Institutional and retail investor trading behavior in equity markets

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Institutional and retail investor trading behavior in equity markets

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Through three essays, this dissertation elucidates households and institutional investors' stock trading behaviour and its applications to asset pricing.

The first chapter utilizes seventeen years of comprehensive daily portfolio and trading data to analyse the relative trading performance of the universe of households, all domestic financial institutions, and all foreign institutions, in the Finnish market. I introduce a new methodology, dubbed "holding-period-invariant" portfolios, which is demonstrably superior to the conventional calendar-time methodology. Adopting a random informationless trading benchmark, I find that the households who choose to trade for themselves are economically and statistically the superior trades, achieving an impressive internal rate of return of 42.84 percent p.a., against foreign institutions. Households located near company headquarters have a clear informational advantage against all-comers.

The second chapter extends the HPI methodology to relate gender to stock trading performance using data on all individual Finnish investor trades over 1995-2011. Female investors make significant gains against male investors when trading major Finnish stocks, consistent with females tending to have a better ability as per the "theory of mind," and hence better recognizing data patterns with superior trading intuition. Further, female investors prefer purchasing underpriced and selling overpriced stocks based on the trading signal of the difference between the contemporaneous price and moving averages over the short term to the long term. The result holds even after excluding spouse trading accounts, especially in regions close to Nokia and other company headquarters.

The third chapter makes an "apples-to-apples" comparison between hedge funds and "other institutions" such as mutual funds' trading performance. Eleven years of data on daily portfolios on institutional transactions suggests that hedge funds are economically and statistically smarter traders with "other institutions" as exclusive counterparties, consistent with some empirical literature. The superior trading performance of hedge funds can be explained by their receipt of daily private signal of fundamental value received from the entire history of informed trades and prices, statistically rejecting the nested noisy partially revealing rational expectations equilibrium hypothesis.

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ORIGINALITY STATEMENT

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Signed ....

Date

I would like to dedicate this dissertation to my loving parents for everything they’ve given up

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Abstract

Through three essays, this dissertation elucidates households and institutional investors' stock trading behavior and its applications to asset pricing.

The first chapter utilizes seventeen years of comprehensive daily portfolio and trading data to analyze the relative trading performance of the universe of households, all domestic financial institutions, and all foreign institutions, in the Finnish market. I introduce a new methodology, dubbed "holding-period-invariant" portfolios, which is demonstrably superior to the conventional calendar-time methodology. Adopting a random informationless trading benchmark, I find that the households who choose to trade for themselves are economically and statistically superior traders, achieving an impressive internal rate of return of 42.84 percent p.a., against foreign institutions. Households located near company headquarters have a clear informational advantage against all-comers.

The second chapter extends the *HPI* methodology to relate gender to stock trading performance using data on all individual Finnish investor trades over 1995-2011. Female investors make significant gains against male investors when trading major Finnish stocks, consistent with females tending to have a better ability as per the "theory of mind", and hence better recognizing data patterns with superior trading intuition. Further, female investors prefer purchasing underpriced and selling overpriced stocks based on the trading signal of the difference between the contemporaneous price and moving averages over the short term to the long term. The result holds even after excluding spouse trading accounts, identified by matching family names, especially in regions close to Nokia and other company headquarters.

The third chapter makes an "apples-to-apples" comparison between hedge funds and "other institutions" such as mutual funds' trading performance. Eleven years of data on the

daily portfolios and institutional transactions suggests that hedge funds are economically and statistically smarter traders with “other institutions” as exclusive counterparties, consistent with some empirical literature. The superior trading performance of hedge funds can be explained by their receipt of a daily private signal of fundamental value derived from the entire history of informed trades and prices, statistically rejecting the nested noisy partially revealing rational expectations equilibrium hypothesis.

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Chapter 1

Introduction

1.1 Objectives of the Dissertation

This dissertation examines how individual and delegated institutional investors make investment decisions in stock markets and the relative trading performance between individual and institutional investors, also making intragroup comparisons within individual and institutional investor groups. The aim of this dissertation is to address three questions corresponding to the existing literature in measuring investors' trading performance. Following the growing interest in the Kyle (1985) model, which assumes an irrational group of "noise traders" that systematically lose money to informed traders, rather than postulating that two counterparties are fully rational, I develop a new informed traders trading model to evaluate collective individuals' investment decisions. Hence, the first question is whether, at the aggregate level, households who choose to manage their own portfolio are truly less informed than institutional investors. As I find that is not the case, the second question arises: within this group of household investors, when all trades in the entire market are considered, with males as one counterparty and females as the other, which group is the dominant trader in the long term? The role of gender in stock markets is of increasing interest to academics, regulators, and practitioners. Third, this dissertation proposes to answer a more mainstream question in the investment management industry: what is the relative trading ability of hedge fund managers pitted against "other institutional investors", mainly mutual funds and plan sponsors in the U.S. stock market? Do the more performance-based incentives of hedge fund managers really result in superior trading performance?

