

# **Personal Trading by Brokers, Analysts, and Fund Managers**

November 2017

Henk Berkman  
Department of Accounting and Finance  
University of Auckland Business School  
Auckland, New Zealand  
[h.berkman@auckland.ac.nz](mailto:h.berkman@auckland.ac.nz)

Paul Koch  
School of Business, University of Kansas  
Lawrence, KS  
[pkoch@ku.edu](mailto:pkoch@ku.edu)

P. Joakim Westerholm\*  
University of Sydney Business School  
Sydney, Australia  
[joakim.westerholm@sydney.edu.au](mailto:joakim.westerholm@sydney.edu.au)

\*Corresponding author. Please do not cite without permission. We acknowledge the helpful comments of Ferhat Akbas, Tor-Erik Bakke, Susan Christoffersen, Chris Cunningham, Bob DeYoung, Rich Evans, Timothy Dunne, Chitru Fernando, Mark Fisher, Christopher Girardi, Shan Lei, Lei Li, Laurian Lytle, Bill Megginson, Felix Meschke, Stanislov Nikolova, Luke Taylor, Paula Tkac, Kevin Tseng, Larry Wall, Jide Wintoki, Julie Wu, Pradeep Yadav, and Shan Yu, as well as seminar participants at the Australian National University, the University of Kansas, the University of Oklahoma, the University of Nebraska, the University of Otago, the University of Sydney, the Federal Reserve Bank of Atlanta, the FMA Applied Finance Conference, the New Zealand Finance Colloquium, and the SFS Cavalcade Conference.

# **Personal Trading by Brokers, Analysts, and Fund Managers**

## **Abstract:**

When brokers, analysts and fund managers buy or sell for their own account, they outperform retail investors over short windows up to a month. They earn particularly high abnormal returns when they trade simultaneously with other financial experts and when they trade before earnings announcements, revisions of analyst recommendations, and unexpected large price changes. We also find evidence consistent with front running and information leakage before the public disclosure of corporate insider trades, the execution of block trades by foreign and domestic institutions, and revisions of recommendations by analysts working at the same brokerage firm as the expert trading.

**Key Words:** Informed trading, information asymmetry, leakage, front running, tipping, insider trades, block trades, social network analysis, broker, analyst, fund manager, institutional investor.

*JEL* codes: G12, G14, G18.

## I. INTRODUCTION

Most developed countries require company insiders 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 for those with privileged access to private information.<sup>1</sup> In Finland the regulator has taken this reasoning one step further, to also require that employees of financial intermediaries who have regular access to material private information (i.e., ‘access employees’) must publicly disclose all of their personal trades in any stock listed on the Nasdaq Nordic Helsinki Exchange.

In this study, we examine the personal trading activity of 1,249 access employees from 40 different Finnish financial institutions. At any point in time, these Finnish financial intermediaries are required to publicly disclose all trades by their access employees made over the previous five years. We analyze hand collected trade data from the public Insider Trading Registers of these 40 Finnish intermediaries over the five-year period, August 2006 - August 2011. These 40 intermediaries represent 99 percent of the market share in the Finnish brokerage industry and 90 percent of the market share in the fund management industry.<sup>2</sup>

We begin our analysis with an examination of the *selection and timing* of the personal stock transactions by these financial experts. We find that the likelihood of an expert trading a given stock increases sharply if there is similar trading on the same day or the previous four days by other experts in the same firm, or the same financial services group, or the same empirical trading network.<sup>3</sup> We also show that an expert is more likely to trade if he or she is more

---

<sup>1</sup> See Bhattacharya (2014) for a literature review.

<sup>2</sup> The market share of the brokerage firms in our sample drops to 37% if we include foreign brokers and HFT firms.

<sup>3</sup> A financial services group refers to a group of firms that have the same parent company and might include one or more brokerage firms, fund management firms, or asset management firms. An empirical trading network is defined as a community of investors heavily connected by similar trading among themselves, but sparsely connected with others (Ozsoylev et al., 2014; Clauset, Newman, and Moore, 2004).

prominent within the network of Finnish financial experts. Finally, we document that these experts are more likely to trade on 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 short term stock-picking skills on both the buy-side and the sell-side. For example, experts significantly outperform retail investors by an average of 11 basis points (bps) on the day following purchases made the previous day, and by another 5 bps per day based on earlier purchases made over the past week (but excluding the previous day). On the sell side, we also find that experts significantly outperform by -8 bps on the day following sales made the previous day, and another -3 bps per day based on earlier sales made during the past week. In contrast, earlier purchases and sales made by experts over the past quarter (before the previous month) do not significantly outperform retail trades.

Further analysis shows that this extraordinary short term outperformance is concentrated among brokers, analysts, fund managers, and ‘other’ access employees, while there is no significant abnormal performance by the board members of financial intermediaries. We also find that, although stand-alone purchases by individual experts significantly outperform retail trades on the next day, such purchases are significantly more profitable if they are conducted jointly with other experts. For example, purchases of the same stock on the same day by 5 to 10 experts generate an average one-day abnormal return of 28 bps, and this abnormal performance increases to 74 bps for similar purchases by more than 10 experts.

Given the short term nature of this trading performance, we next examine the conjecture that the trades of financial experts are particularly profitable in the days before firm-specific information is made public. We find evidence consistent with this conjecture. For example, when experts trade on the day before quarterly earnings announcements, they generate a mean signed

cumulative abnormal return on days 0 and +1 (i.e.,  $CAR(0,+1)$ ) of 0.8 percent. Likewise, when they trade one day ahead of large idiosyncratic price changes, these experts generate a mean signed  $CAR(0,+1)$  of 2.5 percent. Similarly, when they trade on the day before analysts revise their stock recommendations, they earn a mean signed  $CAR(0,+1)$  of 0.4 percent. On the other hand, these experts do not trade frequently or profitably before takeover announcements, perhaps out of fear that trading ahead of these events is more likely to attract the scrutiny of regulators.

One possible explanation for this exceptional trading performance by financial experts is that these knowledgeable investors may be able to recognize and exploit profitable trading opportunities by using only publicly available information. As a result, we might anticipate that these individuals should outperform other retail investors when they trade for their own account, particularly around highly anticipated and publicized firm-specific events such as earnings announcements. In addition, we could expect these access employees to display similar trading patterns to other financial experts who might tend to analyze the same public information, especially among teams of experts who work for the same organization.

An alternative possible explanation is that financial experts may generate at least some of their profits by trading on material private information obtained through their profession or professional network, implying a potential violation of Finnish securities law. While it is beyond the scope of this study to decisively establish the relative importance of these two alternative explanations, we attempt to shed additional light on this issue by examining situations where a unique opportunity exists for these access employees to trade on material private information that is accessible through their network of financial experts. More specifically, we analyze whether these experts profit from trades made prior to the execution and public disclosure of trades by other informed investors who may include their clients, such as corporate insiders, or

block trades by foreign and domestic institutional investors. In addition, we examine the trades of financial experts around the release of revised recommendations by analysts who work at the same brokerage firm as the expert trading.

We find evidence of significant abnormal trading by financial experts on the day that corporate insider trades are executed (i.e., on day 0) but are not yet publicly disclosed. Some of this abnormal trading originates from brokers who may serve the personal trading needs of these corporate insiders. But this abnormal trading also arises from financial experts who work in other functional roles, suggesting that this private information may be leaked through the personal networks of these financial experts. Moreover, this information is valuable. For example, trades by experts made on the same day that corporate insider trades are executed generate a mean signed cumulative abnormal return over the next ten days,  $CAR(+1, +10)$ , of 1.0 percent.

We also document significant abnormal trading by financial experts on the day before foreign and domestic institutional investors buy or sell large blocks of stock, and we show that these trades are profitable. For example, expert trades made on the day before foreign block trades are executed generate a mean signed  $CAR(+1, +10)$  of 1.1 percent, while expert trades made on the day before domestic block trades are executed generate a mean signed  $CAR(+1, +10)$  of 2.5 percent. Finally, we also present evidence of profitable trading by access employees in the days before the release of revised recommendations by analysts who work at the same brokerage firm. For example, trades by experts at the same firm made on the three days before analyst revisions are released generate a mean signed  $CAR(+1, +10)$  of 1.7%.

Together, this analysis indicates that the community of financial experts profits from being extraordinarily well-informed. This evidence may simply suggest that experts pay greater attention to financial news, or that experts have a greater ability to interpret such news relative to

the general investing population. However, we present evidence that is also consistent with information leakage and front running before the execution or public disclosure of trades by other informed investors who may include clients.

Our study should be of interest to both regulators and financial intermediaries, who may wish to apply greater scrutiny to the personal trading of their access employees. This study also contributes to several strands of academic literature. First, we add to the substantial body of work on insider trading. Most studies in this area examine the return forecasting ability of corporate insider trades, and find that insiders outperform on average when they buy their own company's stock, but not when they sell.<sup>4</sup> Another feature of this literature is that the outperformance of insider purchases tends to accrue over fairly long periods of six to twelve months. In contrast, we show that the access employees of financial intermediaries tend to trade in ways that might be of more concern to regulators, displaying exceptional stock picking skills on both the buy side and the sell side, with profits that accrue over short windows from a few days to a month.

Second, we extend the literature on front running and information leakage in financial markets. Several previous studies present evidence that suggests information leakage ahead of information events such as changes in analyst recommendations and insider trades. For example, Christophe, Ferri, and Hsieh (2010) find increased short selling in the days ahead of analyst downgrades. Irvine, Lipson, and Puckett (2007) find abnormal buying by institutions in the days before the initial release of analyst buy recommendations, consistent with tipping. Chakrabarty

---

<sup>4</sup> For evidence on the performance of corporate insiders in the U.S., see Jaffe (1974), Jeng, Metrick, and Zeckhauser (2003), Lakonishok and Lee (2001), Rozeff and Zaman (1988, 1998), Seyhun (1986), and Ravina and Sapienza (2010). For U.K. evidence, see Fidrmuc, Goergen, and Renneboog (2006), for Finnish evidence, see Berkman, Koch and Westerholm (2017), and for other countries, see Clacher, Hillier, and Lhaopadchan (2009).

and Shkilko (2013) and Khan and Lu (2013) find an increase in short selling on the days when corporate insiders sell, before the trades are officially reported to the public.<sup>5</sup>

Our study adds to this literature by examining the possibility of information leakage and front running by the access employees of financial intermediaries, a group of informed traders who have not previously been examined. While the legal ramifications of the behavior documented here and in the previous literature are not necessarily conclusive, our evidence is consistent with a possible breach of Finnish securities law. For example, we find that access employees profit handsomely when they trade ahead of block trades by foreign and domestic institutional investors, as well as when they trade before the release of revised recommendations by analysts who work at the same brokerage firm as the expert trading – actions that are explicitly prohibited in Finnish securities law.

Third, we extend recent work that documents that valuable information is diffused through social networks. For example, Shiller and Pound (1989) show that the trading decisions of institutional investors are influenced by communication within their peer network. Cohen, Frazzini, and Malloy (2008) find that mutual fund managers earn abnormal returns based on information obtained through their educational networks. Berkman, Koch and Westerholm (2017) show that corporate directors outperform when they buy board interlock stocks, where a co-board member is an insider. Others attribute the similarity of trades by investors in the same geographic area to word-of-mouth communication within their local network.<sup>6</sup> This study provides evidence that is consistent with rapid diffusion of valuable short term private information through the network of access employees at Finnish financial intermediaries.

---

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

<sup>6</sup> For example, see Brown et al. (2008), Ellison and Fudenberg (1995), Hong, Kubik, and Stein (2005), and Ivkovic and Weisbenner (2005, 2007).



## II. INSTITUTIONAL BACKGROUND AND DATA

### II.A. Institutional Background

In most developed countries, financial intermediaries are expected to monitor the personal trading of their employees and ensure that this trading activity complies with insider trading rules. Before we discuss the relevant regulation in Finland, we give a brief overview of the U.S. law, as exemplar of this type of regulation.

#### *II.A.1. Regulation of Personal Trading by Employees of Financial Intermediaries in the U.S.*

The U.S. Investment Company Act was passed in 1940. In 1980 this Act was amended to include Rule 17j-1, which delineates the responsibilities of U.S. investment companies with regard to the personal trading of their employees. Since 2000, amendments to this rule require that certain employees of an investment company who are identified as having regular access to material private information (i.e., ‘access employees’) must report to their employer all of their personal stock holdings annually, and all of their personal stock transactions quarterly. These investment companies are then expected to monitor the personal trades of these access employees to ensure that they are not violating the company’s code of ethics, which must comply with insider trading regulations. It is noteworthy, however, that U.S. intermediaries are not required to disclose the personal stock holdings or transactions of their access employees to the public.<sup>7</sup>

#### *II.A.2. Regulation of Personal Trading by Employees of Financial Intermediaries in Finland*

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 modeled after U.S. insider trading laws. The Finnish Financial Supervisory Authority regulates financial markets in Finland and seeks to enforce the law by monitoring insider trading. What

---

<sup>7</sup> See Legal Information Institute, Cornell University Law School (2004), McCann (2000), and SEC (2015).

makes Finland special is that the basic regulations pertaining to public disclosure of personal trading by corporate insiders, in their own company's stock, are extended to include all trading in any stock by the access employees of financial institutions.

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

“The holding of shares ... subject to public trading ... shall be (made) public if the holder of the security is:

- 1) a member ... of the Board of Directors of ... a securities intermediary ... ;
- 2) (or) a broker, a person employed by the securities intermediary whose duties include investment research relating to such securities or another employee who, by virtue of his position or tasks, learns inside information relating to these securities on a regular basis ...”

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

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

For each access employee subject to the duty to declare, all trades in any Finnish publicly traded security must be disclosed in the intermediary's public Insider Trading Register. The Register must list the securities owned by this person and all his or her transactions; it must be maintained for at least five years; and it needs to be accessible to the public at the premises or website of the intermediary (Securities Market Act, Chapter 5, Section 7).<sup>8</sup>

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

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

Standard 1.3 of the Act continues by stating:

“A supervised entity providing an investment service shall take adequate measures aimed at preventing a relevant person from undertaking personal transactions, if those transactions could give rise to a conflict of interest in relation to a transaction or service in which he is involved on account of his position, if he has access to inside information

---

<sup>8</sup> This declaration requirement also pertains to the trades of a spouse, a minor, or an organization under the direct or indirect control of any access employee of the financial intermediary.

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).”

Finally, the Finnish Association of Securities Dealers has prohibited *short-term* trading by the management or personnel of a member organization or persons associated with them. An investment shall be deemed a short-term investment when the time between the acquisition and disposal and correspondingly between the disposal and acquisition is less than three months.

## **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 access employees at financial intermediaries and the share price performance following their trades. Our main data source is the 40 firm-specific public Insider Trading Registers of Finnish securities intermediaries. At any time, these Registers are required to document all personal transactions in any stocks listed on the Nasdaq Nordic Helsinki Stock Exchange (hereafter, the Exchange) made by the access employees of these financial intermediaries over the previous five years, as well as the trades by their family members or through companies under their control. We use hand-collected data on all publicly disclosed trades by the access employees of these 40 intermediaries during the five-year period, August 2006 through August 2011.

We wish to compare the trading activity and performance of these financial experts with the analogous trades of all other retail investors in Finland made over the same period. For this task we rely on the Euroclear database, which documents daily changes in the shareholdings for every registered investor in Finland. Every investor trading on the Exchange is assigned a unique Euroclear account, even if he or she trades through multiple brokers. During our sample period,

more than half a million Finnish retail accounts were registered with Euroclear, while a total of 152 Finnish stocks were listed on the Exchange.<sup>9</sup>

Finally, we obtain earnings announcement dates from Bloomberg, merger and acquisition announcement dates are taken from SDC Platinum, and analyst recommendations are from S&P Capital IQ. Daily share prices and the number of shares outstanding are obtained from Compustat Global. The market-to-book ratios for all Finnish firms are from Worldscope.

### *II.B.2 Descriptive Statistics*

We partition the sample of all trades by financial experts according to several classification schemes, into trades made by access employees serving in: (i) the five functional roles as reported in the Insider Trading Registers (i.e., brokers, analysts, fund managers, board members, or ‘others’), (ii) the three types of financial services firms distinguished by the Finnish authorities (i.e., brokerage firms, fund management firms, and asset management firms<sup>10</sup>), and (iii) three professional networks (i.e., experts in the same firm, the same financial services group, and the same empirical trading network). In addition, we define ‘network trades’ as similar signed trades made in the same stock on the same day by two or more financial experts.

