 percent. Together with the trading activity around corporate insider trades, this evidence provides support for the view that valuable private and confidential information is shared and traded on throughout the financial services network, constituting a possible breach of fiduciary duty.

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 insider trades, and finds that directors outperform when they buy their own company's stock, but not when they sell.[3] Another 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. Jeng, Metrick, and Zeckhauser (2003)). In contrast, we show that financial experts display exceptional stock picking skills on both the buy and sell side, and we find that 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 tipping and front-running by these experts prior to the public disclosure of material private information. Several previous studies document information leakage ahead of major 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

[3] For example, see Jaffe (1974), Jeng, Metrick, and Zeckhauser (2003), Lakonishok and Lee (2001), Rozeff and Zaman (1988, 1998), Seyhun (1986) and Ravina and Sapienza (2010) for U.S.-based evidence. Fidrmuc, Goergen, and Renneboog (2006) examine U.K. insider trades, Berkman, Koch and Westerholm (2015) examine the trading performance of Finnish insiders and Clacher, Hillier, and Lhaopadchan (2009) discuss the results of insider trading studies in several other countries.

reported to the public, and sometimes even before the insiders are done selling.[4] Our study adds to the literature by providing evidence of frontrunning by employees of financial intermediaries directly benefiting for their personal accounts.

Finally, we extend recent work that shows valuable information diffuses through social networks. For example, evidence in Cohen, Frazzini, and Malloy (2008) suggests that mutual fund managers earn abnormal returns based on information obtained through their educational networks. Berkman, Koch and Westerholm (2015) examine the performance of corporate directors when they trade stocks and show that access to the director network provides them with valuable long term information about stocks for which they are not classified as an insider. Our study shows evidence of very rapid diffusion of exceptionally valuable short term information through the network of employees of 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 extend to employees of financial institutions.

Chapter 5, section 5 of the Securities Markets Act (July 2009) states that the holding of shares subject to public trading shall be public if the holder of the security is a member of the Board of Directors of a securities intermediary, or a broker, or an employee of a securities

[4] In contrast to the studies above, Griffin, Shu, and Topaloglu (2012) find little evidence of information leakage from brokerage houses to favored clients. The authors suggest that publication bias towards shocking inferences might explain the host of studies that find evidence of connected trading.

intermediary who by virtue of his position learns inside information on a regular basis. For each person subject to the duty to declare[5], the public Insider Register has to show the securities owned by him and all itemized transactions. The information in the register is kept for at least five years and needs to be accessible without difficulty (which in practice means at the premises of the securities intermediary).

Chapter 7, section 3 of the Act 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 further states:

"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 public insider trading registers, which provides a set of all transactions in stocks listed on the Helsinki Stock Exchange made by employees of Finnish financial intermediaries during the period, March 2006 through March 2011. The information for each individual includes personal trades, as well as trades on behalf of family members or through companies controlled by the expert.

Comment [h1]: The data used in this study are available as pdf files on a website created by Helsingin Sanomat, with the purpose of facilitating research into trading activities by employees in financial intermediaries and include transaction during the period March 2006 through Mrch 2011. FN: Some of the individuals figuring in this data appealed to the Data Protection Ombudsman in Finland to investigate if the newspaper had acted against data protection legislation. The Data Protection Ombudsman decided in June 2012 that the newspaper had not violated the data protection legislation of individuals in implementing this project.

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

[5] This includes his spouse, a minor whose guardian he is and an organization under his direct or indirect control.

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.

Panel A of Table 1 provides descriptive information about the relative frequencies of the different categories of trades classified by the five functional roles of employees working at the three different financial services groups. The top five rows in Panel A 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 firms. Our sample includes the employees of 16 different brokerage firms, 15 fund management firms, and 9 asset management firms.[6] Over 60% of all employees in our sample (785 of the 1,249 employees) work at brokerage firms, and 38%

[6] 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) ~~collective investments such as mutual funds and exchange traded funds)~~ and asset management firms (collective investments such as mutual funds and exchange traded funds~~institutional investment and investment management for private clients~~).

(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.'

Column 10 (and 11) of Panel A provides the total number (and percent) of stock trading days attributable to experts serving in each functional role.[7] 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.

Panel B of Table 1 presents more detailed summary statistics for the types of trades made by financial experts in each functional role. The first five rows give the trading statistics for the days in which each type of employee makes net *purchases*. The second five rows provide analogous details for net *sales*, and the third five rows give results for days in which purchases and sales in a given stock exactly *offset* one another (i.e., when an expert makes one or more round trip trades).

Column 2 in Panel B reports the total number of stock trading days for experts in each functional role, for the three types of days with net buying, net selling, or offsetting trades.

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

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). The stock trading days in which sales and purchases offset one another are concentrated among the group of fund managers (662) and board members (218), and are rare among the other groups of experts.

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 ~~with the same sign~~. This high proportion of network trades suggests a tight financial community whose members routinely trade based on information acquired 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. Together, ~~this evidence suggests a tight financial community whose members routinely trade based on information acquired through the financial services network.~~

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 follow certain investment styles or focus on stocks with certain attributes. 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 NASDAQ OMX Helsinki Stock Exchange, and adjust them 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 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 a detailed description of these firm characteristics, we refer the reader to Appendix C

The results in columns 6 - 12 of Panel B reveal that all five types of experts have a tendency to trade stocks with relatively high betas and large size. 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). ~~*Compare with our other papers + explain how calculated.*~~

~~Figure 1 displays the network connecting all financial experts who make network trades. In this Figure, each node represents a different financial expert who engages in at least one network trade over the five-year sample period.[8] 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, 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, 10,427 (73.4%) of the networked trades can be traced to people either at the same firm, financial services group, or empirical trading network.~~

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III. LIKELIHOOD OF TRADING BY FINANCIAL EXPERTS

[8] ~~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.~~

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.

W~~As before, w~~e consider ~~the~~ three professional networks defined as employees in the same: (i) financial firm, (ii) financial services group (but not the same firm), and (iii) empirical trading network. This exercise requires that we first construct all three professional networks, and then consider the likelihood of different (groups of) financial experts trading the same stock on any given day. While the first two networks are simple to construct from our data on the employees of Finnish financial intermediaries, our 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 three and a half years of our sample period, March 2005 – 2008. We then analyze the persistence of trading in this network, by examining the likelihood of empirical network trades by experts within the same empirical network during the ~~following~~ year~~,~~s 2009-2011.[9]

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

[9] ~~In this section we discuss the predictive results for 2009, but we find similar results for 2010 and 2011.~~

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 year, 2009. First, the unconditional probability of an expert trading a stock (*i*) on any given day (*t*) during the period 2009 - 2011~~in 2009~~ is 0.0~~35~~19%. This proportion is calculated as the actual number of days~~ in 2009~~ on which a financial expert is a net buyer or seller of a stock (18,003~~6,828~~), divided by the total number of trading days on which these experts could have traded a stock (roughly 95~~19~~ million).[10]

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~~6,828~~ stock trading days by experts during 2009 - 2011, similar network trades by at least one other expert at the same firm occur on 2,208~~748~~ 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~~193,064~~), to obtain the ratio of 0.39%.[11] 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 3,23~~5.24~~ %, which is more than 100 times greater than the unconditional probability of any expert trading. Similarly, the probability

[10] The latter figure is the total number of experts that trade in the period 2009 through 2011 -(~~537~~883) times the number of stocks (152) and trading days (~~258~~735), excluding, for each director, the days when a stock was not traded by any retail investor (~~2~~3 million, which is 34~~7~~24 stock trading days times the number of directors (~~537~~883).
[11] Note that this number of 831,069~~116,508~~ is much larger than the total number of trades by financial experts in 2009 (18,003~~6,828~~) 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 firms with 25 employees increases the denominator with 24

of an expert trading a given stock~~,~~ conditional on other experts in the same empirical network being active in the market is 0.~~23~~13%, which is about ~~7~~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 0.064~~10~~%, which is more than ~~twice~~ three times the unconditional probability of any expert trading. This last probability is higher for analyst recommendations (0.06~~9~~8%) and earnings announcements (0.080~~125~~), relative to large price change events (0.032~~65~~%) or takeover announcements (0.0~~48~~27%).