Taken together, these three investigations form the basis of determining whether behavioral biases and informed trading are present in the Finnish and U.S. investment industry, and in particular, whether individual and institutional investor trading behavior is detrimental to their managed portfolio performance and overall market efficiency.

1.2 Motivation and Importance of the Dissertation

A growing body of theoretical and empirical work highlights the importance of investor trading behavior in driving asset prices and investment and consumption decisions. The preponderance of research in modern economics has been built on the notion that human beings are rational agents who attempt to maximize their expected utility given their risk preferences. These agents have their own level of risk aversion and prudently access all possible investment options corresponding to certain risk and return combinations. The most remarkable asset pricing model based on these assumptions is the Capital Asset Pricing Model introduced by Treynor (1961, 1962), Sharpe (1964), Lintner (1965a, b) and Mossin (1966) independently, documenting investors' well-diversified portfolio comprising a market portfolio and a risk-free investment. This is followed by the seminal work of the rational expectations models by Grossman and Stigliz (1980) who conclude that, as informed traders receive an informed signal that approaches perfection, the market will close down, or become illiquid, because the stock price will be fully reflective of information. However, Ou-Yank and Wu (2017) reveal a flaw in their key theorem, such that the stock price in the Grossman-Stiglitz model can never fully reflect all the information possessed by the informed trader, leaving scope for the informed to continue to trade aggressively. Hence, a market can be both fully efficient and simultaneously highly liquid. Kim and Verrecchia (1991, a, b), Wang (1993, 1994), Brennan and Cao (1996, 1997), Orosel (1998), Spiegel (1998), and Watanabe (2008) extend the rational expectations approach. Brennan and Cao (1997) argue that there is a dichotomy between foreign and domestic investors with the latter being more informed.

Numerous researchers, starting with Jensen (1968), have examined the skill of a fund manager and have used a variety of methods. Through the late 1990s, more published studies have focused almost exclusively on the performance of institutional investors, and in particular, mutual funds. This was partially driven by data availability. Overall, the results are mixed. While the study of institutional investor performance remains an active research area, much of it is now focused on hedge funds. This research topic is studied in depth in Chapter 4.

In the investment world, trading is always a zero-sum game. For every buy, there is a sell. If one investor outperforms the market, a subpar investor's portfolio wealth must depreciate. Collectively, the earnings of investors with superior trading abilities must exceed the market return before considering costs. Hence, in the financial market, the trading behavior of the notable number of individual investors, who comprise another important investor category, as the exclusive counterparty of institutional investors, deserves more attention by researchers. Furthermore, from a macroeconomic perspective, individual investor participation in the stock market is important. If more retail investors participate in the stock market, this contributes to the liquidity of capital markets, and liquid capital markets allow firms to have a reliable alternative funding channel to traditional banking. This in turn results in faster economic growth. Their funding thus helps shape the country's economic structure by allocating funds among different industries and sectors.

With a few notable exceptions (e.g., Kaniel, Saar, and Titman, (2008), Kaniel, Liu, Saar, and Titman, (2012), and Kelley and Tetlock (2013)), the evidence indicates that individual investors are not able to beat the market (see e.g., Grinblatt and Keloharju (2000) and Barber and Odean's (2013) excellent survey). A large body of empirical research argues that individual investors behave differently from institutional investors by holding under-diversified portfolios. They are supposedly uninformed and less skilled traders compared with delegated money managers. Moreover, as a group, individual investors make biased buying and selling decisions, influenced by the media and current fads and fashions. Furthermore, as per these critics, transaction cost is another unambiguous factor dragging down individual investors' overall portfolio performance as they allegedly trade too much. Some studies even claim to show that individual investors earn poor returns even before considering costs of trading. Thus, the mainstream literature encourages individuals to pool their money in money manager funds to avail of the fund managers' superior ability to extract information and make sound investments decisions on behalf of households.