The top five rows in Panel A of Table 1 present information about the number of experts in each functional role and their trading activity. Row six provides the aggregate numbers across functional roles. Column 2 shows that 306 individuals are classified as brokers, 92 as analysts, 99 as fund managers, 157 as board members, and 595 individuals are included in the category, ‘other employees.’ In total we have trading information for 1,249 financial experts.

---

<sup>9</sup> Grinblatt and Keloharju (2000) provide a detailed description of the Euroclear database.

<sup>10</sup> Fund management firms manage collective investments such as mutual funds and exchange traded funds, while asset management firms manage accounts for institutional investors and private clients.

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

Columns 10 and 11 of Panel A provide the total number and percent, respectively, of ‘stock trading days’ that are attributable to the access employees serving in each functional role.<sup>11</sup> Roughly one third (36%) of all personal ‘stock trading days’ (hereafter, trades for short) by the financial experts in our sample are made by brokers. This group is closely followed by trades in the ‘other’ category, which comprise another 30% of all expert 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.<sup>12</sup>

---

<sup>11</sup> Trades in every stock are aggregated for every individual investor on each day, and we use the daily net change in an investor’s position of a given stock (i.e., a ‘stock trading day’) as our unit of observation. Note that, for each access employee, we include the trades by a spouse, a minor, or an organization under the control of this employee.

<sup>12</sup> We note that most experts in our database are not employed by the same reporting entity for the full 5-year period.

Panel B of Table 1 presents more detailed information about the trades made by financial experts in each functional role, plus analogous results for all retail traders. The first six rows provide the statistics for purchases, while the second six rows present similar details for sales.<sup>13</sup>

Columns 2 and 3 in Panel B report the total number and percent of all stock trading days for the different groups. Columns 4 and 5 provide the average number of shares traded and the average monetary value (in €) of the trades in each category. For all functional roles, experts tend to buy more frequently than they sell, but they buy in smaller transaction amounts of € (except for fund managers who tend to buy larger amounts). Retail investors display similar behavior.

Column 6 of Panel B reports the proportion of trades by each type of financial expert that are classified as ‘network trades,’ in which two or more experts buy (or sell) the same stock on the same day. It is noteworthy that almost 50 percent of all purchases by financial experts are network trades, suggesting that employees of financial intermediaries routinely purchase stocks based on common information analyzed or shared throughout the financial services network. Network sales are somewhat less prevalent, but still range between 21% and 29% of all sales by each category of experts. For both purchases and sales, the tendency to make network trades is greatest for analysts and lowest for board members.

Columns 7 - 13 in Panel B provide information about the characteristics of the stocks traded by each type of investment professional, as well as by all retail investors. This information shows whether different types of investors tend to focus on stocks with certain attributes, or follow particular investment styles. The entries in these columns are calculated as follows. First, every day we compute the decile rank values for every firm characteristic across all stocks traded

---

<sup>13</sup> We also identify 961 stock trading days on which an expert’s purchases and sales in a given stock exactly offset one another (i.e., days with round trip trades). These observations are concentrated at one fund manager during the first years of the sample period. We do not include these expert trades in our main analysis.

on the Helsinki Stock Exchange, and we adjust these ranks to range from -0.5 (for the lowest decile rank) to +0.5 (for the highest decile rank). Next we assign the appropriate adjusted decile rank for every firm characteristic to each stock trade by every accountholder in the sample. The mean values presented in columns 7 - 13 are obtained by averaging these adjusted decile ranks across all stock trading days by investors within every category. For additional details on the construction of the firm characteristics, we refer the reader to Appendix A.

The results in columns 7 - 13 of Panel B reveal that all types of investors (i.e., financial experts and retail traders) have a tendency to trade stocks with relatively large size and high betas. In addition, most types of investors tend to buy and sell stocks with high market-to-book ratios. These investors 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). Rows 6 and 12 reveal that, relative to financial experts, retail investors tend to trade stocks that are larger and have higher market-to-book ratios. In addition, retail investors tend to be somewhat less contrarian than experts. However, the differences in these firm attributes across the different categories of investors are relatively small in magnitude, given that the change in scaled ranks between any pair of adjacent deciles is 0.1.

### **III. LIKELIHOOD OF TRADING BY FINANCIAL EXPERTS**

In this section we estimate the likelihood of a financial expert trading any particular stock on any given day, conditional on other experts in the same professional network trading the same stock on the same day. We also condition on a major firm event occurring on the surrounding days, and we account for additional factors such as the functional role of the expert, the expert's prominence within the financial services network, overall retail trading activity, and other attributes of the stock traded.

We conjecture that financial experts may actively seek to benefit from their access to valuable information, which leads us to specify two testable hypotheses. First, we expect experts to be more active during the short period around major firm-specific events, when information asymmetry is likely to be high. Second, we anticipate that experts are more likely to buy (or sell) a stock if other experts in the same professional network are buying (or selling) the same stock on the same day. This expectation is based on prior research, discussed in the introduction, which establishes that valuable information tends to spread through social networks.

As described above, we consider three professional networks defined as employees in the same: (i) financial firm, (ii) financial services group (but not the same firm), or (iii) empirical trading network. The first two networks are simple to construct from our data that identify the access employees of Finnish financial intermediaries. The third 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 trades by access employees during the first half of our five-year sample period, August 2006 through December 2008.

We then apply logit analysis to examine all purchases (or sales) by these experts that are made during the last half of our sample period, January 2009 - August 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 purchases (or sales) made on or before day ( $t$ ) by other experts in the same professional network of each type. In addition, we account for the presence of major firm events on the surrounding days, the total trading volume of all other retail investors in stock  $i$  on day  $t$ , the centrality of the expert ( $e$ ) in the empirical



trading network<sup>14</sup>, and other firm attributes. This analysis is specified in the following panel logit model, which is estimated separately for purchases and sales by all experts:

$$\begin{aligned}
\text{Log}\{P(\text{Trade}_{i,e,t} = 1)/P(\text{Trade}_{i,e,t} = 0)\} &= a_0 + a_1 \text{Analyst}_e + a_2 \text{Fund\_Mgr}_e + a_3 \text{Board}_e + a_4 \text{Other}_e \\
&+ \sum_{k=0}^4 a_{5k} \text{Firm-NW}_{i,e,t-k} + \sum_{k=0}^4 a_{6k} \text{Group-NW}_{i,e,t-k} + \sum_{k=0}^4 a_{7k} \text{Emp-NW}_{i,e,t-k} + \sum_{k=-3}^3 a_{8k} \text{Event}_{i,t-k} \\
&+ a_{10} \ln(\#\text{Trades})_{i,t} + a_{10} \text{Centrality}_e + a_{11} \text{Size}_{i,t} + a_{12} \text{Beta}_{i,t} + a_{13} \text{MB}_{i,y} + \\
&+ a_{14} \text{RYear}_{i,t} + a_{15} \text{Rmonth}_{i,t} + a_{16} \text{RWeek}_{i,t} + a_{17} \text{RDay}_{i,t}, \tag{1}
\end{aligned}$$

where:

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

$\text{Analyst}_e$  = 1 if expert  $e$  is an analyst, or 0 otherwise;

$\text{Fund\_Mgr}_e$  = 1 if expert  $e$  is a fund manager, or 0 otherwise;

$\text{Board}_e$  = 1 if expert  $e$  is a board member of an intermediary, or 0 otherwise;

$\text{Other}_e$  = 1 if expert  $e$  is in the ‘other’ category of functional roles, or 0 otherwise;

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

or = 0 if other experts at the same *firm* as  $e$  do not combine to be either a net buyer or seller of the same stock ( $i$ ), on the same day or an earlier day ( $t-k$ ;  $k = 0-4$ ),

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

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

or = 0 if other experts in the same *group* as  $e$  do not combine to be either a net buyer or seller of the same stock ( $i$ ), on the same day or an earlier day ( $t-k$ ;  $k = 0-4$ );

or = -1 if other experts in the same *group* as expert  $e$  combine to be a net seller of the same stock ( $i$ ), on the same day or an earlier day ( $t-k$ ;  $k = 0-4$ );

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

or = 0 if other experts in the same *empirical network* do not combine to be either a net buyer or seller of stock ( $i$ ), on the same day or an earlier day ( $t-k$ ;  $k = 0-4$ );

or = -1 if other experts in the same *empirical network* as  $e$  combine to be a net

---

<sup>14</sup> We compute the network centrality measure for each 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 each expert by the standard deviation across all experts. We use data from August 2006 - December 2008 to compute these measures. For a detailed explanation about how these (and other) centrality measures are computed and applied in social network theory, see Larcker, So, and Wang (2013) and the website, [http://en.wikipedia.org/wiki/Centrality#Betweenness\\_centrality](http://en.wikipedia.org/wiki/Centrality#Betweenness_centrality).

seller of the same stock ( $i$ ), on the same day or earlier day ( $t-k$ ;  $k = 0-4$ ),

Event $_{i,t-k}$  = 1 if a firm specific information event for firm  $i$  occurs within  $k$  days before or after day  $t$  ( $t-k$ ;  $k = -3$  to  $+3$ ), or 0 otherwise;<sup>15</sup>

ln(#Trades) $_{i,t}$  = the natural log of the total number of trades in stock  $i$  on day  $t$  across all retail investors, excluding the financial experts in our sample;

Centrality $_e$  = centrality of expert  $e$  within the empirical trading network (see footnote 14).

Size $_{i,t}$  = adjusted decile rank of the market capitalization for stock  $i$  on day  $t$  (based on a 21-day period ending 20 days earlier);

Beta $_{i,t}$  = adjusted decile rank of the Dimson beta for stock  $i$ , estimated on day  $t$  (based on a 250-day period ending on day  $t-1$ );

MB $_{i,y}$  = adjusted decile rank of the market-to-book ratio for stock  $i$  in year  $y$  (based on the value at the end of the prior fiscal year);

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

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

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

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

The control variables are motivated by Grinblatt, Keloharju, and Linnainma (2012), and are further described in Appendix A. We also include dummy variables for the days of the week.

The results of this analysis are presented in Table 2. The left side of Table 2 provides the estimates for Equation (1) where the dependent variable,  $Trade_{i,e,t}$ , equals one if expert  $e$  is a net *buyer* of stock  $i$  on day  $t$ , or 0 otherwise. The right side presents the analogous results when the dependent variable equals one if expert  $e$  is a net *seller* of stock  $i$  on day  $t$ , or 0 otherwise.

First consider the coefficients of the dummy variables for the different functional roles. On both sides of Table 2, the probability of buying or selling by analysts, fund managers, board members or ‘other’ experts is significantly lower than that by brokers (the omitted group).

---

<sup>15</sup> The firm-specific information events incorporated in the Event dummy variable include earnings announcements, takeover announcements, revisions of analyst recommendations, and large price changes. We further discuss the selection criteria for these respective samples of firm-specific events in section IV.C below.

Second consider the results for the dummy variables that identify similar trades in the same stock on each of the four days leading up to day  $t$ , by other experts in each of the three professional networks. For expert purchases on the left side of Table 2, an expert is significantly more likely to buy a stock if other experts in the same firm are net buyers of the same stock on the same day, or any of the previous four days. Similarly, an expert is significantly more likely to buy a stock if other experts in the same financial services group or empirical network are net buyers of the same stock on the same day, or several of the previous four days. We find similar results on the right side of Table 2, indicating that an expert is significantly more likely to sell a stock if other experts in each of the three professional networks are net sellers of the same stock on the same day, or several of the previous four days.<sup>16</sup>

We also find that the probability of buying (or selling) by financial experts increases significantly on several of the days before and after a firm-specific information event. This evidence is consistent with our conjecture that financial experts are more likely to trade on days with high information asymmetry.

Consider next the coefficients of the control variables. First, financial experts are significantly more likely to buy or sell a stock on day  $t$  if there are a greater number of trades in that stock on that day among all retail investors. Also, experts who are more central within the empirical trading network (based on the first half of the sample period) are significantly more likely to buy or sell on any given day (in the second half of the period). In addition, experts are more likely to trade stocks with a lower market-to-book ratio, and they are contrarian (i.e., they tend to buy after price declines and sell after price increases).

---

<sup>16</sup> Note that this direct relation is implied by the significant *negative* coefficients for the network variables on the right side of Table 2, because these network variables assume a value of -1 if other experts in the network combine to be a net seller (instead of a value of +1 when other experts in the same network combine to be a net buyer).

Overall, the results in Table 2 are consistent with the view that access employees at financial intermediaries actively trade on common information that is analyzed or shared within their professional social networks, and these financial experts tend to be more active around days with high information asymmetry.

#### **IV. TRADING PERFORMANCE OF FINANCIAL EXPERTS**

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

##### **IV.A. Performance of Trades by All Financial Experts**

We analyze the investment skills of financial experts using a regression approach similar to Grinblatt, Keloharju, and Linnainma (2012). The sample period covers all 1,268 trading days during the five-year period, August 2006 - August 2011. First, for each day ( $t$ ) in our sample, we identify all Finnish individual accounts that trade in any stock ( $i$ ) over some recent time frame that spans the period from  $x$  days earlier to  $y$  days earlier. This process identifies the recent trades by all (more than half a million) Finnish retail investors, including the 1,249 financial experts. Then we separate these trades into purchases versus sales, resulting in two cross-sections for every day ( $t$ ) that contain the purchases and sales, respectively, across all stocks ( $i$ ) over the recent portfolio formation period covering days ( $t-x$ ,  $t-y$ ).

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

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

where:

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

$\text{Expert}_{i,e,t}$  = 1 for trades in stock  $i$  made 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) both with and without the firm-specific control variables.

When the control variables are omitted, the intercept ( $b_0$ ) reflects the trade-weighted average return on day  $t$  based on recent purchases (or sales) made by the benchmark omitted group, which includes all retail investors. Thus, the coefficient of the Expert dummy ( $b_1$ ) reveals the average trade-weighted *abnormal* return on day  $t$ , relative to this benchmark retail return, for the purchases (or sales) made by all financial experts during the formation period,  $(t-x, t-y)$ .<sup>17</sup>

#### *IV.A.1. Abnormal Performance of Trades by All Financial Experts made One Day Earlier*

Table 3 reports the Fama-MacBeth mean coefficients from estimating the daily cross-sectional regression in Equation (2), averaged across all 1,268 days in the sample period. In Panel A we present the results for the performance on day  $t$  based on trades made on the previous day,  $t-1$ . The p-values in Table 3 are obtained from t-ratios based on the Newey-West adjusted standard errors for the mean coefficients across all daily cross sectional regressions.

We first concentrate on the results for purchases made on the previous day ( $t-1$ ), from the model without control variables, on the left side of Panel A in Table 3. The mean intercept ( $b_0$ ) is an insignificant -1.2 basis points (bps) per day (p-value = 0.81). This outcome indicates that, during our sample period, retail investors earn a slightly negative average return on day  $t$  based

---

<sup>17</sup> This regression approach is attractive because it documents the marginal effect of being a financial expert on trading performance, while controlling for other attributes of the firms traded and the accountholder trading.

on their purchases made one day earlier. The Expert dummy coefficient ( $b_1$ ) indicates that the recent purchases of financial experts significantly outperform the recent purchases of retail investors by an average of 13 bps on the next day ( $p$ -value = 0.00). This one-day outperformance for expert purchases is economically significant, corresponding to an annualized return of 32% per annum (i.e., 250 days per year times .129% per day).

The analogous intercept ( $b_0$ ) for sales made on day  $t-1$ , on the right side of Panel A in Table 3, shows that sales by retail investors are followed by a negative but insignificant mean return of -5.6 bps on day  $t$  ( $p$ -value = 0.24). Now the Expert dummy coefficient ( $b_1$ ) is -6.8 bps ( $p$ -value = 0.03), which indicates that recent sales by financial experts significantly outperform recent sales by retail investors. This daily abnormal performance is again economically significant, at -17% per annum (i.e., 250 times -.068%).