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

In this section we apply logit analysis to examine all trades by these experts in 2009 - 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 of each type (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:

$$\begin{aligned}
\mathrm{Log}\{(\mathrm{Buy}_{i,e,t} = 1) / (\mathrm{Buy}_{i,e,t} = 0)\} &= a_0 + a_1\,\mathrm{Analyst}_e + a_2\,\mathrm{FM}_e + a_3\,\mathrm{BM}_e + a_4\,\mathrm{Other}_e + \\
&+ \sum_{k=0}^{4} a_{5k}\,\mathrm{Firm\text{-}NW}_{i,e,t-k} + \sum_{k=0}^{4} a_{6k}\,\mathrm{Group\text{-}NW}_{i,e,t-k} + \sum_{k=0}^{4} a_{7k}\,\mathrm{Emp\text{-}NW}_{i,e,t-k} + \sum_{k=-3}^{3\quad \text{?? -4 to +4 ?}} a_{8k}\,\mathrm{Event}_{i,e,t-k} \\
&+ a_9\,\ln(\mathrm{Volume})_{i,t} + a_{10}\,\mathrm{Centrality}_e + a_{11}\,\mathrm{Size}_{i,t} + a_{12}\,\mathrm{Beta}_{i,t} + a_{13}\,\mathrm{MB}_{i,y} + \\
&+ a_{14}\,\mathrm{RYear}_{i,t} + a_{15}\,\mathrm{Rmonth}_{i,t} + a_{16}\,\mathrm{RWeek}_{i,t} + a_{17}\,\mathrm{RDay}_{i,t}\,, \qquad (1)
\end{aligned}$$

where

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

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

$Firm\text{-}NW_{i,e,t-k}$ = 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 expert at the same *firm* as *e* make ~~the~~ 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),

$Group\text{-}NW_{i,e,t-k}$ = 1 if other experts at 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 expert in the same *group* trade stock *i* on day– *t-k*,

or = -1 if other experts at 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),

$Emp\_NW_{i,e,t-k}$ = 1 if other experts at 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 expert in the same *empirical network* trade stock i on day– *t-k*,

or = -1 if other experts at 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),

$Event_{i,e,t-k}$ = 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;

$\ln(Volume)_{i,t}$ = the natural log of the total number of trades in stock *i* on day *t*;

$Centrality_e$ = the centrality of director *e* within the empirical trading network.[12]

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

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

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

[12] 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 2006 - 2008 to compute these centrality measures. See Berkman, Koch, and Westerholm (2015) for similar analysis.

The firm-specific events incorporated in the Event dummy variable include earnings announcements, takeover announcements, revisions of analyst recommendations, and large price changes. In Appendix A we further discuss the selection criteria for these respective samples of firm-specific events. The other control variables are motivated by Grinblatt, Keloharju, and Linnainma (2012), and described in Appendix C~~section II.B~~. We also include dummy variables for 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 side of Panel B, the probability of *buying* by analysts, board members fund managers and 'other' experts is significantly ~~greater~~ lower than that of brokers (the omitted group)~~, while fund managers and 'other' experts are significantly less likely to buy than brokers~~. ~~The propensity for board members to buy is not significantly different than that for brokers.~~ Similarly~~In contrast~~, on the right side of Panel B, the probability of *selling* by analysts, fund managers, board members, and 'other' experts is significantly lower than that by brokers.

Second, ~~consider how~~ the likelihood of a given expert trading a stock is associated with similar trading activity by other financial experts in each of the three social networks, in Panel B of Table 2. Consistent with expectations, an expert is significantly more likely to *buy* on a given day (t), if another expert in any of the three social networks buys the same stock on the same day, or on one or more of the previous four days.[13] The right three columns in Panel B show that an expert is significantly more likely to *sell* on a given day (t), if another expert in any of the three social networks sells the same stock on the same day, or on one or more of the previous

[13] Contrary to expectations, one coefficient at lag *t-4* for the group network dummy is significantly negative for buys.

four days.[14] In addition, the probability of buying and selling by financial experts increases significantly on the same day as a firm-specific event (*t*), ~~but~~ and there is ~~little significant~~ evidence of significantly increased buying or selling on the days before or after the event.

The coefficients of the control variables indicate that 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 investors. Also, experts who are more central to the empirical trading network are significantly more likely to buy or sell on any given day. Controlling for retail trading activity, experts are relatively less likely to trade stocks with a low book-to-market 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 ~~on~~ around corporate event days, consistent with our expectations.[15]

IV. TRADING PERFORMANCE OF FINANCIAL EXPERTS

In this section we first examine the relative performance of trades by all financial experts. 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 of network trades, when two or more experts make similar trades. Finally, we focus on the stock picking skills of experts around information events.

IV.A. The Performance of Trades by All Financial Experts

[14] Contrary to expectations, one coefficient at lag *t*-~~3~~*1* for the group network~~empirical network~~ dummy is significantly positive for sells.

[15] We have also estimated Equation (1) with fixed effects for the experts and the stocks traded, with robust results.

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.[16] 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) retail investors as well as the accounts of 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:

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

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 retail investors over the recent portfolio

[16] This approach is attractive because it documents the marginal effect of being a financial expert on performance, while controlling for other relevant attributes such as the characteristics of the investors trading and the firms traded. In Appendix XX, we show that a calendar time portfolio approach produces similar results.

formation period, (t-x, t-y) and the coefficient of the Expert dummy variable (b_1) reveals the abnormal return relative to the average, for the purchases (or sales) made by financial experts.

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 of Table 3, we present the results for the performance on day *t* based on trades made during day *t-1*. Panel B provides analogous results for Equation (2) based on several alternative earlier portfolio formation windows. The p-values in Table 3 are based on Newey-West adjusted standard errors for the mean coefficients.

~~In Panel A of Table 3, w~~We first concentrate on the results for purchases for the model without control variables in Panel A of Table 3,. The mean intercept (b_0) is an insignificant -1.2 basis points (bp) per day (p-value = 0.81), indicating that during our sample period retail investors earn a slightly negative average return on day *t*, based on their purchases made on day *t-1*. The corresponding Expert dummy coefficient (b_1) indicates that recent purchases by financial experts significantly outperform recent purchases by retail investors, by an average of 13 bp on the next day (p-value = 0.00). This daily outperformance for expert purchases on day *t-1* is economically significant, at 33% per annum (= 250 ~~days~~ x .13%~~/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 average return of -5.6 bp on day *t* (p-value = 0.24). Now the Expert dummy coefficient (b_1) is -6.8 bp (p-value = .03), which indicates that recent sales by financial experts significantly outperform recent sales by retail investors. This daily outperformance for expert sales is again economically significant, at -17% per annum (= 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 exceptional performance on the sell side contrasts with most prior work, which typically finds that sales are less informative than purchases.[17]

In Panel A of Table 3, the mean coefficients of the control variables from Equation (2) generally conform to expectations. For purchases, one control variable has a mean coefficient that is significantly negative (RDay), indicating that stocks which have recently increased in value tend to have a reversal on the following day. Two other control 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) all previous trades made over the past quarter excluding the last month,

[17] 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.

covering days (*t-90*, *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.

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, 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 are 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. The 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 experts into the five functional roles, as follows:

$$(3)\quad Return_{i,t} = c_0 + c_1\,Analyst_{i,e,t} + c_2\,Broker_{,i,e,t} + c_3\,Fund\_Mgr_{i,e,t} + c_4\,Board_{,i,e,t} + c_5\,Other_{i,e,,t} + c_7\,Size_{i,t} + c_8\,Beta_{i,t} + c_9\,MB_{i,t} + c_{10}\,RYear_{i,t} + c_{11}\,RMonth_{i,t} + c_{12}\,RWeek_{i,t} + c_{13}\,RDay_{i,t} + \varepsilon_{i,t}\,,$$

where:

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

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

$Fund\_Mgr_{i,e,t}$ = 1 for trades in stock *i* during the formation period, (*t-x*, *t-y*), if

Formatted: Indent: Left: 0", Hanging: 1.18" accountholder *e* is a fund manager, or 0 otherwise;

$Board_{i,e,t}$ = 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;

$Other_{i,e,t}$ = 1 for trades in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* is classified as 'others', 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 return 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 different portfolio formation periods, while Panel B provides the analogous results for sales. The only change in the specification of Equation (3) is to partition all experts into the five functional roles. Thus, the results for all control variables in Equation (3) duplicate those from estimating Equation (2), and are not reported here.

The top row of Panel A or B in Table 4 duplicates the evidence for all financial experts from Table 3. The next five rows present the separate results for the five functional roles of these experts. The following three rows provide the analogous evidence for experts serving in the three financial service groups of firms. Finally, the remaining rows render 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 daily abnormal return of 26 bp (p-value = 0.01). This performance is followed by analysts with a daily abnormal return of 20 bp (p-value = 0.01), brokers with an abnormal return of 15 bp (p-value = 0.01), and 'other' experts at 13 bp (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 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 daily abnormal return of -26 bp (p-value = 0.02). The one-day sell portfolios of 'others' also generate significant abnormal returns of -9 bp (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. The Performance of Trades by Experts in the Three Financial Services Groups of Firms

We next estimate an alternative specification of Equation (3), 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:

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

where:

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

$Asset\_Mgt_{i,e,t}$ = 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 average performance of all retail trades, and has the same interpretation as b_0 in Equation (2). Thus, the dummy coefficients (d_1 to d_3) from Equation (4) reveal the abnormal return for experts serving at the three respective financial services groups of firms, relative to retail investors.

The results are provided in rows 7 to 9 of each Panel in Table 4. On the buy side in Panel A, the daily abnormal returns based on a one-day horizon are significant, and similar in magnitude across brokerage firms (12 bp, p-value = 0.00), fund management firms (11 bp p-value = 0.03), and asset management firms (12 bp, 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 abnormal return based on expert selling over a one-day horizon at asset management firms (-11 bp, p-value = 0.02), but no significant abnormal return at brokerage firms or fund management firms. S ~~Likewise, s~~ell portfolios based on a longer formation period do not generate significant negative abnormal returns.