By contrast, Hayek (1945) argued that every individual possesses unique information that provides him with an advantage, but only if he is the one to make his own critical decisions free of agency issues. Thus, following Hayek (1945), one would expect that collective individuals who possess private information to forecast future stock performance would choose to use it themselves to maximize utility over their lifetime and not delegate investments to professionals (or at least not entirely). Hence, in the entire stock market, some individual investors will be well informed while others will make their investment decisions based on public information already reflected in prices.

With data obtained from Euroclear Finland Ltd (formerly Finnish Central Securities Depository), Chapter 2 starts with an examination of relative trading performance between individual and domestic institutional investors, individual and foreign institutional investors, and domestic institutional and foreign institutional investors in the Finnish stock market by adopting a new methodology dubbed as the "holding-period-invariant" (*HPI*) portfolio approach.

The reason for introducing a new *HPI* methodology is that the conventional calendar-time portfolio approach (*C-T*) that is widely used in the literature to measure relative trading performance has serious limitations. The survey by Barber and Odean (2013) provides a summary of this *C-T* portfolio approach and related literature. Their methodology imposes uniform holding periods for all investor categories in the sense that positions are assumed to no longer be held post the determined holding period. This assumption is unrealistic. In addition, the buy and sell portfolios record the presence of trades but not their magnitude. Thus, a value-weighting approach along the lines of the present contribution possesses advantages over an equal-weighting approach. The *HPI* methodology, in addition to offering the advantages documented by the *C-T* portfolio approach, also utilizes the actual trades of an investor group and their matched counter-parties, without imposing a heroic assumption of a fixed portfolio turnover horizon. Hence, the profit and loss measured in *C-T* precisely captures the timing ability of each trading party to foresee future price movements.

Corresponding to the important role played by individual investors' investment activities in the financial market, this dissertation proceeds to explore another research topic that has received more attention within the individual investor category. By splitting the entire universe of investors in the Finnish market into four sub-groups, including males, females, non-males and non-females investors,[1] Chapter 3 examines the gender difference on the effect of trading performance in the Finnish stock market. There have been an extensive academic literature documents that gender effect in a number of different domains, including consumption, labor market, investment and corporate governance (e.g. compensation among top executives), but less amount of researches contributed to examine the relative trading performance between males and females investors in the stock market. To my best of knowledge, this dissertation is the first study to deliberately conduct 'apples to apples' comparisons using matched trades in the pairs of trading groups to evaluate whether males, as a group of investor, show their overconfidence and too much trading activities (e.g., Sunden and Surette (1998), Agnew, Balduzzi, and Sunden (2003), Eckel and Grossman (2008), Croson and Gneezy (2009), Bertrand (2011), as well as Niederle (2014)) documented in the corresponding existing literature and thus female investors as the exclusively counterparty outperform.

Individual investors are no longer targeted in the fourth chapter, as it expands the scope to the well-documented yet active research topic – examining the relative trading performance of hedge funds and "other institutional investors" (i.e., mutual funds and plan sponsors) in the U.S. market. As the existing literature focuses on the *C-T* portfolio approach, I borrow the new *HPI* methodology, first conducting matched trades in a group of trading pairs to investigate institutional investor investment decisions. Given the mixed results in the literature and the recent extremely volatile economic environment, a key issue that should attract the attention of investors who hire money managers for their assets is finding a precise methodology to evaluate and compare money managers' performance to meet their return and risk objectives. Furthermore, regulators are also concerned the risk-taking behaviors of different types of money managers, in particular during financial crises. Their mission is to ensure market stability and provide investor protection for fund industry investors. Hence, this chapter first conducts actual matched trades in pairs of trading groups without imposing heroic assumptions about fixed portfolio rebalancing

[1] Non-males investors include the female investors and all institutional investors plus all other categories of investor. Non-females investors refer to the male investors and all institutional investors plus all other categories of investor.

time intervals and provides an analysis identifying managers, who are likely informed, that utilize their superior ability to beat the market in both the short and long term. Next, it attempts to understand the informed managers' trading signal based on the model of informed trading developed in Lu, Swan and Westerholm (2016).

This dissertation limits itself to examining trades between different counterparties such as households and delegated money managers, male and female investors, and hedge fund managers and "other institutional investors", rather than analyzing the performance of their overall stock portfolios and the degree of commonality between the portfolios held by different investor types. Thus, this dissertation does not claim to offer a comprehensive treatment of the overall performance of all investor types; it rather concentrates on differences in both knowledge and timing abilities that are reflected in matched counterparty trades over extended time periods.