When we include the control variables from Equation (2) in Panel A of Table 3, the Expert dummy coefficient ( $b_1$ ) is similar and the conclusions remain the same: financial experts are exceptional stock pickers. On average, the stocks they buy significantly outperform those bought by other retail investors on the following day, while the stocks they sell experience significant negative abnormal returns relative to those sold by other retail investors. This significant outperformance on the sell side contrasts with most prior work on selling by informed investors, which typically finds that sales are not informative.<sup>18</sup>

For expert purchases on the left side of Panel A in Table 3, the mean coefficients of the control variables indicate a marginally significant larger average daily return for stocks with smaller size and a lower beta. In addition, the significant negative coefficient for the return from

---

<sup>18</sup> For example, Kraus and Stoll (1972), Cohen, Frazzini, and Malloy (2008), and Grinblatt, Keloharju, and Linnainma (2012) find that purchases by informed investors are informative, but not sales. In contrast, Cohen, Malloy, and Pomorski (2012) find that discretionary purchases and sales by corporate insiders are informative.

the previous day (RDay) indicates a tendency for a return reversal after one day. In contrast, two other lagged return variables have a significant positive mean coefficient (RYear and RMonth), consistent with momentum for stocks based on the return during the previous year and the previous month. For expert sales, the only significant control variable is RDay, again indicating a tendency for a reversal in stock prices after one day.

#### *IV.A.2. Abnormal Performance of Earlier Trades by All Financial Experts*

In Panel B of Table 3, we investigate how the average daily outperformance of financial experts depends on the portfolio formation period. We estimate Equation (2) using alternative formation windows that span three earlier 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,  $(t-30, t-8)$ , and (iii) previous trades made over the past quarter excluding the last month,  $(t-90, t-31)$ . We only report the mean daily coefficient for the *Expert* dummy ( $b_1$ ), since the results for the control variables are nearly unchanged.

First consider the performance of expert purchases on the left side of Panel B in Table 3. As we examine portfolio formation periods that begin in the more distant past, the mean daily abnormal performance of experts tends to decline in magnitude and significance. For example, expert purchases made over the past week excluding the previous day,  $(t-7, t-2)$ , generate a mean abnormal return of 4.7 bps per day (p-value = 0.0). Likewise, earlier expert purchases made over the past month excluding the previous week,  $(t-30, t-8)$ , yield an additional mean abnormal return of 2.2 bps per day (p-value = 0.03).<sup>19</sup> Importantly, earlier expert purchases made more

---

<sup>19</sup> The results for purchases in Table 3 imply that an expert portfolio constructed at the end of trading day  $t$  earns 11 bps more than retail trades on the next trading day  $t+1$ , another 4.7 bps per day more on the following four trading days (from  $t+2$  to  $t+7$ ), and an additional 2.2 bps per day more on the subsequent 16 trading days (from  $t+8$  through  $t+30$ ). Thus, the abnormal return on a portfolio that is rebalanced once a month is  $(0.110 + 4*0.047 + 16*0.022) = 0.65\%$  per month, or 7.8% per annum.

than a month ago do not continue to outperform earlier purchases by retail investors. Likewise, on the right side of Panel B, expert sales made in the previous week still significantly underperform retail sales, but expert sales made more than one week ago do not continue to outperform.

#### **IV.B. Different Functional Roles, Financial Service Firms, and Network Trades**

##### *IV.B.1. Abnormal Performance by Experts in the Five Functional Roles*

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

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

where:

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

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

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

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

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

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



The top row of each Panel in Table 4 reproduces the evidence for all expert trades from estimating Equation (2) in Table 3. The next five rows present the analogous results for experts in the five functional roles from estimating Equation (3). In Panel A, using a one-day formation period, fund managers have the best performance with a mean daily abnormal return of 26 bps (p-value = 0.01), followed by analysts with a mean abnormal return of 20 bps (p-value = 0.01), brokers at 15 bps (p-value = 0.01), and ‘other’ experts at 13 bps (p-value = 0.00). We find no significant abnormal performance for purchases by the board members of financial intermediaries. When we consider earlier portfolio formation periods, brokers and analysts significantly outperform based on trades made up to one month in the past, while ‘other’ experts significantly outperform based on trades over the past week.

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

#### *IV.B.2. Abnormal Performance by Experts in the Three Types of Financial Services Firms*

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

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

where:

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

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

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

The results are provided in rows 7 to 9 of each Panel in Table 4. This model replaces the single dummy variable in Equation (2) with three dummy variables that identify the three different types of financial services firms that employ these experts. On the buy side in Panel A, the mean daily abnormal returns based on a one-day horizon are significant and similar in magnitude across trades by experts working at brokerage firms (12 bps, p-value = 0.00), fund management firms (11 bps, p-value = 0.03), and asset management firms (12 bps, p-value = 0.00). For each firm type, this average daily outperformance tends to remain significant for portfolios constructed over earlier formation periods extending up to one month ago, although it declines in magnitude. On the sell side in Panel B, there is a significant negative mean abnormal return based on expert selling over a one-day horizon at asset management firms (-11 bps, p-value = 0.02), but no significant abnormal return at brokerage or fund management firms. Once again, sell portfolios based on longer formation periods do not generate significant negative mean abnormal returns for experts employed by any group of firms.

#### *IV.B.3. Abnormal Performance of Stand-Alone Trades versus Network Trades*

We also estimate a model to assess the relative performance of stand-alone trades made by a single expert versus similar trades made by two or more experts (which we label network trades). We conjecture that, relative to stand-alone trades, such network trades are more likely to be motivated by private information. On the one hand, private information that is particularly value-relevant could be more likely to be uncovered by several experts working independently

(i.e., without sharing this information). On the other hand, if such private information is shared across the financial services network, we would also expect multiple experts to trade. In either case, if more experts make similar trades on the same day, we would expect these network trades to have a higher probability of being informed, and thus greater outperformance relative to non-network trades. We test this conjecture by replacing the single expert dummy in Equation (2) with five new dummy variables 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:

$$(5) \text{ Return}_{i,t} = e_0 + e_1 \text{Expert\_1}_{i,e,t} + e_2 \text{Expert\_2}_{i,e,t} + e_3 \text{Expert\_3-4}_{i,e,t} + e_4 \text{Expert\_5-10}_{i,e,t} \\ + e_5 \text{Expert\_>10}_{i,e,t} + e_6 \text{Size}_{i,t} + e_7 \text{Beta}_{i,t} + e_8 \text{MB}_{i,t} + e_9 \text{RYear}_{i,t} \\ + e_{10} \text{RMonth}_{i,t} + e_{11} \text{RWeek}_{i,t} + e_{12} \text{RDay}_{i,t} + \varepsilon_{i,t},$$

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 additional experts buy (sell) 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 additional 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 additional 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 additional experts also buy (sell) stock  $i$  on the same day, or 0 otherwise;

$\text{Expert\_>10}_{i,e,t} = 1$  for purchases (sales) in stock  $i$  during the formation period,  $(t-x, t-y)$ , if accountholder  $e$  is an expert and 10 or more additional 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, and are consistent with our conjecture. First consider network purchases by experts, at the bottom of Panel A.<sup>20</sup> Using a one-day formation period, there is a monotonic increase in the mean abnormal return as we move down across these network dummy coefficients, to consider network trades made by an increasing number of experts buying the same stock on the same day. Purchases of stocks by a single financial expert are followed by a significant mean abnormal return on the next day of 6.5 bps (p-value = 0.01). This one-day abnormal return increases to 13 bps (p-value = 0.01) for stocks bought by 2 financial experts, 19 bps (p-value = 0.01) for stocks bought by 3 or 4 experts, 28 bps (p-value = 0.02) for stocks bought by 5 to 10 experts, and this average one-day outperformance increases to a striking 74 bp for network purchases by more than 10 experts (p-value = 0.06).<sup>21</sup> When we consider earlier portfolio formation periods up to one month in the past, in the other columns of Panel A, there is some additional evidence of significant longer term outperformance for network purchases by 2 experts, but there is no longer a monotonic relation between the mean abnormal returns and the number of experts making similar trades. On the sell side, Panel B of Table 4 indicates that expert sales are followed on the next day by a negative mean abnormal return that tends to grow in magnitude when more experts enter a similar sale. However, the significance of these successive dummy coefficients declines as we consider network sales with more and more experts selling on the same day, due to a decreasing sample size (see footnote 20 above). Further unreported tests show that the mean abnormal

---

<sup>20</sup> In our sample there are 11,764 stand-alone purchases by a single expert, 2,219 network purchases by 2 experts, 976 network purchases by 3 or 4 experts, 293 network purchases by 5 to 10 experts and 51 network purchases of the same stock on the same day by 10 or more experts. Similarly, there are 10,387 stand-alone sales by a single expert, 1,355 network sales by 2 experts, 297 network sales by 3 or 4 experts, 38 network sales by 5 to 10 experts and 11 network sales of the same stock on the same day by 10 or more experts.

<sup>21</sup> For the one-day portfolio formation window, the mean abnormal performance of similar network purchases by 3 or 4, 5 to 10, or more than 10 experts (i.e., each coefficient,  $e_3$ ,  $e_4$ , or  $e_5$ ) is significantly greater than the analogous performance of stand-alone purchases by a single expert (i.e.,  $e_1$ ) at the 5 percent level or better.

returns following multiple-expert sales are never significantly different from the mean abnormal returns following sales by one expert. In addition, when we extend the portfolio formation period further back in time, there is little evidence of significant abnormal returns for earlier sales by experts. Together, this evidence supports our conjecture that network trades involving more financial experts are more likely to be motivated by private information, relative to stand-alone trades.

#### **IV.C. Performance of Expert Trades made before Firm-Specific Information**

##### **Events**

The previous section documents that financial experts possess a significant short-term information advantage that leads to superior stock returns on the days immediately following both their purchases and sales. Given the short-term nature of this apparent information advantage, we suggest that this superior performance may be concentrated among expert trades made during the period just before major corporate events that are commonly associated with increased information asymmetry.

In this section we apply an event study approach to investigate the performance of 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 market-adjusted price changes, which presumably reflect the arrival of substantive firm-specific information. We focus on the mean cumulative abnormal return on the day of and the day after each type of event ( $CAR(0, +1)$ ).

Our sample of earnings announcements is obtained from Bloomberg, and consists of 2,291 quarterly announcements made by Finnish firms over the sample period, August 2006 to August 2011. Our sample of changes in analyst recommendations is from Capital-IQ, and

consists of all 2,254 revisions during the same sample period (i.e., all cases where an analyst changed his or her previous recommendation). Data on mergers and acquisitions are obtained from SDC Platinum, and include 55 takeover announcements for all Finnish firms during the sample period. We also analyze a sample of large price changes, which we generate by selecting the two days each calendar year with the largest and smallest market-adjusted abnormal returns for every stock. We exclude such price change events if they occur within five days of an earnings announcement, analyst revision, or acquisition announcement, or if they occur within one month of another large price change event for the same stock but with the opposite sign. This sample contains 1,460 large price change events over the sample period.

We first compute the market-adjusted daily abnormal return for every stock, as the actual return minus the return on the value-weighted average return across all stocks on the Helsinki Stock Exchange, where the maximum weight of any stock is limited to 10% of the total market value of the index.<sup>22</sup> Next we sum this abnormal return on days 0 and +1 and we “sign” this market-adjusted  $CAR(0, +1)$ , multiplying it by -1 for all expert sales. Then, for each event, we calculate the average signed  $CAR(0, +1)$  across all expert purchases and sales made on day -1, -2, or -3, or during week -1, -2, or -3, respectively, prior to that event. In the final step, we calculate the mean of these average signed  $CAR(0, +1)$ ’s across all relevant events (i.e., events where at least one expert traded during the relevant event windows). The standard error of this mean signed  $CAR(0, +1)$  across all events is used to test the null hypothesis that the mean signed  $CAR(0, +1)$  is zero.

The results are provided in Table 5. Panel A presents the analysis of expert trades made just before earnings announcements. Panel B similarly analyzes expert trades before revisions of

---

<sup>22</sup> This weight limit mitigates the influence of Nokia, Finland’s largest stock, on the value-weighted market index.

analyst recommendations. Panel C presents the results for takeover announcements, and Panel D provides the evidence for large price changes. The left side of every Panel presents results for the group of expert trades made on each of the three days before the event, while the right side gives analogous results for expert trades made during each of the three weeks before the event.

First consider expert trades made in the three days before earnings announcements, on the left side of Panel A in Table 5. There are 343 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). For expert trades made two or three days before earnings announcements, we find no further evidence of significant outperformance. The right side of Panel A indicates 742 earnings announcements where at least one expert traded in the week before the event, with a mean signed  $CAR(0,+1)$  of 0.5% (p-value = 0.02). There is no evidence of outperformance based on earlier expert trades made two or three weeks before earnings announcements.<sup>23</sup>

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

---

<sup>23</sup> Note that, on the left side of the table, the events included in the sample of all expert trades made on days -1, -2 and -3 may refer to the same event. As a result, the total number of events in week -1 (742) may be lower than the sum of the number of events across days -1, -2 and -3 considered separately (i.e., 343+283+299).

For the sample of Finnish takeover targets analyzed in Panel C of Table 5, there are too few trades by experts on each of the three days before the M&A announcements to conduct a meaningful analysis. This low number of observations reflects, in part, the low number of M&A announcements for the firms in our sample (55), but might also indicate that these experts are reticent to trade before these uncommon events that might attract the scrutiny of regulators. On the right side of Panel C, we find somewhat larger samples of 23 to 26 such events where at least one expert traded in each of the three weeks before the takeover announcement. While the mean signed  $CAR(0, +1)$  is 2.6% based on expert trades in the week before the M&A announcements, the paucity of trades and the lack of precision in their performance suggests that financial experts do not reliably profit from trading on information about upcoming mergers and acquisitions.

Finally, consider the evidence for trades made on the three days before large price changes, on the left side of Panel D in Table 5. This evidence shows that financial experts tend to trade in the correct direction of these large unexpected price changes. For example, there are 128 events where at least one access 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 large and marginally significant for earlier trades made three days before the price change ( $CAR(0, +1) = 2.0\%$ , p-value = 0.07), and is significant based on trades made during the first or second week before these events ( $CAR(0, +1) = 1.5\%$  and  $1.2\%$  (with p-values = 0.02 and 0.05, respectively)).<sup>24</sup>

This event study analysis provides strong evidence that financial experts outperform when they trade just before major firm-specific information events. Similar to our other evidence in Tables 3 and 4, it is possible that this performance is due to a superior ability of experts to

---

<sup>24</sup> When we split the trades by experts into sales and purchases prior to each type of event, the mean signed  $CARs$  that are significant in Table 5 have the same sign and similar magnitude for both the samples of sales and purchases. However, for earnings announcements the  $CARs$  are significant for sales but not for purchases, and for the sample of large price change events the significant abnormal returns in Table 5 are significant for purchases but not for sales.



trade ahead of these events by using only publicly available information. Alternatively, this evidence is also consistent with the view that these experts trade on private information about these events, obtained through their profession or their professional network.

## **V. FRONT RUNNING AND INFORMATION LEAKAGE BY FINANCIAL EXPERTS**

In this section, we attempt to shed more light on whether financial experts profit from front running or the sharing of private information across their professional network. Here we investigate the timing and performance of trades made by experts in the days before the execution and public disclosure of trades by other informed investors who may include their clients, such as corporate insider trades, as well as the block trades of domestic or foreign institutional investors. In addition, we examine expert trades made just prior to revisions of recommendations by analysts working at the same brokerage firm as the expert trading.

We use event study methodology and assign ‘day 0’ to the day on which a corporate insider trade is executed, or a day with exceptional net order flow by domestic or foreign institutions, or the day when a brokerage firm releases a revised analyst recommendation. We then examine the timing and performance of trading by financial experts around these events.

In each of the four cases we examine, any trading by financial experts appears to constitute a breach of the Finnish securities regulations pertaining to the access employees of Finnish financial institutions, delineated in the “Securities Trading Instructions for Member Organisations of the Federation of Finnish Financial Services” (hereafter, the Instructions). We discuss the relevant details of the Instructions in each of the subsequent subsections.