IV.C.3. The 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 (3) 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:

$$(5)\ \ \text{Return}_{i,t} = e_0 + e_1\,\text{Expert\_1}_{i,e,t} + e_1\,\text{Expert\_2}_{i,e,t} + e_1\,\text{Expert\_3-4}_{i,e,t} + e_1\,\text{Expert\_5-10}_{i,e,t} + e_1\,\text{Expert\_11+}_{i,e,t} + e_5\,\text{Size}_{i,t} + e_6\,\text{Beta}_{i,t} + e_7\,\text{MB}_{i,t} + e_8\,\text{RYear}_{i,t} + e_9\,\text{RMonth}_{i,t} + e_{10}\,\text{RWeek}_{i,t} + e_{11}\,\text{RDay}_{i,t} + \varepsilon_{i,t}\,,$$

where

$\text{Expert\_1}_{i,e,t}$ = 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;

$\text{Expert\_2}_{i,e,t}$ = 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;

$\text{Expert\_3-4}_{i,e,t}$ = 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;

$\text{Expert\_5-10}_{i,e,t}$ = 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;

$\text{Expert\_11+}_{i,e,t}$ = 1 for purchases (sales) in stock *i* during the formation period, (*t-x*, *t-y*), if accountholder *e* is an expert and more than 10 *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 abnormal returns as we move down across these network dummy coefficients, to consider 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 abnormal return of

6.5 bp (p-value = 0.01) on the next day. This abnormal return increases to 13 bp (p-value = 0.01) for stocks bought by 2 financial experts, and 19 bp (p-value = 0.01) for stocks bought by 3 or 4 financial experts. If 5 to 10 financial experts buy the same stock on the same day, the next day's abnormal return is 28 bp (p-value = 0.02), and this outperformance increases to a striking 74 bp for network purchases by more than 10 experts (p-value = 0.06).[18] 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 longer term outperformance for network purchases by 2 experts, but there is no longer a monotonic relation between abnormal returns and the number of experts trading.

On the sell side, Panel B of Table 4 suggests that expert sales on one day are followed on the next day by a negative 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 because of a decreasing sample size. Further unreported tests show that the abnormal returns following multiple-expert sales are never significantly different from abnormal returns following sales by 1 expert. In addition, when we extend the portfolio formation period, 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 for network trades in which more than one expert makes the identical trade. While not being conclusive, this evidence suggests the possibility that financial experts in Finland ~~may~~ share and

[18] The out performance of stocks bought by 3 or 4, 5 to 10 and more than 10 experts relative to stocks bought by 1 expert ~~is~~ significantl~~y higher than the performance of stocks bought by 1 expert~~ at the 5 percent level.

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Formatted: Font: (Default) Times New Roman trade on their special 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, such as earnings announcements, revisions of analyst recommendations, takeover announcements, and large price changes. 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 period, 2006 to 2011. Our sample of changes in analyst recommendations is from Capital-IQ, and consists of all 2,254 revisions during the sample period. 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, 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 period, 2006 - 2011.

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 one stock is limited to 10% of the total market value of the index). Next we sum this abnormal return on the event day and the next day, and we "sign" this market-adjusted *CAR(0,+1)* by multiplying the *CAR(0,+1)* by -1 for all expert sales. Then, for each event, we calculate the mean signed *CAR(0,+1)* across all 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 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. In Panel D we present the results for takeover announcements, and finally in Panel E we document the results for large price changes. The left side of every Panel provides results for director trades made on each of the 3 days before the event, and the right side gives analogous results for trades made during each of the 3 weeks before the event.

First consider trades made in the three days before earnings announcements, on the left side of Panel A in Table 5~~4~~. There are 343 such announcements where at least one expert traded on the day before the earnings release, with a mean signed *CAR(0,+1)* of 0.8% (p-value = 0.02).

In contrast, for trades made two or three days before earnings announcements, we find no 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).T~~ Again, t~~here is no evidence of outperformance based on trades made two or three weeks before earnings announcements.

Second, Panel B of Table 4 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 announcement, with a significant mean signed *CAR(0,+1)* of 0.4% (p-value = 0.01). Similarly, the mean signed *CAR(0,+1)* based on trades 2 days before the recommendation change is also 0.4% (p-value = 0.02). The right side of Panel B indicates 1,468 recommendation changes where at least one expert traded in the week before the event, with a mean signed *CAR(0,+1)* of 0.3% (p-value= 0.01). Earlier trades made two or three weeks before recommendation changes display no significant outperformance.

In Panel C of Table 4, we consider the subset of these trades made prior to revisions of recommendations by analysts who work at the same brokerage firm as the expert trading. There are 134 such events where at least one employee traded on the day before the announcement of a revision by an analyst at his own firm, with a mean signed *CAR(0,+1)* of 1.6% (p-value = 0.00). There are fewer events where an expert trades 2 or 3 days before a revision by analysts at his own firm, and they yield no significant abnormal return. When we focus on trades during the first or second week before the revision, we find a mean signed *CAR(0,+1)* of 0.6% (p-value= 0.04 ~~or~~ and 0.06, respectively).

For the sample of Finnish listed takeover targets in Panel D of Table 4, there are too few trades by financial experts in the three days before the announcements to conduct a meaningful analysis. On the right side of Panel D, we find somewhat larger samples of roughly 25 such events, whe~~n~~re at least one expert traded in each of the three weeks before the 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 robustness in their performance suggests that financial experts do not reliably profit from trading on information about upcoming mergers or acquisitions.

Finally, consider the evidence for trades in the three days before large price changes, on the left side of Panel E in Table 4. 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 significantly positive based on trades made 3 days before the price change (*CAR(0,+1)* =2.0%, p-value= 0.07), and based on trades made in the one or two weeks before these events.[19]

Together, this event study analysis provides strong evidence that financial experts outperform when they trade just before major firm-specific information events. We conclude that a relatively large proportion of these trades is motivated by access to superior private information that is about to become public.

V. FRONT-RUNNING AND INFORMATION LEAKAGE BY FINANCIAL EXPERTS

The previous section documents that a large proportion of the trades by employees of financial intermediaries is motivated by superior private information. In this section we explore whether some of these trades suggest a breach of fiduciary duty, by testing for front-running and information leakage in the days before public disclosure of corporate insider trades and ~~block~~

[19] When split the trades by experts into sales and purchases, we find that the abnormal returns that are significant in Table 5 ~~are~~ also tend to be significant for the sample of sales and purchases separately. The exceptions are ~~, with the exception of~~ earnings announcements where the CARs are ~~still~~ significant for sales, but not for purchases, and ~~whereas for the~~ large price change events where~~,~~ the significant abnormal returns in Table 5 are ~~still~~ significant for purchases, but not for sales.

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days with exceptional net buying or selling by ~~trades by~~ Finnish mutual funds. Early access to this value relevant information by brokers or fund managers may tempt some of these experts to front-run or to share this information with other experts who may trade prior to public disclosure.

We apply event study methodology, and assign 'day 0' to the day on which a corporate insider trade~~s~~ takes place or the day on which there is an exceptionally large net order flow from the mutual funds in our sample. We then examine the timing and performance of ~~abnormal~~ trading ~~activity~~ by financial experts in the days around these events.

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

There are a total of 2,513 trades by Finnish corporate insiders during our sample period. We exclude insider trades in the same stock that occur within three days after an insider trade, and we exclude trades by corporate insiders who ~~are~~ also appear in our sample financial experts (as employee or 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 occurs. For each stock (*i*), we focus on 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 trading days $t = (-25, +5)$. The first four weeks of this window, $t = (-25,-6)$, represent the pre-event period to establish 'normal' trading behaviour, 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 day in the event window (*t*) and for each event (*i*), we define abnormal expert trading ~~activity~~, $TRADES_{i,t}$, as the difference between the actual number of expert trades on day *t* and the daily average number of expert trades for ~~that~~ event *i* during the window, $t = (-25,-6)$. Next, we calculate the average abnormal trading activity across all events and use the standard

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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.[20]

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 different functional roles of experts, followed by the results for experts serving in the three different financial services groups of firms. Finally, the last two rows analyze non-network trades versus network trades.

Several findings stand out. In the first row of Panel A in Table 6, there is a significant increase in abnormal trading activity by all experts in the days around insider purchases, beginning two days before the purchase and persisting through the day after the purchase. This abnormal trading peaks on day 0, with an average of 0.30 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 brokers that are not executed on the same trading day. The first column indicates that experts were active at least once in the window (-25, +5) for 605 events (i.e. purchases by corporate insiders).

Rows 2 to 6 of Panel A in Table 6 show that this increase in abnormal trading by financial experts is not limited to brokers. For example, the largest increase in abnormal trades on day 0 is for the last category of 'other' experts, which is closely followed by brokers, and then

[20] Consistent with most studies in this area ~~that examine the cross-sectional return forecasting ability of insider trades~~, Berkman et al (2015) 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).

board members and analysts. Similarly, rows 7 to 9 reveal that the 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 show a particularly sharp increase around day 0 in abnormal expert trading for event days with more than one expert trade. The average increase in such network trades on day 0 is 0.50 (p-value = 0.01), compared to an average increase of 0.07~~8~~ (p-value = 0.00) for non-network trades. This outcome indicates that information about insider purchases is quickly shared and acted upon by participants in the network of financial experts.