The theoretical framework in this dissertation crystallizes the importance of endogenous market timing ability's role in investors' portfolio performance. The first main finding of this dissertation is that households would be better off if they invest independently rather than seek agents such as fund managers to manage their portfolios; this contrasts the suggestions of the existing literature. The second findings suggest that females on average are smarter than males in stock trading activities. The third study shows that hedge fund managers have superior trading abilities over mutual fund managers and plan sponsors; this is consistent with previous findings. In the process, this dissertation presents researchers, regulators, and practitioners with a better understanding of the role of individual and institutional investors in the transmission of information to markets, and thereby elucidates whether the trading behaviors of investors aid or hinder market efficiency.

1.3 Structure and Contents of the Dissertation

The remainder of this dissertation is organized as follows. Chapter 2 first introduces the new *HPI* framework to examine and compare the trading behavior between Finnish households and both domestic and foreign institutional investors over a period of seventeen years from 1995 to 2011. By employing the same comprehensive data set, Chapter 3 extends this new *HPI* theoretical model within collectively individuals' groups to investigate whether the gender effect is anticipated in the Finnish stock market. Chapter 4 applies the *HPI* methodology to discuss the trading behavior of professional managers, another important investor group, focusing on the U.S stock market. Chapter 5 concludes the dissertation.

1.4 Summary

This chapter offers a brief summary of how this new *HPI* portfolio methodology is vital in assisting academies, regulators, and practitioners to understand individual investors and fund managers' trading behaviors, outlines this dissertation's structure, and presents its contribution to the extant literature.

The *HPI* portfolio approach employs actual daily common trades between each pair of trading groups at the investor level and does not impose a heroic assumption on portfolio turnover, in contrast to the conventional *C-T* portfolio approach that mechanically rebalances portfolios at the same assumed intervals but for different investor categories. It builds upon the framework of the efficient market hypothesis (partially noisy expectation models), investigating the impact of private trading signals and conducting comparisons between individual and institutional investors, and within individual investor and institutional investor groups across three important dimensions: risk aversion, overconfidence, and mutual trust.

Chapter 2

"Other People's Money": The Trading Performance of Household Investors vs. Delegated Money Managers

“Other People’s Money” 1991. Danny DeVito’s character: “I love money. ... There are only three things in this world with ... unconditional acceptance: dogs, doughnuts and money. Only money is better. You know why? Because it don’t make you fat and it don’t poop all over the living room floor. There’s only one thing I like better. Other people’s money.”

2.1 Introduction

This paper has limited aims. In particular, I am only concerned with trades between different counterparties such as households and delegated money managers and not at all with the performance of their overall stock portfolios and the degree of commonality between the portfolios held by different investor types. Thus I do not claim to offer a comprehensive treatment of the overall performance of each investor type but rather concentrate on differences in both knowledge and timing ability that are reflected in matched counterparty trades over extended time periods.

With a few exceptions (e.g., Kaniel, Saar, and Titman, (2008), Kaniel, Liu, Saar, and Titman, (2012), and Kelley and Tetlock (2013)), nearly all research contrasting the performance of individual household and professional investors finds that delegated money managers outperform (see e.g., Grinblatt and Keloharju (2000) and Barber and Odean’s (2013) excellent survey). By contrast, Hayek (1945) in his classic article highlighted the impossibility of delegating private information by pointing out that every individual possesses unique information that provides him with an advantage, but only if he is left to make his own critical decisions free of agency issues.[1] Thus, following Hayek (1945), one would expect that individually and collectively households who possess private information about future stock performance would choose to act on it themselves to maximize utility over their lifetime and not delegate to professional investors (or at least not entirely). Overall it is expected that some individual investors will be well informed while others will make their investment decisions based on public information already reflected in price. The informed individuals may have access to valuable private information as a result of their profession, their network of connections or their insider status (see Berkman, Koch and Westerholm (2014) who show that the investigated market has a significant number of informed individual investors). The uninformed individual investors on the other hand

[1] In his classic best-seller, The Road to Serfdom (1944), Hayek argued the benefits of economic freedom and markets over central planning, essentially because markets are better aggregators of individual information than are central planners and statisticians.

would be expected to equally often be on the wrong side as they are on the right side of the market, hence in my analysis the aggregate individual investor performance will be driven by the skill of the informed traders in the category.