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

In Finland, trades by corporate insiders must be publicly disclosed four to seven days after their execution (i.e., from day +4 to day +7). During our five-year sample period, the

Finnish public Insider Trading Register contains a total of 2,513 trades by corporate insiders in the stock of their own firm, across all listed firms on the Nasdaq Nordic Helsinki Exchange. We omit insider trades that occur within three days after another insider trade for the same firm. We also exclude trades by corporate insiders who appear in our sample of financial experts as an access employee or a board member of a Finnish securities intermediary. These screens leave 1,541 corporate insider trades in our sample of events.

Section 2.7 of the Instructions motivates our analysis of expert trading around corporate insider trades. In this section inside information is defined as, "... information of an exact nature ... which has not been made public ... and which is likely to have a material effect on the value of said financial instrument." Also relevant is section 4.1 of the Instructions, which addresses information leakage by stating, "Nor may a person exercising significant influence give advice or guide a third party to execute or refrain from executing a transaction on a financial instrument, which would be prohibited as his/her personal transaction".

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

We define event day 0 as the day on which the corporate insider trade is executed. For each such insider trade event ( $j$ ), we consider all trades by our sample of financial experts that are made in the insider's stock ( $i$ ) during the 61-day window extending from eleven weeks before the insider trade to one week after the trade, covering days  $t = (-55, +5)$ . The first ten weeks of this window,  $t = (-55, -6)$ , represent the pre-event period that we use to establish 'normal' trading activity in the corporate insider's stock ( $i$ ) by the group of financial experts. The remaining 11 days,  $t = (-5, +5)$ , represent the event window.

The blue line in Figure 1.A shows the total number of trades by financial experts over all days during the period,  $(-55, +5)$ . The daily total number of expert trades slowly increases during

the pre-event window, from a total number of 227 trades per day on day -55, to 292 trades on day -6, and then spikes to 490 expert trades on day 0. The red line in Figure 1 shows the total trading activity of a matched group of retail investors that we label as ‘pseudo-experts.’ We construct this sample of pseudo-experts by uniquely pairing each financial expert with a retail investor who exactly matches that expert in terms of the total number of trades during that calendar year. Figure 1.A shows that the group of financial experts generally trade less frequently during the pre-event window than the matched group of pseudo-experts. The average difference over the pre-event period, (-55,-6), is 33 trades per day. However on the day of the corporate insider trade (event day 0) this pattern reverses, with 490 trades by financial experts, which far exceeds the 411 trades by the matched sample of pseudo-experts.

The evidence in Figure 1.A motivates a formal analysis of the abnormal trading activity by financial experts over the eleven-day event window, (-5,+5). We follow a four-step procedure to conduct a difference-in-difference test that examines whether the increase in trading activity by financial experts around corporate insider trades, relative to their own pre-event trading, is significantly greater than any analogous increase in trading by the matched group of pseudo-experts, relative to their own pre-event trading. First, for each insider trade event ( $j$ ) and for every day in the event window,  $t = (-5, +5)$ , we compare the actual number of expert trades in stock ( $i$ ) with the average daily (normal) number of expert trades in this stock over the pre-event period, as follows:

$$\text{abn\_trades\_expert}_{i,j,t} = (\#\text{expert trades}_{i,j,t}) - \text{Mean}(\#\text{expert trades}_{i,j,t-55,t-6});$$

where  $\#\text{expert trades}_{i,j,t}$  = the daily number of expert trades in the insider’s stock ( $i$ ) for every day in the event window,  $t=(-5, +5)$ , for the  $j^{\text{th}}$  event;

and  $\text{Mean}(\#\text{expert trades}_{i,j,t-55,t-6})$  = mean daily number of expert trades in the insider’s stock ( $i$ ) over the pre-event window,  $t=(-55,-6)$ , for the  $j^{\text{th}}$  event.

Second, we account for possible systematic patterns in overall trading activity by comparing this abnormal trading from the group of financial experts, relative to their own pre-event trading, with the analogous abnormal trading by the group of pseudo-experts, relative to their own pre-event trading.<sup>25</sup> This daily abnormal trading for pseudo-expert retail investors is calculated in the same way as specified above for the financial experts themselves, as follows:

$$\text{abn\_trades\_retail}_{i,j,t} = (\# \text{retail trades}_{i,j,t}) - \text{Mean}(\# \text{retail trades}_{i,j,t-55,t-6});$$

where  $\# \text{retail trades}_{i,j,t}$  = the daily number of trades in the insider's stock ( $i$ ) by the matched sample of retail investors, for every day in the event window,  $t = (-5, +5)$ , for the  $j^{\text{th}}$  event;

and  $\text{Mean}(\# \text{retail trades}_{i,j,t-55,t-6})$  = the mean daily number of trades in the insiders stock ( $i$ ) by the matched sample of retail investors over the pre-event window,  $t = (-55, -6)$ , for the  $j^{\text{th}}$  event.

Third, for every day in the event window,  $t = (-5, +5)$ , and for each event ( $j$ ), we compute the difference between these two measures of abnormal trading by experts versus the matched sample of pseudo-expert retail investors. The resulting difference-in-difference represents our measure of abnormal expert trading ( $AET_{i,j,t}$ ), as follows:

$$AET_{i,j,t} = \text{abn\_trades\_expert}_{i,j,t} - \text{abn\_trades\_retail}_{i,j,t}.$$

Finally, for every day in the event window,  $t = (-5, +5)$ , we calculate the mean abnormal expert trading ( $AET_t$ ) across all insider trade events ( $j$ ), and we use the standard error of this mean to test the null hypothesis that the mean  $AET_t$  is zero.

The first row of Table 6 presents the resulting mean abnormal expert trading activity ( $AET_t$ ) across all financial experts, for every day in the event window,  $t = (-5, +5)$ , around corporate insider purchases or sales. The next five rows present the analogous evidence for trades made by experts serving in the five functional roles, followed by three rows of results for

---

<sup>25</sup> For example, the increase in trading by experts around day 0 documented in Figure 1.A could be due to corporate insider trades clustering in the days after corporate disclosures, when overall trading activity also tends to be high.

the trades of experts working in the three types of financial services firms. Finally, the last two rows analyze non-network trades versus network trades (by more than one expert).

Several findings stand out. The first row in Table 6 indicates that financial experts or pseudo-experts are active at least once in the window,  $(t-55, t+5)$ , around 1,207 corporate insider trade events.<sup>26</sup> On the day the insider trade is executed (day 0), there is significant mean abnormal trading activity by all financial experts relative to the matched sample of pseudo-experts, with an average of 0.093 additional ‘abnormal’ expert trades per event (p-value = 0.00). This average  $AET_{t=0}$  implies that there are 112 (i.e.,  $0.093 \times 1,207$ ) more events with a financial expert trading on day 0 than is expected under the null hypothesis of no difference in trading activity between financial experts and pseudo-experts on day 0.<sup>27</sup>

Rows 2 to 6 of Table 6 show that this abnormal expert trading on day 0 is not limited to brokers, but is also significant for analysts, board members and ‘other’ experts.<sup>28</sup> Rows 7 to 9 reveal that the mean abnormal expert trading activity on day 0 is only significant for the employees of brokerage firms. Finally, the last two rows of Table 6 indicate a particularly sharp increase in abnormal trading by more than one financial expert relative to trading by more than one pseudo-experts on day 0, with an average of 0.14 additional network trades per event (p-value = 0.03).<sup>29</sup>

---

<sup>26</sup> It is important to note that the subsample of retail investors that constitutes our matched group of pseudo-experts is treated in exactly the same way as the sample of financial experts in this analysis. Hence, the sample of events considered in Table 6 contains all corporate insider trade events where, during the 61-day period covering days  $t = (-55, +5)$ , at least one financial expert or pseudo-expert trades at least once.

<sup>27</sup> Note that this number (112) is the same as the difference between the actual number of expert trades on day 0 and the number of pseudo-expert trades on day 0 plotted in Figure 1.A, minus the average difference in daily pre-event trading activity between the two groups of investors (i.e.,  $490 - 411 - (-33)$ ).

<sup>28</sup> The total number of events for experts in each functional role is smaller than the total number of events for all experts (1,207) because, for some events, there are no trades during the period  $(-55, +5)$  by financial experts or pseudo-experts with a particular functional role. Note that the sum of abnormal expert trading on day 0 multiplied by the number of events across all functional roles adds up to 112.

<sup>29</sup> Across financial experts and pseudo-experts, 1,203 events have at least one non-network trade in the window from event day  $(-55, +5)$ , whereas 602 events have at least one network trade in this window. Again, the sum of abnormal expert trading times the number of events across network and non-network trades sums to 112.

The results for day 0 in Table 6 are consistent with the view that information about corporate insider trades is quickly acted upon and shared across the network of financial experts, on the same day that the insider trade is executed. We also note evidence of significant abnormal expert trading on day -1 for fund managers, and on days -1 and -2 for stand-alone expert trades. This ‘early’ trading by experts might indicate a delay between the instruction to buy or sell by the insider and the order execution, for example because of the use of good-till cancel limit orders by some insiders, or because of preceding discussion between the broker and insider. Moreover, of the 55 measures of daily *AET* over days (-5, -1) throughout Table 6, only three are significant, which is only slightly higher than what would be expected by chance at the 5% significance level.

#### *V.A.2. Abnormal Performance of Expert Trades Made on the Day of Corporate Insider Trades*

Table 6 reveals significant abnormal trading activity by experts on the day that insider trades are executed (i.e., day 0), which is prior to public disclosure of these insider trades on day +4 or later. However, this evidence does not indicate whether these expert trades tend to be in the right direction, and thus outperform. We next investigate whether financial experts profit from this abnormal trading activity, by examining the cumulative abnormal returns earned by expert trades made on the same day that corporate insiders buy or sell.

Similar to the event study analysis in Table 5, we begin by computing the market-adjusted daily abnormal returns for each stock (*i*). We then cumulate these abnormal returns over the ten or twenty trading days following expert trades made on the same day that insider trades are executed. This procedure generates two measures of performance,  $CAR(+1, +10)$  and  $CAR(+1, +20)$ , for every expert trade made on the same day as each insider trade event. We consider both a ten-day and a twenty-day window, to ensure that the *CAR* includes performance

that is realized by experts after the insider trade event becomes public knowledge (which happens at the earliest 4 days after the insider trade, and at the latest 7 days after the trade). Once again, we multiply the *CAR* by -1 for expert sales, and calculate the average signed *CAR* across all expert trades for every group of expert trades made on the day of each insider trade event (*j*). Finally we compute the mean of these average signed *CARs* across all events, and use the standard error of this mean to test the null hypothesis that the mean signed *CAR* is zero.

First consider the performance of all expert trades made on the same day as insider purchases or sales, in the top row of Table 7. Experts trade on the same day as corporate insiders for 255 such insider trade events.<sup>30</sup> The 10-day mean signed  $CAR(+1, +10)$  for these expert trades is 0.96% (p-value = 0.05), while the 20-day mean signed  $CAR(+1, +20)$  is 1.63% (p-value = 0.01). The next five rows reveal that these mean signed *CARs* are positive for all functional roles. However, due to the paucity of expert trades for most functional roles, the mean signed  $CAR(+1, +20)$  is only significant for brokers and ‘other’ experts. In the following three rows, we find mean signed *CARs* of a similar magnitude for the employees of brokerage firms, fund management firms, and asset management firms. However, they are significant only for the employees of brokerage firms. Finally, stand-alone trades and network trades are also followed by mean signed *CARs* of a similar magnitude. However, the *CARs* of network trades are less significant due to the smaller number of network trades made on day 0.<sup>31</sup>

The results in this subsection are consistent with the view that financial experts share and trade on material private information related to the execution of corporate insider trades, prior to

---

<sup>30</sup> This number, 255, is lower than the 490 trades by experts on event day 0 in Figure 1.A, because the mean signed *CAR* in Table 7 is averaged across *events*. The analogous mean  $CAR(+1, +10)$  averaged across the 490 *trades* equals 2.5% and the average  $CAR(+1, +20)$  is 2.4%, and both means are significantly different from 0 at the 1% level.

<sup>31</sup> The sum of the number of events with network trades on event day 0 and events with non-network trades on event day 0 (202 + 65) is larger than the total number of events with trades on event day 0 (255). The reason for this outcome is that some events are classified as events with both network trades and non-network trades if, for the same event, 2 or more experts buy (or sell) while 1 other expert sells (or buys).

public disclosure of these trades (which occurs on or after day +4). This trading activity delivers significant abnormal returns to the financial experts who engage in these transactions.

### **V.B. Trading and Performance by Financial Experts around Days with Block Trades by Foreign Institutional Investors**

Foreign institutional investors generally opt for registration on the Nasdaq Nordic Helsinki Exchange in the name of a nominee within the Finnish share registry. During our sample period, the Euroclear database distinguishes 96 investor nominee accounts that trade stocks on the Helsinki Exchange. We use changes in the aggregate daily shareholdings across these 96 nominee accounts as our proxy for the daily net order flow originating from foreign institutional investors. These foreign institutions hold an average of 50 percent of all Finnish shares during the sample period (88 percent for Nokia). Foreign institutional investors also account for a substantial share of traded volume, with a market share that averages around 50 percent of total volume traded across all stocks, and ranges from a low of 2.8 percent to a high of 90.9 percent.

In this subsection, we investigate trading activity by financial experts around the days when these foreign institutional investors, as a group, have exceptionally large net order flow in a given Finnish stock. We use the following procedure to identify these ‘foreign block trade’ events. First, for each day ( $t$ ) and for every stock ( $i$ ), we calculate the daily net order flow that originates from all foreign institutions by aggregating total shares purchased minus shares sold across all 96 foreign investor nominee accounts. Second, we compute the average daily total volume for every stock ( $i$ ) during each calendar year of our sample period, August 2006 - August 2011. Finally, for each stock ( $i$ ) we select the days every year for which the absolute value of the foreign net order flow is more than twice the average daily total volume for that year. We



exclude any such ‘foreign block trade’ days that occur within three days after another foreign block trade day for the same stock. This procedure identifies 2,390 foreign block trade events across all Finnish stocks over the five-year sample period. Almost all Finnish stocks appear in this sample of block trade events, with a maximum number of 56 foreign block trade events for a single stock (which represents 2.3 percent of all foreign block trades in our sample).

As discussed in Booth et al. (2002), traders with large orders, who fear their orders may have a significant price impact in the central downstairs market, may want their orders processed in the "upstairs" market. In this off-exchange upstairs market, the brokerage firm searches for counterparties and negotiates prices. Alternatively, the broker may choose to wait for counterparties and do the transaction “in house”, in order not to inform competitors and their customers about the large pending order. In either case, given the delay in execution of large orders in the upstairs market and the time it might take for the broker and client to decide on order execution strategy, there is a potential opportunity for financial experts to trade ahead of pending foreign block trades.

Our analysis of expert trading around foreign block trades is also motivated by Section 2.7 of the Instructions, which describes several examples of inappropriate use of inside information. For example, it is improper for an access employee to trade on or share information regarding a “customer’s exceptionally large-scale order or order plan that is likely to have an effect on the value of a financial instrument.” Likewise, the restriction on information leakage in Section 4.1 of the Instructions, discussed above in subsection V.A., is also relevant.

#### *V.B.1. Abnormal Trading by Financial Experts around Block Trades by Foreign Institutions*

We use a research design that is similar to our previous test of abnormal expert trading activity around corporate insider trades. Once again we begin by assigning event day 0 to the day

with a foreign block trade event ( $j$ ). Figure 1.B plots the daily total number of trades by all financial experts and the matched sample of pseudo-experts, respectively, over the 65-day event period  $(-55,+5)$  surrounding block trades by foreign institutions. During most of the pre-event window,  $(-55,-6)$ , the group of financial experts makes an average of roughly 40 trades per day more than the pseudo-experts. On days  $-7$  to  $-5$ , this pattern briefly reverses so that the pseudo-experts become more active traders. But thereafter the former pattern resumes so that financial experts again trade more frequently over the remaining days in the event window  $(-5,+5)$ . The largest difference in trading activity between the two groups occurs on day 0, when experts make 149 more trades than the matched sample of pseudo-experts, while the second largest difference is on day  $-1$ , when experts make 99 more trades.