Panel B of Table 6 reveals substantially less abnormal trading by experts around insider sales. This shows up as a lower number of events where experts are active at least once in the window (-25,+5), at only 294. Moreover, the top row indicates that abnormal expert trading is significantly different from zero only on day 0, the day the corporate insider sells (the mean number of abnormal trades on day 0 is 0.17, p-value = 0.00). This increased trading activity is concentrated among experts who serve as brokers, and is significant at the 5 percent level for brokerage firms. Consistent with Table 6 Panel A, Panel B reveals that relative to non-network trades, network trades have a larger abnormal increase around the sales of corporate insiders at 0.38 abnormal trades per event (p-value = 0.03).

V.A.2. The 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).[21] We present the results for expert trades on day 0 on the left side of Table 7, while the results for expert trades 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 of stock *i* 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 one stock is limited to 10% of the total market value of the index). We then cumulate these daily abnormal returns over the ten or twenty trading days following every expert trade, to generate two measures of performance by experts, *CAR(+1,+10)* and *CAR(+1,+20)*. 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 3 days after the trade and at the latest~~least 4~~ 7 days after the trade~~ occurs~~). Once again, we first multiply the *CAR* by -1 for expert sales and ~~. T~~then ~~we~~ calculate the mean signed *CAR* across all expert trades for each event. Finally, we compute the average of these mean signed *CARs* across all events. The standard error of this mean ~~signed *CAR*~~ is used to construct a *t*-test of the null hypothesis that the mean signed *CAR* is zero.

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 mean signed *CAR(+1,+10)* is 1.25% (p-value = 0.00), and the mean signed *CAR(+1,+20)* is 1.69% (p-value = 0.00). Further analysis shows that these mean signed *CARs* are particularly high for analysts and Others, ranging from 1.7% for the 10-day analysis to 2.4% to the 20-day analysis, and insignificant for Board Members and Fund Managers. When we split the trades across the different financial service groups of firms, we find *CARs* of a similar magnitude for the employees of brokerage

[21] In this analysis we do not consider expert trading on days -2, -1, and +1 around insider *sales*, because there is little evidence of abnormal expert trading on these days in Panel B of Table 6.

firms, fund management firms, and asset management firms, but significant only for brokerage employees. Finally, stand-alone trades and network trades are followed by abnormal returns of a similar magnitude.

On the right side of Table 7, we report the mean signed *CARs* following expert trades on days -2,-1, and +1 relative to purchases by corporate insiders. The top row indicates that only the twenty-day *CAR* is significant for these trades by all experts. The analogous results for the subgroups of expert trades show that only trades by analysts and brokers ~~and employees at brokerage firms have~~ marginally significant mean signed *CARs* ~~(p-value = 0.07 and 0.06, respectively)~~. The CARs are similar for employees of the three firms types, but are marginally significant only for employees of brokerage firms.

Overall, we conclude that financial experts profit from significant abnormal trading activity in the short period around trades by corporate insiders. There is evidence of front-running by experts in the two days before insider purchases take place, as well as on the same day that insider purchases or sales are executed. There is also significant abnormal copycat trading that continues one day after the execution of insider purchases, which is still prior to public disclosure of these trades on day +3~~4~~. The private information about forthcoming insider purchases spreads quickly across the community of financial experts, and is not limited to brokers or brokerage firms.

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

In this subsection we investigate ~~the nature and performance of~~ expert trading around the days in which the group of mutual funds in our sample makes unusually large net purchases or net sales in a given stock. We identify these 'large trading days' as follows. First, we identify the Euroclear accounts of the fifteen mutual funds for which we have data on their employees' trading activity. ~~from the Finnish insider trading register.~~[22] 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 value of the net order flow (i.e., shares bought minus shares sold multiplied by the closing price) across these mutual funds. Third, we compute the standard deviation of this daily time series of aggregate net order flow for every stock (*i*), across all days (*t*) during each year of our sample period, 2005 - 2011. Finally, for each stock (*i*), we select the days every year for which the aggregate order imbalance from mutual funds is more than two standard deviations away from zero, and exclude any big order flow days that occur within three days after another big order flow day for the same stock. This procedure identifies 1,650 'large trading days' by mutual funds across all Finnish stocks over the sample period. ~~, 2005 – 2011.~~

In our examination of expert trading around large trading days, it is important to note that delay in public reporting ~~of trades by mutual funds~~ depends on the trading venue. If a fund trades on the Helsinki Stock ~~e~~Exchange, its trades are reported immediately. If a mutual fund trades off-market through a 'lit ' limit order books such as …, then public disclosure of the trade occurs within 90 seconds and this rule also applies to most trades ~~through~~ on dark limit markets such as .. For trades in the over-the- counter (OTC) market, trade reporting typically is as late as 3 days after the trade. Since we cannot separate OTC trades from other trades, our main focus is on expert trading in the days before the large trade day but we note that the largest trades re likely to be OTC trades and are therefore typically not ~~known~~ public until ~~ly for~~ 3 trading days later~~after the trade~~.

[22] We match the holdings of Finnish public mutual funds as reported in Bloomberg with the holdings of mutual funds in Euroclear. We get almost exact matches on all holdings for each of the fifteen funds so that we are confident we have identified the correct accounts in Euroclear.~~.~~

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We use the similar research design as in our tests of front running around corporate insider trades and assign event day 0 to the large trading day. For each day in the event window (t) and for each event (i), we define abnormal expert trading activity, $TRADES_{i,t}$, as the difference between the actual number of expert trades on day t and the daily average number of expert trades for that event during the window, $t = (-25,-6)$.

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

Panel A of Table 8 presents the results for abnormal trading activity by experts around days with exceptional net buying across the fifteen mutual funds. The first row provides the analysis of all trades across all financial experts. The next five rows present the analogous evidence for the five different functional roles of experts, followed by the results for experts serving in the three different financial services groups of firms. Finally, the last two rows analyze non-network trades versus network trades.

The top row of Panel A in Table 8 indicates a significant increase in average trading activity by all financial experts in the days around exceptional net mutual fund buying on day 0. ~~,~~ ~~relative to the pre -event level.~~ This abnormal expert ~~buying~~ trading becomes significant beginning two days before day 0, and persists through the following week (until day +5). This activity peaks on day 3 with an average of 0.46 additional expert trades per event (p-value = 0.00), and is also high on day 0 when there are 0.28 additional expert trades (p-value = 0.00) per event.

The significant abnormal trading by financial experts on day -2 and day -1 suggests front-running prior to mutual fund buying activity (on day 0). The continued abnormal trading activity from day 0 through day 3, might occur before the public disclosure of OTC purchases (at the end of trading on day +3), but we are not able to unambiguously establish whether this is the case.

Rows 2 to 6 of Panel A in Table 8 show that this front-running activity is significant on day -2 or day -1 for ~~each of the 4 functional roles~~ brokers, analysts, board members, and 'others'. However, there is no evidence of front running by fund managers. We also find that employees at brokerage firms are most active in the period before the block purchase, while trading at asset management firms is also high and significant on day -1, indicating that the abnormal trading ahead of block purchases is not limited to brokers. There is no evidence of elevated trading activity by employees of fund management firms either before or after the large net buying days. This result is interesting because the evnt trigger is large net buying or selling by fund management firms and strongly suggests that the information quickly spreads through the network of financial experts. Finally, the last two rows suggest that front-running behavior is 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 exceptional net selling by mutual funds on day 0. However, significant abnormal trading prior to day 0 is limited to brokers trading on day -1. Trading by employees of brokerage firms on day -1 is marginally significant (p-value = 0.08), as is trading in the form of network trades (p-value is 0.06).

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

Table 9 re~~du~~plicates the analysis in Table 7 for days with large net buying or selling by mutual funds, by computing the mean signed *CAR(+1,+10)* and *CAR(+1,+20)* to determine the performance of this abnormal trading activity by financial experts. We focus our analysis on the cumulative abnormal returns that apply to 'front-running' trades by financial experts, on day -2 and day-1. Once again, we first calculate the mean signed *CAR* for each event. Then we calculate the average of these mean signed *CARs* across all events and use the standard error of this mean ~~signed *CAR*~~ to construct a *t*-test of the null hypothesis that the mean signed *CAR* is zero.

The left side of Table 9 presents the mean signed *CARs* for expert trades made on day -2 and day -1. The evidence reveals that ‘front-running’ trades generate significant abnormal returns for all experts, with mean signed 10-day *CAR* of 0.73% (p-value = 0.00) and 20-day *CAR* of 1.01% (p-value = 0.01). This performance is not significant for any of the professions individually, but is relatively high for analysts and fund managers and is concentrated among the employees of asset management firms, followed by brokerage houses.