Over longer-term horizons, individual households that determine their own portfolios as principals, in some cases taking advice from brokers and financial advisors, should thus perform better than do delegated institutional investors investing other people's money. In fact, it would be quite surprising if individuals who choose to trade for themselves and thus self-select into what they are relatively good at do not outperform. Individuals who underperform are naturally weeded out when they eventually run out of funds. While households generally do better than either domestic or foreign institutional investors, the overall winners both in terms of the magnitude of the gain and internal rate of return are domestic institutional investors pitted against foreign institutional investors. For this paired category the locational advantages of domestic funds typically located geographically close to most major company headquarters dominate any relatively minor differences in agency considerations between domestic and foreign institutions.

While households possess a natural advantage over institutions in being able to time the inflow and outflow of funds themselves, it would appear that the overall superior trading ability of households is due to informational advantage. When I pit households located close to the Nokia headquarters in a trading battle with households in the remainder of the country, the more geographically advantaged households prove to be superior. Moreover, households located close to Nokia have a clear trading advantage over both domestic and foreign institutions while more distant households only have a clear advantage over foreign institutions. The clear trading superiority of domestic over foreign institutions is due to geographic proximity. So called "home bias"[2] ceases to be a bias as it defines "home informational superiority".

Institutional investors on the other hand, particularly those that outperform relative to other institutional investors, will presumably survive even when their household clients collectively lose. Moreover, institutional investors will presumably act as agents of relatively uninformed individuals that are reluctant to trade on their own behalf as Brennan and Cao (1996) point out, and for those that have no choice. Thus, one might expect inferior

[2] Choe, Kho and Stulz (2005) document that domestic investors have an edge over foreign investors in the Korea stock market. Dvořák (2005) also find Indonesia domestic investors have higher profits than foreign investors.

delegated performance in the long-run as most lose other people's money rather than their own.[3] There is no clear market mechanism to penalize delegated money managers when they all make losses due to trend following in a herding equilibrium, unlike individuals who lose their own money. Nonetheless, I find that domestic institutions possess considerably more information than do their foreign counterparts and are thus far superior traders in this contest.

In this paper, I find strong empirical support for Hayek's vision when utilizing the collective individual daily trade portfolio of hundreds of thousands households in Finland and the corresponding matched portfolios of all domestic and all foreign institutional investors using a new Holding Period Invariant (*HPI*) methodology. This new methodology contrasts with the conventional Calendar-Time (*C-T*) methodology that figures prominently in the survey by Barber and Odean (2013). The existing literature is based largely on *C-T* portfolios, or related methods, which impose specified investor horizons. At the end of each horizon, be it a day, week, month, or six months, the portfolio is realized and the entire process begins over again irrespective of, or in contradiction to, the actual trades that are generally known to the researcher. Barber and Odean (2013) conclude that "as a group, many individual investors seem to have a desire to trade actively coupled with perverse security selection ability." Barber and Odean (2001) also conclude that "boys will be boys" due to overconfidence and excessive trading. However, these findings may well be a consequence of the methodology used which imposes counterfactual trading at regular intervals rather than reflecting the actual trading ability of individual investors and also the assumption of a 4% round-trip trading costs incurred with a discount broker. I essentially replicate the Barber and Odean (2001) analysis by sorting households into highly active and more passive traders to find that active traders earn 29% trading profitability rate and passive, 42% trading profitability rate[4], when trading with Foreign Nominee institutional investors. Thus I concur with Barber and Odean that highly active trading can lead to lower performance, but nonetheless reject their finding that households are poor performers in general.

To exposit a little more about the popular *C-T* methodology, it is based on an entirely false premise: Performance can be inferred from a single buy or sell transaction. Thus, an

[3] Lakonishok et al. (1992), Coval and Stafford (2007) and Chevalier and Ellison (1999a, 1999b) all identify agency issues that are associated with delegated managers.

[4] The measure of trading profitability rate is defined as the total trading profits after transaction cost divided by the total trading value. I show the results in the following performance tables

agent who buys before a stock price increase or sells prior to a price fall is definitionally superior to an agent who does the reverse. “Smart people anticipate price rises by buying in advance while only dumb ones sell prior to the stock going up in value”. Nothing could be further from the truth. This almost universally adopted methodology confuses “trend following” with “information” while ignoring the actual stock-timing element. To know whether or not an agent performed requires not one but two trading pieces of information: at what price did the the agent buy and at what price did the agent sell, or vice versa? That is, trading performance can only be determined by a consideration of actual completed round-trip trades. While it sounds obvious, this is the basis of the new Holding Period Invariant (HPI) methodology put forward in this thesis for the first time. By contrast, the *C-T* methodology has the name, “Calendar”, in it because it falsely assumes that agents are beholden to the passage of time when they trade. For example, the popular monthly calendar-time portfolio method implicitly assumes that if a “buy” occurs in a particular month that the same asset is sold at the end of that month, regardless of the actual month the asset was sold, perhaps a year or two years later when prices are entirely different from those at the end of the designated month. The researcher presumably knows the actual timing of round-trip trades and thus the actual profit or loss, but ignores this by reporting the false profit or loss based on an end-of-month realization that never happened.