The evidence in Figure 1.B motivates additional analysis to examine whether the abnormal trading by financial experts around foreign block trades is significant. As before, for every day in the event window,  $t = (-5,+5)$ , around the foreign block trade for a given stock ( $i$ ), we conduct a difference-in-difference analysis to compare the abnormal trading by financial experts, relative to their own pre-event trading, with the analogous abnormal trading by the matched sample of ‘pseudo-expert’ retail investors, as follows:

$$AET_{i,j,t} = \text{abn\_trades\_expert}_{i,j,t} - \text{abn\_trades\_retail}_{i,j,t}.$$

Table 8 presents the mean abnormal expert trading activity ( $AET_t$ ) for each day in the event window,  $t = (-5,+5)$ , around the days with foreign block purchases or sales. It is noteworthy that the only evidence of significant *positive* abnormal expert trading in Table 8 occurs on day 0 or day  $-1$ . We focus on the evidence of significant abnormal expert trading prior to the block trade, on day  $-1$ .<sup>32</sup> The additional ‘abnormal’ number of trades by experts is on day

---

<sup>32</sup> When an institutional trade is executed on the Nasdaq Nordic Helsinki Exchange, the trade is immediately disclosed to the public. If an institution trades off-market through limit order books, then public disclosure of the

-1 is 59 (i.e.,  $0.027 \times 2,187$ ).<sup>33</sup> This number is the same as the difference between the number of financial expert trades and pseudo-expert trades on day -1 (i.e., 99) minus the average daily difference of 40 trades during the pre-event period.

Rows 2 to 6 of Table 8 show that this abnormal expert trading on day -1 is also significant for fund managers and ‘other’ experts, whereas board members reveal a significant decline in their trading activity on day -1. Rows 6 to 9 show that this expert trading on day -1 is significant for employees at brokerage firms. On the other hand, there is no evidence of significant abnormal trading on day -1 by access employees at the other two financial services firms, or through network trades.

#### *V.B.2. Abnormal Performance of Expert Trades Made on the Day Before Foreign Block Trades*

Table 9 conducts analysis similar to that in Table 7 for expert trades made on the day that corporate insider trades are executed. In Table 9 we focus on trades by financial experts made on the day before foreign block trades are executed (i.e., day -1). As before, we compute the mean signed  $CAR(+1, +10)$  and  $CAR(+1, +20)$  for the different groups of expert trades made on day -1.

The top row in Table 9 reveals that these trades on day -1 by all experts generate significant abnormal returns, with a mean signed 10-day  $CAR$  of 1.14% (p-value = 0.02) and a mean signed 20-day  $CAR$  of 2.29% (p-value = 0.00). This abnormal performance is also large in magnitude for experts working in all five functional roles, but is statistically significant only for

---

block trade occurs within 90 seconds. In contrast, for block trades in the over-the-counter (OTC) market, public disclosure can occur as late as three days after the trade. Since we cannot distinguish OTC block trades from other block trades, our focus in this section is on abnormal expert trading that occurs on the day *before* large block trades are executed.

<sup>33</sup> When an institution trades on the Helsinki Exchange, the trade is immediately disclosed to the public. If an institution trades off-market through limit order books, then public disclosure of the block trade occurs within 90 seconds. In contrast, for block trades in the over-the-counter (OTC) market, trade reporting can occur as late as three days after the trade. Since we cannot distinguish OTC block trades from other block trades, our focus in this section is on abnormal expert trading that occurs on the day *before* large block trades are executed, which we consider as front-running trades.

brokers, analysts and fund managers. Likewise, the abnormal performance is of similar magnitude for experts serving at all three types of financial services firms, but is significant only for experts at brokerage firms. Finally, this performance is also significant for both stand-alone trades and network trades, with a mean signed  $CAR(+1,+20)$  of 1.68% (p-value = 0.01) and 4.58% (p-value = 0.00), respectively.<sup>34</sup>

This subsection provides evidence consistent with the view that Finnish financial experts profit from trading in their own personal accounts, based on material private information about forthcoming block trades by foreign institutional investors. Similar to expert trading around corporate insider trades, our evidence suggests that this front running behavior is not limited to the brokers involved in the execution of the foreign orders, but may also involve the sharing of material inside information across the network of access employees at financial intermediaries.

### **V.C. Trading and Performance by Financial Experts around Block Trades by Domestic Finnish Mutual Funds**

In this subsection, we discuss similar analysis to that applied in subsection V.B., but we now focus on abnormal expert trading around days on which *domestic* Finnish mutual funds make block purchases or sales in a given stock. In the interest of brevity, we relegate the details and results to the Internet Appendix, and we just summarize the analysis here, as follows:

- We apply the same screens as in section V.C., to identify 452 *domestic* mutual fund block trade events across all Finnish stocks over the five-year sample period.
- Using a research design that is similar to our previous test of abnormal expert trading around block trades by foreign (non-Finnish) institutional investors, we find similar evidence of abnormal expert trading on day -1 that is significant for brokers and the access employees of brokerage firms. We also find evidence of significant abnormal trading on day -1 through network trades involving more than 1 expert.

---

<sup>34</sup> For expert trades made on the day that a foreign block trade is executed (i.e., day 0), we find a mean signed 10-day  $CAR$  of 0.65% (p-value = 0.08) and a mean signed 20-day  $CAR$  of 1.54% (p-value = 0.00). As observed in the previous footnote, we cannot claim that abnormal expert trading observed on day 0 is evidence of front running.

- When experts trade ahead of *domestic* mutual fund block trades on day -1, they generate significant abnormal returns, with a mean signed 10-day *CAR* of 2.45% (p-value = 0.01) and a mean signed 20-day *CAR* of 2.84% (p-value = 0.06).

#### **V.D. Trading and Performance by Financial Experts around Revisions of Recommendations by Analysts at the Same Brokerage Firm as the Expert Trading**

In this subsection we investigate trading by access employees around the release of revised recommendations by analysts who work at the same brokerage firm. Section 4.6.1 of the Instructions motivates these tests, stating that analysts and other persons exercising significant influence are “not permitted to make use of the information derived from market or corporate analyses for their own benefit or for the benefit of another nor give advice to another relating to a transaction in such a financial instrument prior to their publication.” Section 4.6.2 of the Instructions extends the period of this restriction on trading or information sharing, to also include the day of and the day after publication of the investment advice (i.e., days 0 and +1).

##### *V.D.1. Abnormal Trading by Financial Experts around Analyst Revisions at the Same Firm*

The Instructions discussed above can be interpreted as an explicit prohibition against any access employee trading in a stock (*i*) during the period leading up to publication of revisions of recommendations regarding this stock (*i*), which are generated by analysts working at the same brokerage firm. Thus, we argue that it is unnecessary to compare the trading activity of financial experts in this stock (*i*), relative to their own pre-event trading or the trading of a matched sample of retail investors. Instead, we define any expert trades over days (-5,+1) around such revisions by analysts working at the same firm as ‘abnormal.’

Figure 1.C plots the pattern in total trading per day during the period (-55,+5) around analyst revisions by colleagues at the same firm, for both financial experts and their matched group of pseudo-experts. This Figure shows that both groups have similar patterns in daily

trading during the pre-event period. If financial experts abide by the regulations described above, we would expect to see a decrease in trading activity by the group of financial experts closer to event day 0. However, the actual pattern is quite different, as both financial experts and pseudo-experts increase their trading as we move into the event window, with this activity peaking for financial experts on day -1.

Table 10 presents the total number of trades for the different groups of expert trades, summed across all analyst revision events ( $j$ ) for all stocks ( $i$ ), for every day in the event window,  $t = (-5, +5)$ . Note that this table provides no results for trading activity by fund managers, because the brokerage firms in our sample do not employ any experts who serve in this functional role (see Table 1). Likewise, we provide no evidence for trades by experts who work at fund management firms or asset management firms, since we only include trades by access employees at the brokerage firms that employ analysts and make public recommendations.

The top row of Table 10 indicates a maximum number of 91 expert trades on the day before the release of a revised recommendation by an analyst at the same firm. Furthermore, although explicitly prohibited in the Instructions, there are 68 and 57 trades, respectively, by experts at the same firm trading on the day of and the day following publication of the investment advice. This suspicious trading behavior is most prevalent among brokers, but it also appears among ‘other’ employees, the analysts themselves, and even board members. Finally, there are many cases of identical network trades by more than one expert in the same stock on the same day during the period,  $(-5, +1)$ .

*V.D.2. Abnormal Performance of Trades by Financial Experts around Revised Recommendations of Analysts at the Same Firm*

Panel A of Table 11 conducts analysis similar to that in Tables 7 and 9, for expert trades made in the three days before the release of revisions of recommendations by analysts at the same firm as the expert trading (day -3 through day -1). Panel B presents similar analysis for expert trades made on the day of and the day after these revisions are released (days 0 and +1).

The top row in Panel A of Table 11 indicates a total of 151 such events where one or more experts trade in the 3-day period before event day 0. The 10-day mean signed  $CAR(+1, +10)$  for these expert trades is 1.72% (p-value = 0.02), while the 20-day mean signed  $CAR(+1, +20)$  is 2.75% (p-value = 0.00). The next five rows reveal that these mean signed  $CARs$  are positive for all functional roles, but are only significant for brokers and analysts. Stand-alone trades do not have significant mean signed  $CARs$ . Instead, the profitable front running trades are concentrated among the group of network trades.

In contrast, Panel B of Table 11 reveals no evidence of significant outperformance for any groups of trades by financial experts that are made on the day of or the day after the release of analyst revisions. Overall, this evidence is consistent with the view that that Finnish financial experts violate Finnish securities law by trading ahead of revisions of recommendations by analysts at the same brokerage firm, and that this trading activity generates significant abnormal returns.

## **VI. SUMMARY AND CONCLUSIONS**

This study examines the personal trading activity of employees at Finnish financial institutions who are identified as having regular access to material private information. These ‘access employees’ include brokers, analysts, fund managers, board members, and other financial experts who work at brokerage firms, fund management firms, and asset management firms. This analysis is possible because Finnish insider trading laws require that all access

employees of securities intermediaries must publicly disclose all of their personal trades in any stock listed on the Nasdaq Nordic Helsinki Exchange.

We show that these financial experts generate significant short term abnormal returns, relative to other retail investors, when they trade for their own personal accounts. They earn particularly high mean abnormal returns when they trade simultaneously with other experts and when they trade before large price changes, earnings announcements, and revisions of recommendations by analysts. This significant abnormal performance is concentrated in the few days and weeks following the personal trades of these experts, and does not extend beyond one month.

It is possible that financial experts recognize and exploit such profitable trading opportunities by using only publicly available information. However, we present additional evidence which is also consistent with the conjecture that these experts trade in their own personal accounts based on valuable private information that is obtained through their profession or professional networks, prior to the time that this information is publicly available. In particular, we document increased trading activity in the personal accounts of these financial experts: (i) on the day that corporate insider trades are executed (which is four to seven days prior to public disclosure of these trades), (ii) on the day before execution of block trades by foreign and domestic institutional investors, and (iii) on the days before the release of revised recommendations by analysts working at the same firm. This personal trading activity generates mean cumulative abnormal returns that are statistically and economically significant.

Our evidence suggests that these financial experts may be engaging in illegal insider trading activities, by front running ahead of client orders and the release of proprietary analyst research, as well as by leaking this information through the network of access employees at



Finnish financial intermediaries. Taken together, this body of evidence is consistent with a breach of the securities laws in Finland by the access employees of Finnish financial institutions. This evidence is particularly remarkable given that it is gleaned from readily available data on the personal trades by these financial experts, who are required to publicly disclose all of their trading activity in any stock listed on the Nasdaq Nordic Helsinki Exchange. This analysis calls for further discussion of the costs and benefits of establishing similar regulation in the U.S. and elsewhere, which might compel public disclosure of all trading activity by the employees of financial institutions who have regular access to material private information. Of course, to enhance the fairness and integrity of financial markets, such regulation should be accompanied by adequate monitoring and enforcement to guard against the potential breach of securities law that is suggested by our analysis.

## References

- Berkman, Henk, Paul D. Koch, and Joakim Westerholm, "Informed Trading through the Accounts of Children," *Journal of Finance*, 69 (2014), 363-404.
- \_\_\_\_\_, "Inside the Director Network: When Insiders Trade Outside Stocks," Working Paper, 2017.
- Bhattachary, Uptal, "Insider Trading Controversies: A Literature Review," *Annual Review of Financial Economics* 6 (2014), 385-403.
- Bhattacharya, Utpal, and Hazem Daouk, "The World Price of Insider Trading," *Journal of Finance*, 4 (2002), 75–108.
- Blau, Benjamin, and Chip Wade, "Informed or Speculative Short Selling Analyst Recommendations," 2011, Working Paper.
- Booth, G. G., Lin, J. C., Martikainen, T., & Tse, Y. (2002). Trading and pricing in upstairs and downstairs stock markets. *The Review of Financial Studies*, 15(4), 1111-1135.
- Brown, Jeffrey R., Zoran Ivkovic, Paul A. Smith, and Scott Weisbenner, "Neighbors Matter: Causal Community Effects and Stock Market Participation," *Journal of Finance*, 63 (3) (2008), 1509–1531.
- Chakrabarty, Bidisha, and Andriy Shkilko, "Information Transfers and Learning in Financial Markets: Evidence from Short Selling around Insider Sales," *Journal of Banking and Finance* 37 (No. 5, 2013), 1560-1572.
- Christophe, Stephen, Michael Ferri, and Jim Hsieh, "Informed Trading before Analyst Downgrades: Evidence from Short Sales," *Journal of Financial Economics* 95 (2010), 85-106.
- Clauset, Aaron, Mark Newman, and Christopher Moore, "Finding Community Structure in Very Large Networks," *Physical Review E* 70, (Issue 6, 2004), 066111.

- Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, "The Small World of Investing: Board Connections and Mutual Fund Returns," *Journal of Political Economy*, 116 (2008), 951–979.
- Cohen, Lauren, Christopher Malloy, and Lukasz Pomorski, "Decoding Inside Information," *Journal of Finance* 67 (Issue 3, 2012), 1009-1043.
- Ellison, Glenn, and Drew Fudenberg, "Word-of-Mouth Communication and Social Learning," *Quarterly Journal of Economics* 110 (No. 1, 1995), 93-125.
- Fidrmuc, Jana P., Marc Goergen, and Luc Renneboog, "Insider Trading, News Releases, and Ownership Concentration," *The Journal of Finance*, 61 (6) (2006), 2931–2973.
- Griffin, John, Tao Shu, and Selim Topaloglu, "Examining the Dark Side of Financial Markets: Do Institutions Trade on Information from Investment Bank Connections?" *Review of Financial Studies* 25 (2012), 2155-2188.
- Grinblatt, Mark, and Matti Keloharju, "The Investment Behavior and Performance of Various Investor Types: A Study of Finland's Unique Data Set," *Journal of Financial Economics*, 55 (2000), 43–67.
- Grinblatt, Mark, Matti Keloharju, and Juhani Linnainma, "IQ, Trading Behavior, and Performance," *Journal of Financial Economics*, 104 (2012), 339–362.
- Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, "Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers," *The Journal of Finance*, 60 (2005), 2801–2824.
- Irvine, Paul, Marc Lipson, and Andy Puckett, "Tipping," *Review of Financial Studies* 20 (2007), 741-768.

- Ivkovic, Zoran, and Scott Weisbenner, “Local Does as Local Is: Information Content of the Geography of Individual Investors’ Common Stock Investments,” *Journal of Finance*, 60 (2005), 267-306.
- \_\_\_\_\_, “Information Diffusion Effects in Individual Investors’ Common Stock Purchases: Covet Thy Neighbors’ Investment Choices,” *Review of Financial Studies*, 20 (2007), 1327–1357.
- Jaffe, Jeffrey F., “Special Information and Insider Trading,” *Journal of Business*, 47 (No. 3, 1974), 410–428.
- Jeng, Leslie A., Andrew Metrick, and Richard Zeckhauser, “Estimating the Returns to Insider Trading: A Performance-Evaluation Perspective,” *Review of Economics and Statistics* 85 (No. 2, 2003), 453-471.
- Khan, Mozaffar, and Hai Lu, “Do Short Sellers Front-Run Insider Sales?” *The Accounting Review* 88 (No. 5, 2013), 1743-1768.
- Lakonishok, Josef, and Inmoo Lee, “Are Insider Trades Informative?” *Review of Financial Studies*, 14 (1, Spring) (2001), 79–111.
- Legal Information Institute, Cornell University Law School, “17 CFR 270.17j-1 – Personal Investment Activities of Investment Company Personnel,” July 9, 2004, <https://www.law.cornell.edu/cfr/text/17/270.17j-1>.
- McCann, Craig, “Detecting Personal Trading Abuses,” <https://www.sec.gov/rules/other/f4-433/mccann1.htm>.
- Ozsoylev, Han N., Johan Walden, M. Deniz Yavuz, and Recep Bildik, “Investor Networks in the Stock Market,” *Review of Financial Studies* 27, (No. 5, 2014), 1323-1366.