The right side of Table 9 provides similar evidence for subsequent trades by experts over days 0, +1, ~~*and*~~ *+2,and +3 but before the block trades are publicly disclosed. For all such expert trades, the mean signed 10-day CAR is 0.*~~*65*~~*58% (p-value = 0.00) and the 20-day CAR is 0.9*~~*1.0*~~*1% (p-value = 0.00). This performance is significant for brokers, and is also* ~~*once again*~~ *concentrated among* ~~*analysts and the*~~ *employees of brokerage firms and asset management firms.*

Overall, based on the evidence in this section, we conclude that Finnish financial experts share and trade on private and confidential information, constituting a possible 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 ~~similar~~ requirement for employees of financial institutions to disclose their personal trading in any listed stock. ~~We investigate the likelihood that these sophisticated investors trade on material private information that is shared through their professional networks, which include other employees at the same financial firm, or the same financial services group of firms, or the same empirical trading network. We also examine the performance of this trading activity based on all expert trades, as well as trades made just before major firm-specific information events, and those made before and after the execution of corporate insider trades and large block trades by mutual funds.~~

We find that these financial experts reveal a significant propensity for abnormal trading activity in their 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 abnormal returns from this trading activity. For example, these experts outperform when they trade ahead of major firm-specific events such as earnings announcements, revisions of analyst recommendations, and large price changes. Furthermore, they appear to tip other experts ~~through~~ in the financial services network, and benefit when they act on these tips by front-running in their own accounts. For example, we document a penchant for these experts to trade in the days before insider trades and ~~large~~ days with large net buying of selling by Finnish mutual funds~~block trades are executed or disclosed to the public~~. This trading activity generates mean abnormal returns that are economically and statistically significant.~~t, and are larger in magnitude when the trades are connected through the financial services network.~~ This evidence documents that these financial experts engage in ~~a significant amount of~~ front-running and leak information to other financial experts~~information leakage behavior~~, and that they profit handsomely from this behavior. Taken together, this body of evidence makes a ~~fairly~~

Formatted: Indent: First line: 0", Space After: 10 pt strong case for a ~~likely~~ possible breach of fiduciary duty by the employees of Finnish financial institutions. A result even more remarkable given that

~~The trading behavior of financial experts documented in this study is noteworthy, given its prevalence in Finland where~~ these experts are required to publicly disclose all of their personal trades. ~~This evidence raises the question about whether employees of financial institutions in other developed markets might be even more inclined to engage in such front-running behavior, given that other countries do not require such trading disclosure for the experts who serve in their financial services sector. We propose that such disclosure requirements ought to be considered for all developed financial markets, in order to illuminate and influence the behavior of these sophisticated investors. Combined with effective enforcement, such a development may help to enhance the discharge and fulfilment of fiduciary duty by individuals who serve in the financial services sector worldwide, and thereby promote the fairness and integrity of global financial markets.~~

~~Too Don Quizote? I LIKE – to dream the impossible dream…~~

~~Need a footnote or appendix to discuss and/or document the level of ***enforcement*** (or lack thereof) of insider trading laws in Finland, relative to that elsewhere in the EU & world?~~

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C. Measurement of Firm Characteristics

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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.[23] The mean adjusted rank values in Panels A and B of Table C.2 are then obtained by averaging these adjusted ranks across all stock trading days within every trade category.

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

Figure 1. Network of Financial Experts

~~Description.~~

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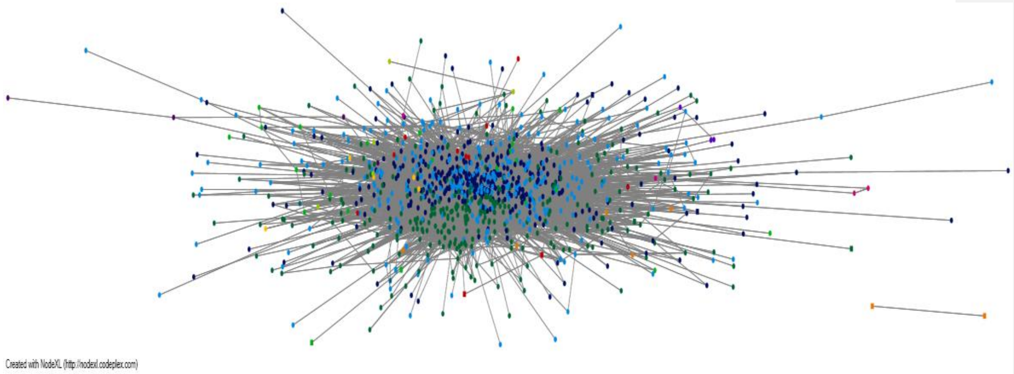
Figure 1 displays the network connecting all financial experts who make network trades. In this Figure, each node represents a different financial expert who engages in at least one network trade over the five-year sample period.[24] The individual with the largest number of such connections makes over 250 network trades during our sample period. Out of the roughly 14,200 network trades, 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, 10,427 (73.4%) of the networked trades can be traced to people either at the same firm, financial services group, or empirical trading network.



[24] 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 (analysts, brokers, fund managers, board members, and 'others') who work in the three types of financial firms: 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 in the three types of firms. In addition, Panel A summarizes the total number of trades made by each category of financial expert. Panel B presents additional information about the attributes of the trades made by these five categories of experts. This information is presented separately for all purchases and sales, as well as for the subset of round trip trades made within one day by these experts. For each category of financial expert, 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 percent of trades that constitute network trades. Network trades are identified as similar trades made in the same stocks 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 attrbutes include the firm's market capitalization (Size), beta (Beta), market-to-book ratio (MB), and past returns measured over 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 Types of Financial Experts at Different Financial Firms

	Relative Frequency of Different Types 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
Analyst	92	7%	80	10%	0	0%	12	5%	2,389	6%	26
Broker	306	24%	303	39%	1	0%	2	1%	13,377	36%	44
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				

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											
Analyst	1,445	796	4,831	50%	.24	.20	.00	-.05	-.06	-.03	-.03
Broker	7,911	1,270	5,398	47%	.25	.20	.02	-.07	-.09	-.05	-.04
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
All Retail	5,872,696	991	2,287		.32	.23	.06	-.03	-.03	-.02	-.02
Sales											
Analyst	938	-1,998	-7,659	29%	.14	.15	-.04	-.02	.08	.01	.02
Broker	5,397	-1,781	-9,414	24%	.21	.19	-.01	-.04	.06	.04	.03
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
All Retail	4,101,047	-1,326	-35,301		.30	.21	.06	.01	.02	.02	.03
Round Trip Trades Within One Day											
Analyst	6	NA	NA	0%	.41	.30	-.11	-.13	.09	-.19	-.11
Broker	69	NA	NA	2%	.10	.09	.01	-.14	-.06	-.01	-.08
Fund Mgr	662	NA	NA	1%	.26	.15	.04	-.06	-.01	.00	-.02
Board	218	NA	NA	5%	.41	.33	.14	-.02	-.02	.01	.05
Other	6	NA	NA	0%	.37	.21	.11	-.12	.06	-.09	-.17
All Retail	468,476	0	0		.39	.30	.09	-.01	.00	.00	.00
Total Trades By Experts	37,309										

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 March, 2005 - 2008. Then we use this information to compute the measures of trading probability for the subsequent year (2009) in Panel A, or for the remaining years in our sample (2009 - 2011) in Panel B. 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:

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

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

$$+ a_9 \ln(\text{Volume})_{i,t} + a_{10} \text{Centrality}_e + \text{Other Controls.} \qquad (1)$$

The variables in this model are described in the text.

Panel A. Descriptive Statistics for the Probability of Experts Trading

	# Trades of Interest	# Trades Possible	Probability of Trading
	N_1	N_2	(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	831069	0.266%
N_1 = # Trading Days where More Than One Expert at the Same Firm Traded;			
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	26230	3.225%
N_1 = # Trading Days where More Than One Expert in the Same Group Traded;			
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	3250262	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	1981763	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.			

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

	Purchases		Sales	
	Coeff	p-value	Coeff	p-value
Intercept	**-12.164**	**0.00**	**-12.021**	**0.00**
Analyst	**-0.127**	**0.00**	**-0.428**	**0.00**
Fund Manager	**-0.149**	**0.00**	**-0.599**	**0.00**
Board Member	**-0.116**	**0.00**	**-0.650**	**0.00**
Other	**-0.277**	**0.00**	**-0.379**	**0.00**
Firm-NW$_{i,e,t}$	**0.772**	**0.00**	**-0.810**	**0.00**
Firm-NW$_{i,e,t-1}$	**0.390**	**0.00**	**-0.317**	**0.00**
Firm-NW$_{i,e,t-2}$	**0.286**	**0.00**	**-0.255**	**0.00**
Firm-NW$_{i,e,t-3}$	**0.154**	**0.00**	**-0.151**	**0.03**
Firm-NW$_{i,e,t-4}$	**0.226**	**0.00**	-0.035	0.62
Group-NW$_{i,e,t}$	**2.339**	**0.00**	**-1.566**	**0.00**
Group-NW$_{i,e,t-1}$	0.028	0.76	**0.898**	**0.00**
Group-NW$_{i,e,t-2}$	-0.128	0.25	-0.137	0.65
Group-NW$_{i,e,t-3}$	**0.407**	**0.00**	0.300	0.32
Group-NW$_{i,e,t-4}$	**-0.548**	**0.00**	**0.518**	**0.07**
Emp-NW$_{i,e,t}$	**0.308**	**0.00**	**-0.183**	**0.00**
Emp-NW$_{i,e,t-1}$	**0.089**	**0.00**	**-0.174**	**0.00**
Emp-NW$_{i,e,t-2}$	**0.106**	**0.00**	**-0.132**	**0.00**
Emp-NW$_{i,e,t-3}$	0.067	**0.01**	**-0.125**	**0.00**
Emp-NW$_{i,e,t-4}$	**0.094**	**0.00**	**-0.086**	**0.02**
Event$_{i,e,t+1}$	**0.287**	**0.00**	**0.259**	**0.00**
Event$_{i,e,t+2}$	**0.068**	0.11	**0.127**	**0.02**
Event$_{i,e,t+3}$	**0.085**	**0.06**	**0.183**	**0.00**
Event$_{i,e,t}$	**0.080**	**0.09**	0.076	0.23
Event$_{i,e,t-1}$	**0.142**	**0.00**	0.054	0.37
Event$_{i,e,t-2}$	-0.030	0.60	**0.114**	**0.08**
Event$_{i,e,t-3}$	0.043	0.44	0.084	0.22
ln(# Trades)	**0.766**	**0.00**	**0.669**	**0.00**
Centrality	**0.136**	**0.00**	**0.153**	**0.00**
Size	-0.036	0.54	-0.065	0.34
Beta	-0.013	0.79	**0.107**	**0.07**
MB	**-0.236**	**0.00**	**-0.252**	**0.00**
RYear	0.003	0.92	**-0.077**	**0.05**
RMonth	**-0.315**	**0.00**	**0.544**	**0.00**
RWeek	**-0.269**	**0.00**	**0.352**	**0.00**
RDay	**-0.171**	**0.00**	**0.302**	**0.00**
Monday	**-0.080**	**0.01**	**0.137**	**0.00**
Tuesday	**-0.059**	**0.05**	**0.124**	**0.00**
Wednesday	-0.025	0.40	**0.090**	**0.02**
Thursday	0.010	0.74	**0.137**	**0.00**