- Price Waterhouse Coopers (PwC) Report, “Avoiding the headlines: How financial services firms can implement programs to prevent insider trading,” 2011, a publication by PwC’s Financial Services Institute, available at <https://www.pwc.com/us/en/financial-services/publications/viewpoints/assets/viewpoint-insider-trading-prevention.pdf>.
- Ravina, Enrichetta, and Paola Sapienza, “What do Independent Directors Know? Evidence from Their Trading,” *Review of Financial Studies*, 23 (3) (2010), 962–1003.
- Securities and Exchange Commission, “SEC Extension of Rule 17j-1,” Federal Register Volume 80, Number 211, FR Doc No: 2015-27802, Nov. 2, 2015, pages 67452-67454, <http://www.federalregister.com/Browse/AuxData/D000A569-5E96-4BFC-8DB2-37444A469E1F>.
- Seyhun, H. Nejat, “Insiders’ Profits, Costs of Trading, and Market Efficiency,” *Journal of Financial Economics*, 16 (1986), 189–212.
- Shiller, Robert J., and John Pound, “Survey Evidence on the Diffusion of Interest and Information Among Investors,” *Journal of Economic Behavior*, 12 (1989), 47–66.

## Appendix A. Measurement of Firm Characteristics

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

Second, we transform each control variable into decile ranks by first sorting the cross section of stocks each day into 10 groups. Next, we assign a value to the stocks in each decile, where the values are adjusted to range from -0.5 (for the lowest decile) to +0.5 (for the highest decile). This adjustment serves to attenuate the influence of outliers.<sup>35</sup> The mean adjusted rank values in Panel B of Table 1 are then obtained by averaging these adjusted ranks across all stock trading days within every trade category.

---

<sup>35</sup> See Grinblatt, Keloharju and Linnainma (2012) and Berkman, Koch and Westerholm (2014) for similar analysis.

## Table 1. Summary of Personal Trading Activity by Access Employees at Financial Intermediaries

This Table presents summary statistics for personal trades by the five categories of access employees (brokers, analysts, fund managers, board members, and 'others') who work at the three types of securities intermediaries in Finland (brokerage houses, fund management firms, and asset management firms). These trading data are obtained from the public Insider Trading Registers of the 40 Finnish intermediaries who report the trades of these financial experts, and cover the 5-year period August 2006 - August 2011. Panel A summarizes the relative frequencies of the five categories of experts who work at the three types of firms along with their trading activity.

Panel B presents additional information about the purchases and sales by the five categories of financial experts, as well as by all other retail investors. For each category of trader, this information includes the total number of trades in our sample, the average number of shares traded, the average value (in €) of each trade, and the percentage of trades that constitute network trades. Network trades are defined as similar signed trades made in the same stock on the same day by more than one expert in our sample.

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

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

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

Table 1, continued

**Panel B. Summary Statistics for Trades by Different Categories of Financial Experts and All Other Retail Traders**

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Attributes of Trades					Attributes of Firms Traded						
Type of Trader	# Trades	% of all Trades	# Shares per Trade	Value (€) per Trade	% Network Trades	Size	Beta	MB	RYear	RMonth	RWeek	RDay
<b>Purchases</b>												
Broker	7,911	0.079%	1,270	5,398	47%	.25	.20	.02	-.07	-.09	-.05	-.04
Analyst	1,445	0.014%	796	4,831	50%	.24	.20	.00	-.05	-.06	-.03	-.03
Fund Mgr	2,343	0.023%	12,280	34,676	42%	.22	.18	.03	-.04	-.07	-.05	-.02
Board	3,131	0.031%	6,644	51,389	41%	.29	.23	.03	-.01	-.04	-.02	-.03
Other	7,062	0.071%	1,689	8,698	48%	.29	.22	.03	-.07	-.08	-.04	-.03
Retail	5,872,696	58.67%	991	7,013	-	.32	.23	.06	-.03	-.03	-.02	-.02
<b>Sales</b>												
Broker	5,397	0.054%	-1,781	-9,414	24%	.21	.19	-.01	-.04	.06	.04	.03
Analyst	938	0.009%	-1,998	-7,659	29%	.14	.15	-.04	-.02	.08	.01	.02
Fund Mgr	1,958	0.020%	-3,884	-30,589	23%	.19	.17	.01	-.01	.04	.02	.03
Board	2,112	0.021%	-9,998	-77,177	21%	.25	.20	.02	.02	.03	.03	.05
Other	4,051	0.040%	-4,414	-20,227	26%	.24	.19	.02	-.02	.05	.03	.02
Retail	4,101,047	40.97%	-1,326	-10,001	-	.29	.21	.06	.01	.02	.02	.03



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

This Table presents our analysis of the likelihood that the access employees of financial intermediaries will trade certain stocks, conditional on similar trades being made by other experts in the same professional network of each type, on the same day or the previous four days, as well as conditional on a major firm event occurring on the surrounding days. The panel logit model is specified in Equation (1) and is estimated separately for the purchases and sales of financial experts.

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

<sup>a</sup> Coefficients highlighted in **bold** are significant at the .10 level or better.

**Table 3. Performance of Recent Trades made by All Financial Experts**

This Table presents the mean Fama-MacBeth daily coefficients from estimating the following daily cross sectional regression model:

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

For each day ( $t$ ), the model is estimated separately for the cross sections of recent purchases or sales made by all retail accounts during the window covering days, ( $t-x, t-y$ ). When the control variables are excluded, the intercept  $b_0$  represents the average return on day  $t$  (in %) across the benchmark (omitted) group of recent retail trades made during this window, while the coefficient  $b_1$  indicates the mean abnormal return for analogous trades by all financial experts, relative to this benchmark return. Panel A presents the results for purchases and sales, respectively, that are made one day earlier. Panel B provides the mean daily abnormal return for earlier trades made over several non-overlapping windows. The left side of each Panel presents the evidence for purchases, and the right side for sales, with and without the control variables. The mean coefficients in the Table are averaged across all 1,268 trading days in the five-year sample period, August 2006 - August 2011. The p-values are based on Newey-West adjusted standard errors for the mean coefficients. Coefficients highlighted in **bold** are significant at the .10 level.

**Panel A. Mean Daily Coefficients from Equation (2) for Expert Trades: 1-day Portfolio Formation Window, ( $t-1, t$ )**

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

**Panel B. Mean Daily Coefficients from Equation (2) for Expert Trades: Earlier Portfolio Formation Windows**

Formation Window	days ( $t-x, t-y$ )		Purchases				Sales			
			Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
	( $t-7, t-2$ )	$b_1$	<b>.050%</b>	.00	<b>.047%</b>	.00	<b>-.029%</b>	.06	<b>-.029%</b>	.04
	( $t-30, t-8$ )	$b_1$	<b>.018%</b>	.03	<b>.022%</b>	.00	-.005%	.65	-.005%	.57
	( $t-90, t-31$ )	$b_1$	-.009%	.62	.001%	.85	-.022%	.31	.004%	.58
Controls:			no		yes		no		yes	

**Table 4. Performance of Different Groups of Trades by Financial Experts**

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

**Panel A. Mean Daily Abnormal Returns for Different Groups of Expert Purchases**

Dependent Variable:		Portfolio Formation Period Covering Days ( $t-x, t-y$ ) <sup>a</sup>			
Return on Portfolio of		( $t-1, t$ )	( $t-7, t-2$ )	( $t-30, t-8$ )	( $t-90, t-31$ )
Trades by:		Equation (2): Trades by All Experts			
1. All Experts	$b_1$	<b>.110%</b>	<b>.047%</b>	<b>.022%</b>	.001%
	p-value	0.01	0.00	0.00	0.85
Trades by:		Equation (3): Trades by Experts in the Five Functional Roles			
2. Brokers	$c_1$	<b>.147%</b>	<b>.028%</b>	<b>.023%</b>	.001%
	p-value	0.01	0.06	0.01	0.89
3. Analysts	$c_2$	<b>.196%</b>	<b>.062%</b>	<b>.087%</b>	-.004%
	p-value	0.01	0.10	0.01	0.74
4. Fund Managers	$c_3$	<b>.256%</b>	.055%	.025%	.018%
	p-value	0.01	0.12	0.15	0.14
5. Board Members	$c_4$	-.025%	.034%	.016%	-.004%
	p-value	0.56	0.15	0.31	0.70
6. Others	$c_5$	<b>.128%</b>	<b>.040%</b>	.011%	.000%
	p-value	0.00	0.02	0.30	0.96
Trades by Experts at:		Equation (4): Trades by Experts at the Three Types of Firms			
7. Brokerage Firms	$d_1$	<b>.120%</b>	<b>.043%</b>	<b>.023%</b>	-.003%
	p-value	0.00	0.00	0.00	0.63
8. Fund Mgt Firms	$d_2$	<b>.106%</b>	<b>.064%</b>	.011%	.014%
	p-value	0.03	0.01	0.45	0.17
9. Asset Mgt Firms	$d_3$	<b>.120%</b>	<b>.040%</b>	<b>.026%</b>	-.003%
	p-value	0.00	0.05	0.04	0.68
Identical Trades by:		Equation (5): Non-Network Trades versus Network Trades			
10. 1 Expert	$e_1$	<b>.065%</b>	<b>.052%</b>	<b>.027%</b>	.002%
	p-value	0.01	0.01	0.00	0.72
11. 2 Experts	$e_2$	<b>.132%</b>	<b>.059%</b>	<b>.027%</b>	.003%
	p-value	0.01	0.02	0.05	0.74
12. 3 or 4 Experts	$e_3$	<b>.194%</b>	.046%	.012%	-.006%
	p-value	0.01	0.16	0.48	0.65
13. 5 to 10 Experts	$e_4$	<b>.277%</b>	-.021%	.000%	.006%
	p-value	0.02	0.67	1.00	0.78
14. > 10 Experts	$e_5$	<b>.742%</b>	.194%	-.104%	-.045%
	p-value	0.06	0.21	0.13	0.48

Table 4, continued

## Panel B. Mean Daily Abnormal Returns for Different Groups of Expert Sales

Dependent Variable:		Portfolio Formation Period Covering Days ( $t-x, t-y$ ) <sup>a</sup>			
Return on Portfolio of		( $t-1, t$ )	( $t-7, t-2$ )	( $t-30, t-8$ )	( $t-90, t-31$ )
Trades by:		Equation (2): Trades by All Experts			
1. All Experts	$b_1$	<b>-.077%</b>	<b>-.029%</b>	-.005%	.004%
	p-value	0.00	0.04	0.57	0.58
Trades by:		Equation (3): Trades by Experts in the Five Functional Roles			
2. Brokers	$c_1$	-.061%	.000%	.010%	.009%
	p-value	0.13	0.99	0.51	0.30
3. Analysts	$c_2$	<b>-.256%</b>	.007%	-.033%	-.002%
	p-value	0.02	0.88	0.19	0.91
4. Fund Managers	$c_3$	-.026%	-.061%	-.023%	.000%
	p-value	0.70	0.12	0.29	0.99
5. Board Members	$c_4$	-.070%	-.012%	-.023%	-.001%
	p-value	0.24	0.77	0.26	0.95
6. Others	$c_5$	<b>-.088%</b>	<b>-.051%</b>	.007%	.000%
	p-value	0.04	0.09	0.53	0.99
Trades by Experts at:		Equation (4): Trades by Experts at the Three Types of Firms			
7. Brokerage Firms	$d_1$	-.052%	-.025%	.004%	.006%
	p-value	0.12	0.11	0.71	0.45
8. Fund Mgt Firms	$d_2$	.049%	-.009%	-.019%	.025%
	p-value	0.46	0.85	0.48	0.13
9. Asset Mgt Firms	$d_3$	<b>-.111%</b>	-.043%	-.014%	-.009%
	p-value	0.02	0.15	0.26	0.33
Identical Trades by:		Equation (5): Non-Network Trades versus Network Trades			
10. 1 Expert	$e_1$	<b>-.055%</b>	-.009%	-.005%	.005%
	p-value	0.04	0.51	0.60	0.49
11. 2 Experts	$e_2$	<b>-.116%</b>	-.074%	.002%	.013%
	p-value	0.08	0.11	0.93	0.28
12. 3 or 4 Experts	$e_3$	-.106%	-.041%	-.034%	.011%
	p-value	0.46	0.50	0.43	0.73
13. 5 to 10 Experts	$e_4$	-.234%	-.125%	-.057%	-.073%
	p-value	0.41	0.36	0.42	0.33
14. > 10 Experts	$e_5$	-.163%	<b>-.252%</b>	.122%	.017%
	p-value	0.13	0.08	0.28	0.85

<sup>a</sup> Mean daily abnormal returns highlighted in **bold** are significant at the .10 level or better.

**Table 5. Performance of Trades made by Financial Experts prior to Major Firm Events**

Panels A - D of this Table provide an event study analysis of the performance of trades made by financial experts in the three weeks prior to four kinds of firm-specific information 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. We measure the cumulative abnormal return on the day of and the day after each type of event,  $CAR(0,+1)$ . For net purchases by experts, we then use the  $CAR(0,+1)$ . For net sales, we 'sign' the  $CAR(0,+1)$  by multiplying it by -1. Then, for each event, we compute the average 'signed'  $CAR(0,+1)$  for the different groups of trades made by financial experts during each of the three days or weeks before each type of event. Finally, we calculate the mean of these average signed  $CAR(0,+1)$ s across all events where at least one expert traded during the relevant event window. The standard error of this mean signed  $CAR(0,+1)$  across all events is used to test the null hypothesis that the mean signed  $CAR(0,+1)$  is zero. Mean signed CARs highlighted in **bold** are significant at the .10 level.

**Panel A. Earnings Announcements**

	Mean Signed $CAR(0,+1)$	p-value	# Events with $\geq 1$ trade		Mean Signed $CAR(0,+1)$	p-value	# Events with $\geq 1$ trade
1 Day Before	<b>0.83%</b>	0.02	343	1 Week Before	<b>0.50%</b>	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 Analyst Recommendations**

1 Day Before	<b>0.36%</b>	0.01	842	1 Week Before	<b>0.29%</b>	0.00	1468
2 Days Before	<b>0.38%</b>	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. 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 D. Large Price Changes**

1 Day Before	<b>2.46%</b>	0.01	128	1 Week Before	<b>1.47%</b>	0.02	293
2 Days Before	1.06%	0.26	112	2 Weeks Before	<b>1.22%</b>	0.05	302
3 Days Before	<b>2.04%</b>	0.07	117	3 Weeks Before	0.37%	0.59	312

**Table 6. Abnormal Trading by Financial Experts around Corporate Insider Trades**

This Table analyzes the abnormal trading by different groups of experts in the days around the execution of insider trades (on day 0). First, for every expert, we select a retail investor who exactly matches the expert in terms of the number of trades made during that calendar year. Second, for each group of expert trades, for every day ( $t$ ) in the event window, and for each insider trade event ( $j$ ), we compute abnormal trading by experts ( $abn\_trades\_expert_{i,j,t}$ ) as the difference between the number of expert trades in the insider's stock ( $i$ ) on day  $t$  and the average daily number of expert trades in this stock ( $i$ ) during the pre-event window,  $t=(-55,-6)$ . Third, we also construct the analogous measure of abnormal trading for the matched sample of 'pseudo-expert' retail investors ( $abn\_trades\_retail_{i,j,t}$ ) for every day in the event window,  $t=(-5,+5)$ , for each insider trade event ( $j$ ). Fourth, the difference between these two measures of abnormal trading by experts versus retail investors is defined as our measure of *Abnormal Expert Trading* (i.e.,  $AET_{i,j,t} = abn\_trades\_expert_{i,j,t} - abn\_trades\_retail_{i,j,t}$ ). Finally, for each day in the event window,  $t=(-5,+5)$ , we compute the mean  $AET_t$  across all insider trade events ( $j$ ) in all stocks ( $i$ ), and we use the standard error of this mean to test the null hypothesis that the mean  $AET_t$  is zero. Figures highlighted in **bold** are significant at the .10 level or better.

	#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 Expert trades	1,207	-0.003	0.015	0.022	0.028	0.028	<b>0.093</b>	-0.001	0.008	-0.005	0.017	0.010
p-value		.87	.45	.31	.32	.27	.00	.96	.72	.82	.42	.63
2. Brokers	1,051	0.007	-0.003	0.017	0.021	0.001	<b>0.034</b>	-0.019	-0.005	-0.007	0.014	-0.002
p-value		.62	.82	.26	.20	.96	.07	.21	.74	.65	.33	.89
3. Analysts	608	-0.015	0.013	0.013	0.006	0.009	<b>0.029</b>	0.024	0.013	0.004	0.001	0.016
p-value		.12	.24	.22	.66	.44	.02	.11	.23	.64	.92	.14
4. Fund Managers	663	-0.006	-0.003	0.006	0.013	<b>0.031</b>	-0.003	0.016	-0.001	0.014	-0.006	-0.009
p-value		.64	.84	.55	.34	.05	.88	.28	.93	.25	.68	.52
5. Board Members	684	-0.007	0.000	-0.013	0.006	-0.013	<b>0.025</b>	0.009	<b>0.022</b>	-0.001	0.002	0.015
p-value		.51	.99	.31	.62	.34	.09	.45	.04	.91	.89	.15
6. Others	984	0.007	0.015	0.005	-0.005	0.015	<b>0.044</b>	-0.013	-0.007	-0.010	0.007	0.000
p-value		.61	.29	.71	.78	.36	.02	.53	.63	.47	.59	.99
7. Brokerage Firms	1,145	-0.007	0.019	0.026	0.032	0.014	<b>0.073</b>	-0.012	0.017	-0.014	0.011	0.014
p-value		.64	.25	.13	.16	.48	.00	.54	.33	.40	.52	.40
8. Fund Mgt Firms	757	-0.001	-0.011	-0.012	-0.002	-0.002	0.015	0.009	-0.014	0.011	-0.006	-0.011
p-value		.96	.36	.31	.89	.90	.34	.52	.27	.39	.65	.40
9. Asset Mgt Firms	879	0.006	0.006	0.007	-0.002	0.021	0.020	0.006	0.001	0.002	0.014	0.005
p-value		.66	.63	.56	.89	.17	.21	.73	.92	.86	.25	.74
10. 1 Expert trading	1,203	0.000	0.020	-0.005	<b>0.033</b>	<b>0.036</b>	0.023	-0.002	<b>0.022</b>	-0.011	0.010	0.009
p-value		.97	.14	.75	.03	.02	.13	.89	.10	.43	.49	.54
11. >1 Expert trading	602	-0.007	-0.011	0.053	-0.011	-0.017	<b>0.141</b>	0.001	-0.027	0.013	0.014	0.003
p-value		.83	.75	.16	.84	.71	.03	.98	.50	.71	.68	.94

**Table 7. Performance of Trades made by Financial Experts on the Day that Corporate Insider Trades are Executed**

This Table presents the mean 'signed' CARs over the 10 or 20 days following different groups of trades made by financial experts on the day that corporate insider trades are executed (i.e., day 0). For net purchases by experts we use the CAR. For net sales we 'sign' the CAR by multiplying it by -1. The p-values are based on the standard errors of the mean 'signed' CARs. We also provide the number of events (*n*) for which at least one expert in each group trades the stock on the day of the event (i.e., day 0). Figures highlighted in **bold** are significant at the .10

Groups of Trades	CARs following Expert Trades made on the day (0) that Corporate Insider Trades are Executed		
	CAR(1,10)	CAR(1,20)	<i>n</i>
1. All Expert trades p-value	<b>0.96%</b> .05	<b>1.63%</b> .01	255
2. Brokers p-value	0.94% .12	<b>1.24%</b> .10	131
3. Analysts p-value	1.97% .25	1.56% .45	26
4. Fund Managers p-value	1.08% .37	.60% .72	29
5. Board Members p-value	.70% .47	1.34% .33	57
6. Others p-value	1.20% .17	<b>2.17%</b> .03	110
7. Brokerage Firms p-value	<b>1.02%</b> .07	<b>1.33%</b> .04	188
8. Fund Mgt Firms p-value	.79% .40	2.17% .16	45
9. Asset Mgt Firms p-value	0.89% .33	1.48% .18	83
10. 1 Expert p-value	<b>0.95%</b> .08	<b>1.44%</b> .03	202
11. >1 Expert trading p-value	.85% .35	1.81% .13	65

**Table 8. Abnormal Trading by Experts around the Block Trades of Foreign Financial Institutions**

This Table analyzes abnormal trading by different groups of experts in the days around block trades by foreign institutions. First, for every expert we select a retail investor who exactly matches the expert in terms of the number of trades during that calendar year. Second, for each group of expert trades, for every day ( $t$ ) in the event window, and for each block trade event ( $j$ ), we compute abnormal trading by experts ( $abn\_trades\_expert_{i,j,t}$ ) as the difference between the number of expert trades in the stock ( $i$ ) on day  $t$  and the average daily number of expert trades in this stock ( $i$ ) during the pre-event window,  $t = (-55,-6)$ . Third, we construct the analogous measure of abnormal trading for the matched sample of 'pseudo-expert' retail investors ( $abn\_trades\_retail_{i,j,t}$ ) for every day in the event window,  $t = (-5,+5)$ , for each block trade event ( $j$ ). Fourth, the difference between these two measures is our measure of *Abnormal Expert Trading* (i.e.,  $AET_{i,j,t} = abn\_trades\_expert_{i,j,t} - abn\_trades\_retail_{i,j,t}$ ). Finally, for each day in the event window,  $t = (-5,+5)$ , we compute the mean  $AET_t$  across all block trade events ( $j$ ) in all stocks ( $i$ ), and we use the standard error of this mean to test the null hypothesis that the mean  $AET_t$  is zero.

	#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 Expert trades	2,187	<b>-0.024</b>	-0.010	0.021	-0.002	<b>0.027</b>	<b>0.050</b>	-0.008	0.012	-0.004	-0.003	-0.012
p-value		.04	.50	.14	.86	.06	.06	.54	.39	.76	.80	.34
2. Brokers	1,795	-0.006	-0.011	0.004	-0.010	0.015	0.018	-0.011	-0.001	-0.014	0.006	0.000
p-value		.51	.24	.72	.25	.12	.15	.21	.92	.13	.46	.97
3. Analysts	922	<b>-0.010</b>	0.001	0.008	0.006	0.005	0.003	-0.001	-0.002	0.012	0.002	0.011
p-value		.05	.94	.32	.44	.49	.81	.94	.84	.11	.79	.14
4. Fund Managers	1,208	-0.007	0.001	0.004	0.000	<b>0.017</b>	0.017	0.000	0.010	0.007	0.004	0.004
p-value		.39	.92	.63	1.00	.07	.23	1.00	.32	.45	.61	.58
5. Board Members	1,205	<b>-0.016</b>	0.000	0.005	-0.003	<b>-0.020</b>	0.017	<b>-0.016</b>	0.001	0.004	-0.006	-0.008
p-value		.03	.98	.53	.71	.03	.12	.04	.89	.67	.50	.28
6. Others	1,772	-0.002	-0.002	0.012	0.006	<b>0.017</b>	0.020	0.013	0.009	-0.004	-0.010	<b>-0.018</b>
p-value		.75	.79	.18	.49	.03	.29	.13	.33	.61	.21	.04
7. Brokerage Firms	2,047	-0.009	-0.010	0.018	-0.003	<b>0.019</b>	<b>0.031</b>	-0.007	0.007	-0.008	0.005	-0.003
p-value		.37	.38	.14	.75	.09	.10	.53	.51	.51	.60	.75
8. Fund Mgt Firms	1,415	-0.009	-0.004	-0.006	0.000	0.007	0.012	-0.005	-0.007	0.002	-0.003	-0.015
p-value		.23	.64	.48	.96	.40	.38	.58	.46	.84	.70	.05
9. Asset Mgt Firms	1,564	<b>-0.013</b>	0.003	0.012	0.001	0.006	0.019	0.002	0.014	0.003	-0.009	0.001
p-value		.07	.73	.14	.86	.49	.13	.80	.12	.72	.27	.85
10. 1 Expert trading	2,178	<b>-0.018</b>	0.001	0.009	0.007	0.015	0.005	-0.007	-0.004	0.001	0.006	-0.009
p-value		.05	.92	.38	.43	.12	.63	.45	.71	.92	.53	.34
11. >1 Expert trading	930	-0.014	-0.026	0.030	-0.023	0.028	<b>0.105</b>	-0.001	0.037	-0.012	-0.022	-0.008
p-value		.47	.39	.26	.35	.30	.08	.96	.19	.63	.31	.72

<sup>a</sup> Figures highlighted in **bold** are significant at the .10 level or better.



**Table 9. Performance of Trades made by Experts on the Day before Block Trades by Foreign Institutions**

This Table presents the mean signed CARs over the 10 or 20 days following different groups of trades made by experts on the day before foreign financial institutions buy or sell large blocks of stock. For net purchases by experts we use the CAR. For net sales we 'sign' the CAR by multiplying it by -1. We then present the mean 'signed' CARs for the different groups of trades made by financial experts on day -1 before the foreign block trades are executed (on day 0). The p-values are based on the standard errors of the mean 'signed' CARs. We also provide the number of events (*n*) for which at least one financial expert in each group trades the stock on the day before the foreign block trade is executed. Figures highlighted in **bold** are significant at the .10 level or better.

Groups of Trades	CAR(1,10)	CAR(1,20)	<i>n</i>
1. All Expert trades	<b>1.14%</b>	<b>2.29%</b>	288
p-value	.02	.00	
2. Brokers	<b>1.17%</b>	<b>2.16%</b>	137
p-value	.08	.01	
3. Analysts	1.33%	<b>5.62%</b>	23
p-value	.49	.02	
4. Fund Managers	-.48%	<b>2.42%</b>	63
p-value	.59	.04	
5. Board Members	.75%	2.18%	35
p-value	.48	.11	
6. Others	1.41%	1.20%	107
p-value	.13	.22	
7. Brokerage Firms	<b>1.54%</b>	<b>2.44%</b>	186
p-value	.01	.00	
8. Fund Mgt Firms	-.73%	1.78%	61
p-value	.43	.16	
9. Asset Mgt Firms	1.04%	1.89%	80
p-value	.31	.11	
10. 1 Expert	<b>.88%</b>	<b>1.68%</b>	238
p-value	.07	.01	
11. 2 Experts	2.25%	<b>4.58%</b>	55
p-value	.12	.00	

**Table 10. Trading Activity by Financial Experts around Revisions of Recommendations by Analysts at the Same Firm as the Expert Trading**

This Table presents the total number of trades by different groups of financial experts in the days around revisions of recommendations (which are released on day 0) by analysts working at the same brokerage firm as the expert trading. Note that this sample includes only the trades of experts at brokerage firms (which publish analyst recommendations). Given the explicit prohibition against any trading by a brokerage firm's access employees in the period leading up to publication of revisions by analysts at the same firm, we define any such expert trades over days (-5,+1) as 'abnormal.'

Groups of Expert Trades	Day in the Event Window Relative to the Day that the Analyst Revision is Released (on Day 0)										
	-5	-4	-3	-2	-1	0	1	2	3	4	5
1. All Expert trades	43	47	64	45	91	68	57	73	59	53	62
2. Brokers	30	28	34	30	53	40	27	31	20	25	28
3. Analysts	3	2	6	6	9	9	13	12	15	9	13
4. Fund Managers <sup>a</sup>	-	-	-	-	-	-	-	-	-	-	-
5. Board Members	2	2	3	1	8	3	3	4	7	2	2
6. Others	8	15	21	8	21	16	14	26	17	17	19
7. Brokerage Firms	43	47	64	45	91	68	57	73	59	53	62
8. Fund Mgt Firms <sup>a</sup>	-	-	-	-	-	-	-	-	-	-	-
9. Asset Mgt Firms <sup>a</sup>	-	-	-	-	-	-	-	-	-	-	-
10. 1 Expert trading	26	21	33	25	47	49	37	38	30	32	42
11. >1 Expert trading	17	26	31	20	44	19	20	35	29	21	20

<sup>a</sup> This sample only includes experts at brokerage firms. Panel A of Table 1 shows that there are no fund managers employed at the brokerage firms in our sample.

**Table 11. Performance of Trades by Financial Experts on the Days Around Revisions of Recommendations by Analysts at the Same Firm**

Panel A of this Table presents the mean signed *CARs* over the 10 or 20 days following different groups of trades made by financial experts on the three days before the release of revised recommendations by analysts at the same brokerage firm as the expert trading. Panel B provides analogous results for expert trades made on the day of and the day after the revision is released. Note that the sample includes only the trades of experts at brokerage firms (which publish analyst recommendations). For net purchases by experts we use the *CAR*. For net sales we 'sign' the *CAR* by multiplying it by -1. In Panel A (or B) we present the mean 'signed' *CARs* for the different groups of trades made by experts on the three days before (or the day of and the day after) the analyst revision is released (on day 0). The p-values are based on the standard errors of the mean 'signed' *CARs*. We also provide the number of events (*n*) in which at least one expert in each group trades the stock on the three days before (or the day of and the day after) the analyst revision is released. Figures highlighted in **bold** are significant at the .10 level or better.

**Panel A. *CARs* following Expert Trades made on Days (-3, -2, or -1)**

Groups of Trades	<i>CAR</i> (1,10)	<i>CAR</i> (1,20)	<i>n</i>
1. All Expert trades p-value	<b>1.72%</b> .02	<b>2.75%</b> .00	151
2. Brokers p-value	1.11% .23	<b>2.15%</b> .06	92
3. Analysts p-value	<b>8.05%</b> .00	<b>10.31%</b> .00	19
4. Fund Managers <sup>a</sup>	-	-	-
5. Board Members p-value	3.31% .20	1.97% .37	11
6. Others p-value	.14% .92	1.56% .32	43
7. Brokerage Firms p-value	<b>1.72%</b> .02	<b>2.75%</b> .00	151
8. Fund Mgt Firms <sup>a</sup>	-	-	-
9. Asset Mgt Firms <sup>a</sup>	-	-	-
10. 1 Expert p-value	.01% .99	.79% .49	81
11. 2 Experts p-value	<b>2.99%</b> .01	<b>4.45%</b> .00	76