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

Table 3. The Performance of Trades by All Financial Experts

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

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

This model is estimated for each of the 3,667 days in our sample period, 1997 - 2011. The analysis is applied to all 17,844,388 trades by all individual accountholders in Finland. Variable definitions are provided in the text. Panel A presents the results for purchases or sales made one day earlier (on day *t-1*). Panel B provides analogous results for trades made over several earlier portfolio formation windows, including the past week excluding the previous day, covering days (*t-7*, *t-1*), the past month excluding the last week, over days (*t-30*, *t-8*), and the past quarter excluding the last month, over days (*t-90*, *t-31*). The left side of each Panel presents the results for purchases, while the right side provides the evidence for sales, both 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. P-values 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	-0.012	0.81	-0.008	0.85	-0.056	0.24	-0.010	0.80
Expert	b_1	**0.129**	**0.00**	**0.110**	**0.00**	**-0.068**	**0.03**	**-0.077**	**0.00**
Size	b_2			**-0.123**	**0.09**			-0.082	0.23
Beta	b_3			**-0.078**	**0.09**			-0.056	0.17
MB	b_4			0.016	0.80			0.039	0.50
RYear	b_5			**0.107**	**0.05**			0.015	0.76
RMonth	b_6			**0.116**	**0.02**			0.011	0.79
RWeek	b_7			-0.050	0.28			-0.041	0.33
RDay	b_8			**-0.485**	**0.00**			**-0.566**	**0.00**

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

Formation Window		Purchases				Sales			
		Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
(*t-7*, *t-2*)	b_1	**0.050**	**0.00**	**0.047**	**0.00**	**-0.029**	**0.06**	**-0.029**	**0.04**
(*t-30*, *t-8*)	b_1	**0.018**	**0.03**	**0.022**	**0.00**	-0.005	0.65	-0.005	0.57
(*t-90*, *t-31*)	b_1	-0.009	0.62	0.001	0.85	-0.022	0.31	-0.004	0.58
Controls:		no		yes		no		yes	

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

This Table presents the results from estimating Equations (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

Dependent Variable: Return on Portfolio of	1-day Alphas (%)[a] Portfolio Formation Period Covering Days (*t-x*, *t-y*)			
	(*t-1*)	(*t-7, t-2*)	(*t-31, t-8*)	(*t-90*, *t-32*)
1. All Expert Trades	**0.110**	**0.047**	**0.022**	0.001
p-value	**0.01**	**0.01**	**0.00**	0.85
Experts in the Five Functional Roles				
2. Analysts	**0.196**	**0.062**	**0.087**	-0.004
p-value	**0.01**	**0.10**	**0.01**	0.74
3. Brokers	**0.147**	**0.028**	**0.023**	0.001
p-value	**0.01**	**0.06**	**0.01**	0.89
4. Fund Managers	**0.256**	0.055	0.025	0.018
p-value	**0.01**	0.12	0.15	0.14
5. Board Members	-0.025	0.034	0.016	-0.004
p-value	0.56	0.15	0.31	0.70
6. Others	**0.128**	**0.040**	0.011	0.000
p-value	**0.00**	**0.02**	0.30	0.96
Experts in the Three Financial Services Groups				
7. Brokerage Firms	**0.120**	**0.043**	**0.023**	-0.003
p-value	**0.00**	**0.00**	**0.00**	0.63
8. Fund Mgt Firms	**0.106**	**0.064**	0.011	0.014
p-value	**0.03**	**0.01**	0.45	0.17
9. Asset Mgt Firms	**0.120**	**0.040**	**0.026**	-0.003
p-value	**0.00**	**0.05**	**0.04**	0.68
Non-Network Trades versus Network Trades				
1 Expert	**0.065**	**0.052**	**0.027**	0.002
p-value	**0.01**	**0.01**	**0.00**	0.72
2 Experts	**0.132**	**0.059**	**0.027**	0.003
p-value	**0.01**	**0.02**	**0.05**	0.74
3 or 4 Experts	**0.194**	0.046	0.012	-0.006
p-value	**0.01**	0.16	0.48	0.65
5 to 10 Experts	**0.277**	-0.021	0.000	0.006
p-value	**0.02**	0.67	1.00	0.78
More than 10 Experts	**0.742**	0.194	-0.104	-0.045
p-value	**0.06**	0.21	0.13	0.48

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

Dependent Variable: Return on Portfolio of	1-day Alphas (%)[a] Portfolio Formation Period Covering Days (*t-x*, *t-y*) (*t-1*)	(*t-7, t-2*)	(*t-31, t-8*)	(*t-90*, *t-32*)
1. All trades	**-0.077**	**-0.029**	-0.005	0.004
p-value	**0.00**	**0.04**	0.57	0.58
	Experts in the Five Functional Roles			
2. Analysts	**-0.256**	0.007	-0.033	-0.002
p-value	**0.02**	0.88	0.19	0.91
3. Brokers	-0.061	0.000	0.010	0.009
p-value	0.13	0.99	0.51	0.30
4. Fund Managers	-0.026	-0.061	-0.023	0.000
p-value	0.70	0.12	0.29	0.99
5. Board Members	-0.070	-0.012	-0.023	-0.001
p-value	0.24	0.77	0.26	0.95
6. Others	**-0.088**	**-0.051**	0.007	0.000
p-value	**0.04**	**0.09**	0.53	0.99
	Experts in the Three Financial Services Groups			
9. Asset Mgt Firms	**-0.111**	-0.043	-0.014	-0.009
p-value	**0.02**	0.15	0.26	0.33
7. Brokerage Firms	-0.052	-0.025	0.004	0.006
p-value	0.12	0.11	0.71	0.45
8. Fund Mgt Firms	0.049	-0.009	-0.019	0.025
p-value	0.46	0.85	0.48	0.13
	Non-Network Trades versus Network Trades			
1 Expert	**-0.055**	-0.009	-0.005	0.005
p-value	**0.04**	0.51	0.60	0.49
2 Experts	**-0.116**	-0.074	0.002	0.013
p-value	**0.08**	0.11	0.93	0.28
3 or 4 Experts	-0.106	-0.041	-0.034	0.011
p-value	0.46	0.50	0.43	0.73
5 to 10 Experts	-0.234	-0.125	-0.057	-0.073
p-value	0.41	0.36	0.42	0.33
More than 10 Experts	-0.163	**-0.252**	0.122	0.017
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 present the mean 'signed' size-adjusted cumulative abnormal return on the day of and the day after each type of event, CAR(0,+1), for trades made by experts in each of the three days or weeks before these events. If an expert is a net purchaser, then we consider the CAR(0,+1) for that purchase. For net sellers, we 'sign' the CAR(0,+1) by multiplying it by -1.

	Mean Signed	p-value	# Events with		Mean Signed	p-value	# Events with
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 frequency of different groups of trades made every day in the event window around insider trades, covering days *t* = (-5, +5), by financial experts: (i) in the five functional roles, (ii) in the three financial services groups, and (iii) that comprise network trades versus non-network trades. These estimates are obtained by estimating Equation (6). Panel A provides the results for expert trades made around insider purchases, while Panel B presents analogous results around insider sales.