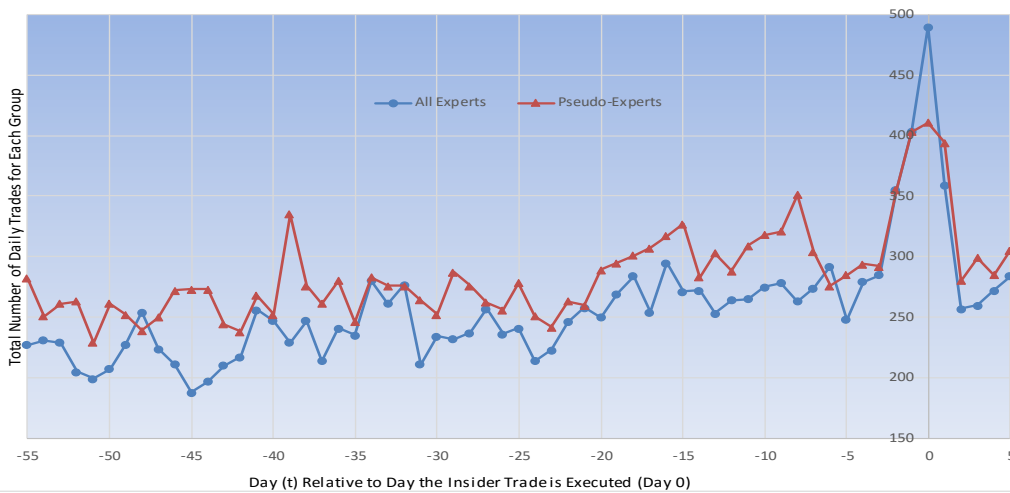
Table 11, continued

**Panel B. CARs following Expert Trades made on Days (0 or +1)**

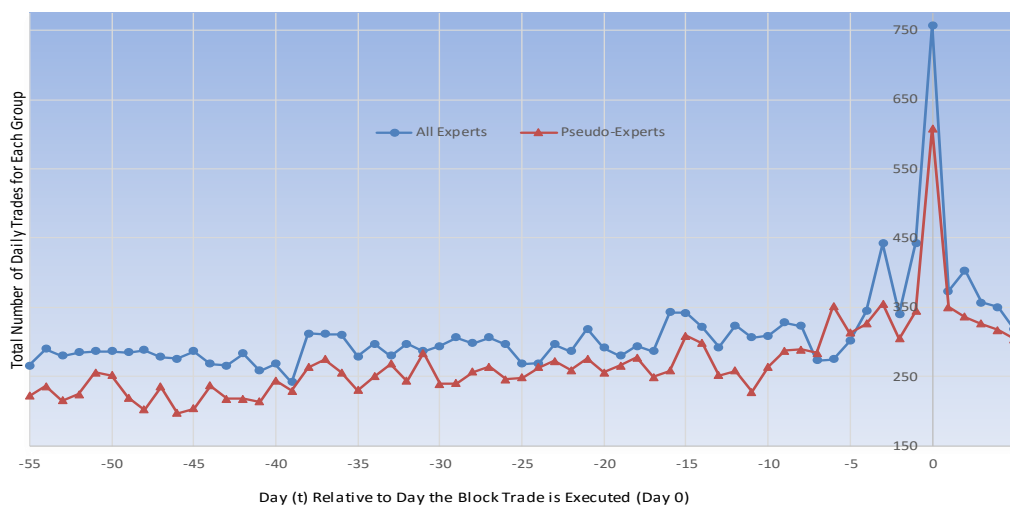
Groups of Trades	<i>CAR(1,10)</i>	<i>CAR(1,20)</i>	<i>n</i>
1. All Expert trades	.38%	.10%	111
p-value	.53	.90	
2. Brokers	.24%	.17%	63
p-value	.76	.88	
3. Analysts	2.45%	.93%	18
p-value	.25	.65	
4. Fund Managers <sup>a</sup>	-	-	-
5. Board Members	-1.48%	-3.65%	5
p-value	.19	.20	
6. Others	.02%	-.12%	28
p-value	.98	.92	
7. Brokerage Firms	.38%	.10%	111
p-value	.53	.90	
8. Fund Mgt Firms <sup>a</sup>	-	-	-
9. Asset Mgt Firms <sup>a</sup>	-	-	-
10. 1 Expert	1.16%	.51%	62
p-value	.16	.66	
11. 2 Experts	-.69%	-.47%	51
p-value	.42	.66	

<sup>a</sup> This sample only includes experts at brokerage firms. Panel A of Table 1 shows that there are no fund managers employed at the brokerage firms in our sample.

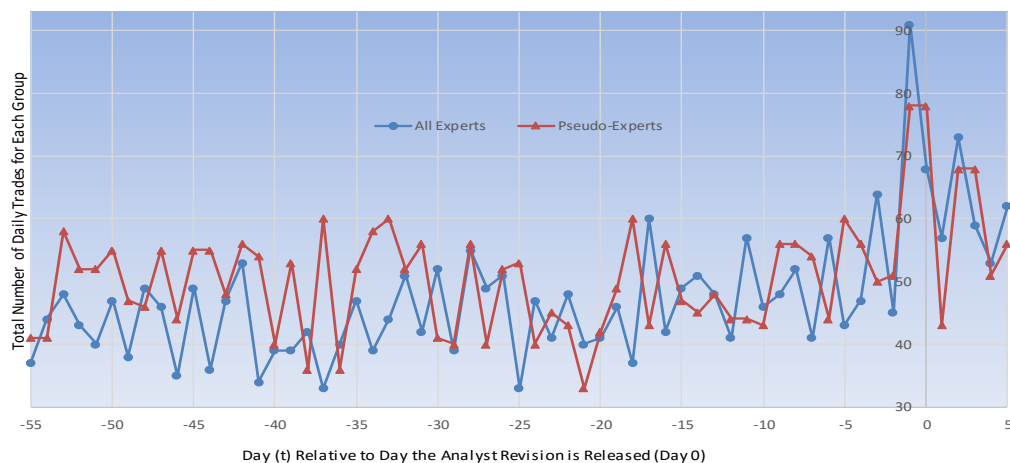
**Figure 1.A. Daily Number of Trades by All Experts and Pseudo-Experts over Event Period covering Days (-55,+5) around Corporate Insider Trades**



**Figure 1.B. Daily Number of Trades by Experts and Pseudo-Experts over Event Period Covering Days (-55,+5) around Foreign Block Trades**



**Figure 1.C. Daily Number of Trades by All Experts and Pseudo-Experts over Event Period covering Days (-55,+5) around Analyst Revisions at Same Firm**



## INTERNET APPENDIX

### Trading and Performance by Financial Experts around Days with Block Trades by Domestic Finnish Mutual Funds

In this Internet Appendix we investigate abnormal expert trading around days on which Finnish mutual funds make block purchases or sales in a given stock. This analysis is again motivated by Sections 2.7 and 4.1 of the Instructions, as discussed above. We follow a similar procedure to section V.B., and identify these block trading day events as follows.

First, we consider the Euroclear accounts of the equity market mutual funds belonging to the six largest Finnish mutual fund families that publicly disclose the trading activity of their access employees. These funds comprise more than 90 percent of the domestic market share of all mutual funds in Finland (in terms of total net asset value).<sup>36</sup> Second, on each day ( $t$ ), and for every stock ( $i$ ), we aggregate the net order flow (i.e., shares bought minus shares sold) across all of these domestic mutual funds. Third, we compute average daily total volume for every stock ( $i$ ) during each calendar year of our sample period, August 2006 - August 2011. Finally, for each stock ( $i$ ) we select the days every year for which the absolute value of the aggregate net order flow by these mutual funds is more than twice the average daily total volume for that year. As before, we exclude any such ‘block trade’ days that occur within three days after another block trade day for the same stock. This procedure identifies 452 domestic mutual fund block trade events across all Finnish stocks over the five-year sample period. Most Finnish stocks are represented in this sample, with a maximum number of 18 block trade events for a single stock (which is 4.0 percent of all block trade events in our sample).

#### *I.A.1. Abnormal Trading by Financial Experts around the Block Trades of Mutual Funds*

---

<sup>36</sup> We match the holdings of Finnish public mutual funds as reported in Bloomberg with the holdings of mutual funds in Euroclear. We find almost exact matches on all holdings for fifteen funds belonging to six fund families.

We begin by assigning event day 0 to the day with a mutual fund block trade event ( $j$ ). Internet Appendix (I.A.) Figure 1 plots the daily total number of trades by all financial experts and the matched sample of pseudo-experts, respectively, over the 65-day event period  $(-55,+5)$  surrounding mutual fund block trades. Similar to the behavior in Figure 1.B, during most of the pre-event window, the group of financial experts makes an average of 18 more trades per day than the pseudo-experts. Over the remaining days in the event window  $(-5,+5)$ , the largest difference in trading activity between the two groups occurs on day 0, when experts make 59 more trades than the matched sample of pseudo-experts. The second largest difference appears on day +2, with 51 more trades by experts, followed by day -1, when experts make 40 more trades.

Next, for every day in the event window,  $t = (-5,+5)$ , around each mutual fund block trade event ( $j$ ), we again conduct a difference-in-difference analysis to compare the abnormal trading by financial experts, relative to their own pre-event trading, with the analogous abnormal trading by the matched sample of ‘pseudo-expert’ retail investors. I.A. Table 1 presents the mean abnormal expert trading activity ( $AET_t$ ) for each day in the event window,  $t = (-5,+5)$ , around the days with mutual fund block purchases or sales. The top row of I.A. Table 1 indicates significant abnormal trading across all experts on days -5, -1, 0 and +2. When we focus on the significant front running activity on day -1, the ‘abnormal’ number of trades by experts is 22 (i.e.,  $0.051 \times 431$ ). This number is the same as the difference between the total number of financial expert trades and pseudo expert trades on day -1, 40, minus the average daily difference of 18 trades during the pre-event period. Rows 2 and 7 of I.A. Table 1 show that this abnormal expert front running activity on day -1 is significant only for brokers and the access employees of

brokerage firms, respectively. The last row of I.A. Table 1 also reveals evidence of significant front running on day -1 through network trades involving more than 1 expert.

*I.A..2. Abnormal Performance by Financial Experts around Block Trades of Mutual Funds*

I.A. Table 2 provides our analysis of the abnormal performance of expert trades made on the day before the execution of mutual fund block trades (on day -1). The top row in I.A. Table 2 reveals that these front running trades generate significant abnormal returns, with a mean signed 10-day *CAR* of 2.45% (p-value = 0.01) and a mean signed 20-day *CAR* of 2.84% (p-value = 0.06). This abnormal performance is large in magnitude for financial experts in all five functional roles, but it is statistically significant only for fund managers, due to the small number of events where experts trade when each functional role is examined separately. Similarly, the abnormal performance is statistically significant for employees at brokerage firms and asset management firms. Finally, the mean signed *CARs* are only significant for stand-alone expert trades, due to the paucity of network trades prior to these events.<sup>37</sup>

The evidence in this Internet Appendix is consistent with the view that Finnish financial experts profit from trading in their own personal accounts based on private information about forthcoming block trades by Finnish mutual funds. As with expert trading around corporate insider trades and foreign block trades, the evidence suggests that this behavior is not limited to the brokers involved in the execution of the orders, but is shared and acted upon across the network of access employees at financial intermediaries.

---

<sup>37</sup> For the expert trades on day 0, we find a mean signed 10-day *CAR* of 2.25% (p-value = 0.03) and a mean signed 20-day *CAR* of 1.83% (p-value = 0.16). Note that we cannot claim that the abnormal activity observed on day 0 is evidence of front running (see footnote 33).



### I.A. Table 1 Abnormal Trading by Experts around the Block Trades of Domestic Financial Institutions

This Table analyzes abnormal trading by different groups of experts in the days around block trades by Finnish mutual funds. First, for every expert we select a retail investor who exactly matches the expert in terms of the number of trades made during that calendar year. Second, for each group of expert trades, for every day ( $t$ ) in the event window, and for each block trade event ( $j$ ), we compute abnormal trading by experts ( $abn\_trades\_expert_{i,j,t}$ ) as the difference between the number of expert trades in the stock ( $i$ ) on day  $t$  and the average daily number of expert trades in this stock ( $i$ ) during the pre-event window,  $t = (-55,-6)$ . Third, we construct the analogous measure of abnormal trading for the matched sample of 'pseudo-expert' retail investors ( $abn\_trades\_retail_{i,j,t}$ ) for every day in the event window,  $t = (-5,+5)$ , for each block trade event ( $j$ ). Fourth, the difference between these two measures is our measure of *Abnormal Expert Trading* (i.e.,  $AET_{i,j,t} = abn\_trades\_expert_{i,j,t} - abn\_trades\_retail_{i,j,t}$ ). Finally, for each day in the event window,  $t = (-5,+5)$ , we compute the mean  $AET_t$  across all block trade events ( $j$ ) in all stocks ( $i$ ), and we use the standard error of this mean to test the null hypothesis that the mean  $AET_t$  is zero.

	#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 Expert trades	431	<b>0.048</b>	-0.030	-0.003	-0.019	<b>0.051</b>	<b>0.095</b>	-0.005	<b>0.076</b>	-0.014	0.002	0.048
p-value		.06	.53	.92	.43	.06	.03	.86	.01	.74	.95	.11
2. Brokers	354	0.021	-0.035	-0.015	-0.004	<b>0.038</b>	0.004	0.007	<b>0.044</b>	-0.007	0.004	0.021
p-value		.21	.17	.36	.81	.09	.85	.74	.06	.78	.81	.27
3. Analysts	204	0.006	0.002	-0.018	-0.008	0.002	0.011	0.002	0.016	-0.033	-0.018	-0.003
p-value		.66	.91	.14	.60	.91	.54	.92	.21	.13	.29	.84
4. Fund Managers	229	0.030	0.008	-0.009	-0.022	-0.005	0.021	0.000	-0.009	0.035	0.004	0.000
p-value		.15	.69	.50	.12	.79	.34	.98	.66	.21	.78	.98
5. Board Members	258	0.000	-0.012	0.019	0.011	0.011	<b>0.031</b>	0.007	<b>0.031</b>	<b>0.042</b>	0.019	0.011
p-value		.97	.45	.26	.43	.38	.09	.62	.05	.02	.17	.48
6. Others	384	0.013	0.000	0.013	-0.007	0.016	<b>0.063</b>	-0.018	0.021	-0.041	-0.007	<b>0.029</b>
p-value		.38	.98	.41	.63	.21	.02	.26	.21	.36	.72	.06
7. Brokerage Firms	401	0.020	-0.020	0.005	0.010	<b>0.057</b>	0.029	-0.008	<b>0.074</b>	-0.035	-0.003	<b>0.042</b>
p-value		.31	.57	.84	.64	.02	.36	.73	.00	.32	.91	.10
8. Fund Mgt Firms	297	0.012	-0.028	-0.021	<b>-0.032</b>	-0.011	-0.001	-0.005	0.012	0.019	0.012	0.006
p-value		.49	.12	.15	.02	.37	.94	.71	.49	.30	.35	.70
9. Asset Mgt Firms	328	<b>0.029</b>	0.010	0.010	-0.008	0.007	<b>0.090</b>	0.007	-0.002	0.007	-0.005	0.007
p-value		.07	.59	.45	.62	.62	.00	.68	.90	.78	.77	.65
10. 1 Expert trading	427	<b>0.037</b>	-0.015	-0.010	-0.029	0.009	-0.003	-0.015	<b>0.042</b>	0.002	0.014	-0.001
p-value		.09	.49	.63	.14	.66	.90	.50	.08	.94	.52	.98
11. >1 Expert trading	187	0.027	-0.037	0.016	0.022	<b>0.097</b>	<b>0.225</b>	0.022	0.081	-0.037	-0.026	<b>0.113</b>
p-value		.40	.72	.69	.48	.01	.01	.66	.11	.68	.64	.04

<sup>a</sup> Figures highlighted in **bold** are significant at the .10 level or better.

## I.A. Table 2. Performance of Trades made by Experts on the Day before Block Trades by Finnish Mutual Funds

This Table presents the mean signed CARs over the 10 or 20 days following different groups of trades made by experts on the day before domestic financial institutions buy or sell large blocks of stock. For net purchases by experts we use the CAR. For net sales we 'sign' the CAR by multiplying it by -1. We then present the mean 'signed' CARs for the different groups of trades made by financial experts on day -1 before the domestic block trades are executed (on day 0). The p-values are based on the standard errors of the mean 'signed' CARs. We also provide the number of events (*n*) for which at least one financial expert in each group trades the stock on the day before the foreign block trade is executed. Figures highlighted in **bold** are significant at the .10 level or better.

Groups of Trades	CAR(1,10)	CAR(1,20)	<i>n</i>
1. All Expert trades	<b>2.45%</b>	<b>2.84%</b>	52
p-value	.01	.06	
2. Brokers	1.93%	1.58%	27
p-value	.13	.53	
3. Analysts	3.08%	4.92%	5
p-value	.34	.38	
4. Fund Managers	<b>3.35%</b>	<b>5.94%</b>	8
p-value	.10	.07	
5. Board Members	2.37%	.50%	7
p-value	.39	.87	
6. Others	1.65%	5.73%	13
p-value	.60	.22	
7. Brokerage Firms	<b>2.68%</b>	2.91%	40
p-value	.02	.14	
8. Fund Mgt Firms	.87%	5.07%	4
p-value	.80	.49	
9. Asset Mgt Firms	<b>3.43%</b>	<b>6.31%</b>	13
p-value	.03	.09	
10. 1 Expert	<b>3.41%</b>	<b>3.00%</b>	44
p-value	.00	.04	
11. 2 Experts	-.44%	3.75%	9
p-value	.91	.60	

I.A. Figure 1. Daily Number of Trades by Experts and Pseudo-Experts over Event Period Covering Days (-55,+5) around Mutual Fund Block Trades