Panel A. Average 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	-0.006	0.009	0.012	**0.121**	**0.224**	**0.295**	**0.164**	0.017	0.012	0.020	0.047
p-value	.	0.82	0.75	0.74	**0.00**	**0.00**	**0.00**	**0.01**	0.59	0.70	0.48	0.21
2. Analysts	221	-0.002	0.035	0.017	**0.062**	**0.057**	**0.062**	0.044	0.039	-0.006	0.007	0.026
p-value	.	0.93	0.09	0.37	**0.01**	**0.01**	**0.04**	0.15	0.07	0.69	0.66	0.24
3. Board Members	269	-0.020	-0.031	0.006	0.024	0.032	**0.106**	0.036	0.002	-0.013	-0.009	0.006
p-value	.	0.28	0.05	0.76	0.29	0.16	**0.00**	0.14	0.92	0.48	0.62	0.76
4. Brokers	490	-0.014	-0.012	0.000	**0.059**	**0.096**	**0.124**	**0.047**	0.000	0.018	0.024	0.022
p-value	.	0.45	0.50	0.99	**0.02**	**0.00**	**0.00**	**0.05**	0.99	0.43	0.27	0.35
5. Fund Managers	226	0.010	-0.012	-0.034	0.041	**0.090**	0.010	0.041	0.006	0.010	0.001	0.001
p-value	.	0.65	0.58	0.08	0.10	**0.01**	0.76	0.16	0.80	0.64	0.96	0.96
6. Others	422	0.016	0.035	0.023	0.035	**0.111**	**0.173**	**0.114**	0.000	0.002	0.002	0.023
p-value	.	0.42	0.10	0.34	0.15	**0.00**	**0.00**	**0.02**	0.99	0.92	0.92	0.34
7. Asset Mgt Firms	366	0.030	-0.022	0.011	0.027	**0.085**	**0.115**	**0.082**	0.003	0.003	-0.025	0.008
p-value	.	0.16	0.26	0.58	0.24	**0.00**	**0.00**	**0.03**	0.89	0.89	0.17	0.72
8. Brokerage Firms	551	-0.028	0.033	0.017	**0.099**	**0.164**	**0.215**	**0.102**	0.026	0.010	0.031	0.042
p-value	.	0.21	0.17	0.56	**0.00**	**0.00**	**0.00**	**0.01**	0.32	0.72	0.22	0.15
9. Fund Mgt Firms	287	0.003	-0.018	-0.021	0.031	0.049	0.063	0.045	-0.018	0.003	0.014	0.007
p-value	.	0.87	0.35	0.28	0.20	0.06	0.18	0.10	0.33	0.89	0.52	0.74
1 Expert trading	602	0.020	0.021	-0.007	**0.050**	**0.078**	**0.073**	**0.046**	0.035	0.026	0.011	0.028
p-value	.	0.24	0.22	0.68	**0.01**	**0.00**	**0.00**	**0.01**	0.06	0.14	0.52	0.10
≥ 2 Experts trading	270	-0.058	-0.028	0.042	0.161	**0.327**	**0.498**	0.264	-0.039	-0.032	0.020	0.042
p-value	.	0.32	0.58	0.57	0.08	**0.00**	**0.01**	0.06	0.53	0.60	0.73	0.60

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

		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	-0.035	0.040	0.054	0.068	0.020	**0.170**	-0.007	-0.052	-0.035	-0.007	-0.021
p-value	.	0.23	0.18	0.09	0.08	0.53	**0.00**	0.80	0.06	0.27	0.82	0.46
2. Analysts	91	-0.026	0.007	0.018	0.018	-0.004	0.018	0.029	-0.026	-0.026	0.007	-0.004
p-value	.	0.12	0.78	0.52	0.53	0.85	0.53	0.44	0.13	0.13	0.79	0.87
3. Board Members	95	-0.023	0.051	-0.002	0.009	-0.023	0.062	-0.023	0.019	-0.002	-0.012	0.030
p-value	.	0.43	0.16	0.96	0.79	0.46	0.19	0.51	0.58	0.96	0.71	0.42
4. Brokers	198	0.015	-0.031	0.050	0.070	0.015	**0.116**	-0.005	-0.041	-0.036	0.005	-0.026
p-value	.	0.58	0.11	0.06	0.02	0.53	**0.00**	0.81	0.04	0.09	0.86	0.17
5. Fund Managers	98	-0.058	0.034	0.014	0.004	0.024	0.044	0.034	-0.058	0.004	-0.037	-0.017
p-value	.	0.02	0.36	0.69	0.92	0.50	0.33	0.39	0.03	0.92	0.22	0.63
6. Others	206	-0.014	0.044	0.015	0.015	0.015	0.073	-0.024	-0.004	-0.004	0.005	-0.009
p-value	.	0.49	0.09	0.55	0.52	0.54	0.06	0.19	0.82	0.84	0.81	0.64
7. Asset Mgt Firms	165	-0.007	0.018	0.018	0.042	-0.001	0.072	-0.007	-0.007	0.012	0.012	0.036
p-value	.	0.80	0.53	0.51	0.17	0.98	0.06	0.80	0.79	0.71	0.67	0.25
8. Brokerage Firms	250	-0.014	0.022	0.054	0.062	0.022	**0.122**	-0.006	-0.026	-0.050	-0.002	-0.038
p-value	.	0.59	0.35	0.05	0.06	0.36	**0.00**	0.82	0.30	0.04	0.95	0.08
9. Fund Mgt Firms	108	-0.052	0.031	-0.006	-0.025	0.003	0.068	0.003	-0.071	0.003	-0.034	-0.025
p-value	.	0.02	0.38	0.84	0.35	0.93	0.26	0.92	0.00	0.92	0.25	0.44
1 Expert trading	291	-0.006	0.049	0.053	0.063	0.036	0.046	0.008	-0.023	-0.033	0.005	0.015
p-value	.	0.82	0.04	0.03	0.02	0.15	0.06	0.73	0.27	0.11	0.83	0.54
≥ 2 Experts trading	97	-0.088	-0.026	0.005	0.015	-0.047	**0.376**	-0.047	-0.088	-0.006	-0.037	-0.109
p-value	.	0.10	0.66	0.95	0.87	0.45	**0.03**	0.42	0.11	0.94	0.61	0.01

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

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

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This Table presents the mean signed *CARs* for portfolios of trades made on the days around corporate insider trades, by financial experts: (i) in the different functional roles, (ii) at the different financial services groups of firms, and (iii) that comprise network trades versus non-network trades. The left side of this Table presents the results for expert trades made on the same day as the insider trades, while the right side provides the analogous results for expert trades made on the days before or after insider purchases.

CARs following Expert Trades:	on Day of Insider Buys or Sales			on Days (-2, -1, +1,) around Insider Buys		
	CAR(1,10)	*CAR(1,20)*	n	*CAR(1,10)*	*CAR(1,20)*	n
1. All trades	1.25%	1.69%	353	0.35%	0.74%	369
p-value	0.00	0.00		0.26	0.05	
2. Analysts	2.39%	2.42%	28	2.17%	2.38%	52
p-value	0.15	0.23		0.09	0.10	
5. Board Members	0.64%	1.04%	67	-0.36%	0.80%	79
p-value	0.49	0.37		0.56	0.30	
3. Brokers	1.30%	1.36%	186	0.67%	1.05%	221
p-value	0.01	0.04		0.19	0.07	
4. Fund Managers	0.66%	1.30%	54	-0.02%	0.46%	86
p-value	0.41	0.31		0.97	0.60	
6. Others	1.67%	2.34%	126	0.46%	0.59%	171
p-value	0.09	0.02		0.31	0.30	
9. Asset Mgt Firms	1.49%	1.96%	91	0.50%	0.50%	136
p-value	0.08	0.06		0.38	0.45	
7. Brokerage Firms	1.41%	1.53%	258	0.43%	0.84%	287
p-value	0.01	0.01		0.24	0.06	
8. Fund Mgt Firms	0.36%	1.60%	73	0.34%	0.99%	102
p-value	0.62	0.16		0.50	0.20	
1 Expert	1.27%	1.57%	298	0.30%	0.56%	339
p-value	0.01	0.01		0.36	0.16	
2 Experts	0.98%	1.98%	69	0.54%	1.05%	103
p-value	0.27	0.10		0.46	0.19	

[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 frequency of different groups of trades made every day in the event window around block trades, covering days *t* = (-5, +5), by financial experts: (i) in the five functional roles, (ii) in the three financial services groups, and (iii) that comprise network trades versus non-network trades. These estimates are obtained by estimating Equation (6). Panel A provides the results for expert trades made around block purchases, while Panel B presents analogous results around block sales.

Panel A. Average 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	617	-0.004	0.040	0.045	**0.111**	**0.160**	**0.281**	**0.114**	**0.148**	**0.458**	**0.249**	**0.142**
p-value	.	0.91	0.29	0.26	**0.00**	**0.00**	**0.00**	**0.01**	**0.00**	**0.00**	**0.00**	**0.00**
2. Analysts	310	0.010	0.010	0.013	-0.006	**0.045**	0.032	0.020	0.032	**0.052**	**0.045**	**0.036**
p-value	.	0.53	0.50	0.41	0.63	**0.03**	0.09	0.26	0.06	**0.01**	**0.01**	**0.05**
3. Board Members	427	-0.004	-0.013	0.027	**0.045**	0.020	**0.057**	0.013	0.022	**0.085**	**0.055**	**0.024**
p-value	.	0.82	0.39	0.18	**0.02**	0.28	**0.01**	0.50	0.23	**0.00**	**0.02**	**0.22**
4. Brokers	558	-0.010	**0.053**	0.010	**0.055**	**0.069**	**0.121**	0.068	0.055	**0.195**	**0.084**	**0.050**
p-value	.	0.61	**0.05**	0.65	**0.02**	**0.01**	**0.00**	0.01	0.03	**0.00**	**0.01**	**0.05**
5. Fund Managers	357	0.006	-0.016	-0.005	0.006	0.001	**0.062**	0.006	0.043	**0.079**	0.045	0.023
p-value	.	0.72	0.22	0.74	0.71	0.97	**0.01**	0.75	0.04	**0.01**	0.07	0.20
6. Others	550	-0.001	0.006	0.015	0.033	**0.068**	**0.090**	0.035	**0.048**	**0.170**	**0.097**	**0.055**
p-value	.	0.95	0.77	0.46	0.13	**0.02**	**0.01**	0.12	**0.05**	**0.00**	**0.01**	**0.03**
7. Asset Mgt Firms	521	0.013	-0.006	0.003	0.040	**0.051**	**0.124**	0.032	**0.051**	**0.159**	**0.088**	0.015
p-value	.	0.48	0.73	0.85	0.07	**0.04**	**0.00**	0.12	**0.01**	**0.00**	**0.01**	0.45
8. Brokerage Firms	599	-0.018	0.058	0.041	**0.073**	**0.121**	**0.174**	**0.089**	**0.098**	**0.283**	**0.146**	**0.101**
p-value	.	0.49	0.07	0.22	**0.02**	**0.00**	**0.00**	**0.01**	**0.01**	**0.00**	**0.00**	**0.01**
9. Fund Mgt Firms	380	0.004	-0.017	0.004	0.012	-0.002	0.012	0.001	0.017	0.080	0.054	0.051
p-value	.	0.82	0.25	0.82	0.52	0.93	0.54	0.95	0.36	0.04	0.02	0.01
1 Expert trading	615	0.002	-0.001	0.010	**0.041**	**0.054**	0.038	0.018	0.031	0.038	0.026	0.002
p-value	.	0.92	0.95	0.61	**0.05**	**0.01**	0.08	0.35	0.14	0.07	0.20	0.92
≥ 2 Experts trading	435	-0.008	0.058	0.049	**0.100**	**0.150**	**0.346**	**0.136**	**0.166**	**0.596**	**0.316**	**0.199**
p-value	.	0.85	0.23	0.35	**0.05**	**0.03**	**0.00**	**0.02**	**0.01**	**0.00**	**0.00**	**0.00**

Panel B. Average 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	637	-0.015	-0.002	-0.026	0.025	0.119	**0.337**	**0.106**	**0.127**	**0.144**	**0.084**	0.003
p-value	.	0.67	0.95	0.47	0.52	0.12	**0.00**	**0.02**	**0.05**	**0.00**	**0.04**	0.94
2. Analysts	311	-0.003	0.013	0.000	0.003	-0.010	0.026	0.026	-0.003	0.013	0.010	0.006
p-value	.	0.83	0.51	1.00	0.84	0.48	0.15	0.23	0.86	0.47	0.59	0.67
3. Board Members	425	-0.051	-0.030	-0.016	0.010	0.006	0.036	0.013	0.031	0.027	0.029	-0.002
p-value	.	0.00	0.06	0.35	0.59	0.77	0.09	0.50	0.11	0.20	0.15	0.93
4. Brokers	537	0.026	0.030	-0.004	0.031	**0.095**	**0.164**	**0.074**	**0.065**	0.054	0.039	-0.006
p-value	.	0.27	0.23	0.86	0.20	**0.02**	**0.00**	**0.01**	**0.05**	0.06	0.10	0.78
5. Fund Managers	375	0.007	-0.004	-0.001	0.007	0.025	**0.065**	-0.017	0.015	**0.039**	0.015	-0.001
p-value	.	0.68	0.79	0.95	0.68	0.20	**0.01**	0.22	0.45	**0.04**	0.41	0.94
6. Others	573	-0.005	-0.012	-0.012	-0.016	0.028	**0.138**	0.037	0.049	**0.058**	0.021	0.007
p-value	.	0.78	0.48	0.55	0.40	0.44	**0.00**	0.09	0.11	**0.02**	0.34	0.73
7. Asset Mgt Firms	533	-0.036	-0.024	-0.017	-0.034	0.028	**0.092**	0.013	0.034	**0.058**	0.022	-0.002
p-value	.	0.02	0.12	0.33	0.04	0.33	**0.01**	0.48	0.22	**0.01**	0.28	0.91
8. Brokerage Firms	601	0.011	0.039	-0.007	0.044	0.093	**0.241**	**0.093**	**0.089**	**0.088**	0.049	-0.004
p-value	.	0.70	0.20	0.80	0.15	0.08	**0.00**	**0.02**	**0.04**	**0.03**	0.10	0.89
9. Fund Mgt Firms	402	0.008	-0.030	-0.007	0.018	0.013	**0.052**	0.013	0.023	0.020	0.030	0.013
p-value	.	0.67	0.03	0.69	0.34	0.53	**0.02**	0.48	0.26	0.27	0.15	0.52
1 Expert trading	635	0.001	-0.015	-0.026	0.006	-0.023	-0.010	0.018	0.007	0.018	-0.005	-0.019
p-value	.	0.96	0.46	0.18	0.77	0.24	0.61	0.38	0.71	0.37	0.79	0.30
≥ 2 Experts trading	426	-0.023	0.019	0.000	0.028	0.212	**0.519**	**0.132**	0.179	**0.188**	**0.134**	0.033
p-value	.	0.63	0.67	1.00	0.59	0.06	**0.00**	**0.04**	0.06	**0.01**	**0.02**	0.51

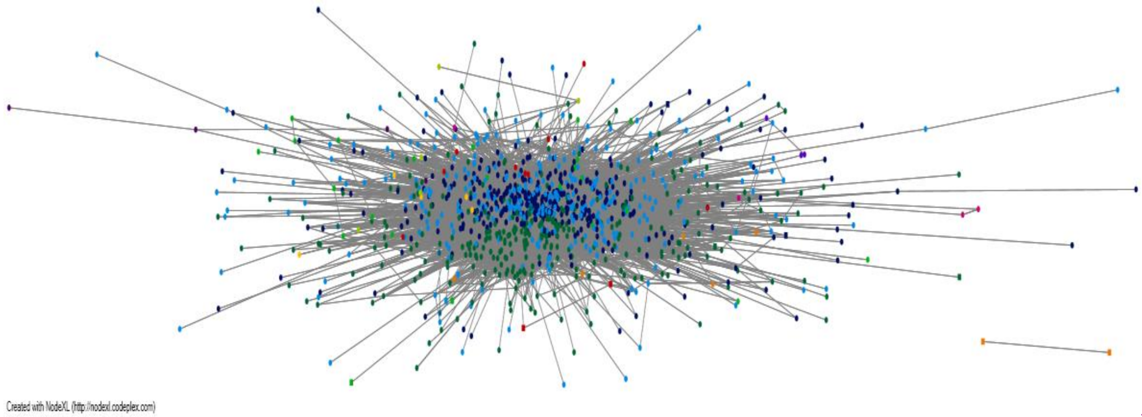
[a] Figures highlighted in **bold** are significant at the .05 level or better.

Table 9. The Performance of Trades by Financial Experts made around Block Trades

This Table presents the mean signed *CARs* for portfolios of trades made on the days around large block trades, by financial exp
(i) in the different functional roles, (ii) at the different financial services groups of firms, and (iii) that comprise network trades vers
non-network trades. The left side of this Table presents the results for expert trades made on the four days before the block trac
while the right side provides the analogous results for expert trades made on the day of and the two days after the block trade.

CARs around Expert Trades:	on Days (-2,-1) before Block Trades			on Days (0,+1,+2+3) before Block Trades are Disclosed		
	CAR(1,10)	*CAR(1,20)*	n	*CAR(1,10)*	*CAR(1,20)*	n
1. All trades	0.73%	1.01%	774	0.58%	0.91%	1036
p-value	0.00	0.01		0.00	0.00	
2. Analysts	0.76%	1.06%	78	0.06%	0.79%	167
p-value	0.50	0.41		0.91	0.30	
5. Board Members	0.26%	0.20%	226	0.11%	0.17%	368
p-value	0.57	0.74		0.72	0.73	
3. Brokers	0.41%	0.83%	416	0.71%	1.03%	635
p-value	0.28	0.14		0.00	0.01	
4. Fund Managers	0.26%	1.20%	148	0.58%	0.95%	267
p-value	0.60	0.10		0.17	0.10	
6. Others	0.08%	0.04%	301	0.62%	0.60%	549
p-value	0.85	0.94		0.02	0.11	
9. Asset Mgt Firms	1.14%	1.40%	258	1.02%	0.93%	493
p-value	0.01	0.03		0.00	0.03	
7. Brokerage Firms	0.58%	0.75%	562	0.62%	0.76%	813
p-value	0.06	0.10		0.00	0.02	
8. Fund Mgt Firms	-0.25%	0.46%	193	0.06%	0.66%	313
p-value	0.59	0.45		0.87	0.18	
1 Expert	0.89%	0.97%	677	0.53%	0.86%	944
p-value	0.00	0.01		0.00	0.00	
2 Experts	-0.24%	0.64%	211	0.58%	0.79%	395
p-value	0.66	0.43		0.09	0.13	

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