To make valid comparisons between investor categories my analysis include time-windows split into four carefully selected sub-periods to capture the full business cycle of boom and bust: First, January 3, 1995 to December 31, 1996, which is the period analyzed by Grinblatt and Keloharju (2000). Second, is the period, January 3, 1997 to July 3, 2003, which is an extended high-tech bubble period of a “bull” followed by a “bear” market. The third period, July 4, 2003 to March 6, 2009, is the boom prior to the financial crisis including the subsequent collapse following the demise of Lehman Brothers, and the fourth, March 7, 2009 to December 30, 2011, is the post financial crisis recovery. Finally, I analyze the entire period, 1995 to 2011, inclusive. Thus my period of analysis includes two “bull-bear” sequences plus the lead-up, and the post financial crisis of 2007/2008 environment. Since foreign nominees are trend followers and households contrarian, foreign nominees will invariably perform better during any given up-swing or down-swing. Valid comparisons require an entire cycle (here from trough to trough), otherwise short-term trend followers will normally dominate with contrarian traders falsely seen to be systematic losers. I also replicate my analysis using periods defined as the troughs in the Finnish Consumer Confidence Index (CCI) with quite similar results.

As an indication that these long-term performance differences are not trivial, I find that domestic households trading directly with foreign institutional investors outperform by EUR 4.92 billion in just one stock alone (Nokia) over a 17-year period. This represents a remarkable internal rate of return (IRR) of 42.84 percent p.a. for households trading with foreign delegated money managers (i.e., foreign nominees). Had households simply bought over the entire period with realization only at the end, the counterfactual “BuyOnly” IRR would have been exceedingly lower with a loss-making return of -25.15 percent p.a.. This indicates the grossly misleading nature of “buy and hold” portfolio analyses that ignore the actual timing of trades.

Domestic households also outperform domestic institutional investors by EUR 354 million, generating a lower IRR of 13.18 percent p.a., and these same domestic institutional investors outperform foreign nominees by a massive EUR 14.1 billion over the same period with an even higher IRR of 51.79 percent p.a. that exceeds the household performance with the same counterparty.[5] Focusing only on trades between different categories of counterparties, trading becomes a zero sum game in my analysis. Hence a negative return almost identical in magnitude[6] applies to the counterparties of domestic households and domestic institutional investors such as foreign nominees. In fact, as far as I am aware, mine is the first to analyze trading performance as a zero sum game. I believe it is the only way in which meaningful trading comparisons can be made.

I confirm the statistical significance of these findings at the 0.001 probability level based on 10,000 Monte Carlo simulations utilizing a random trading direction benchmark.[7] The reason that these numbers for Nokia are so large is not just Nokia’s huge size but, more importantly, its performance as one of the world’s greatest “bubble” stocks, rising in value by around 50-fold during the “high-tech bubble” period prior to its collapse.[8] Adding

[5]The reason that these numbers for Nokia are so large is not just Nokia’s huge size but, more importantly, its performance as one of the world’s greatest “bubble” stocks, rising in value by over fifty-fold during the “high-tech bubble” period (Abreu and Brunnermeier (2003))due entirely from buying pressure from Foreign Nominee (largely U.S. institutional investors) prior to its collapse. Since this group of U.S. investors was the most distant and thus least informed this experience supports the conjecture of Alti, Kaniel, and Yoeli (2012) that trend-following is most likely when the institutional investor is least informed.

[6]The reason there can be minor differences is because of differential transaction costs.

[7]I thank Michael Brennan for suggesting this test.

[8]Heterogeneous Agent Models (HAM) has had some success explaining the boom-bust cycle. See Hommes (2006) for a survey and Boswijk, Hommes, and Manzan (2007) and Hommes and Daan in’t Veld (2014) for applications to stocks.

another 32 major Finnish stocks raises these magnitudes, but not hugely. Consequently, not only is there clear evidence of the influence of agency issues affecting delegated portfolio managers as households outperform domestic institutions but, additionally, there is also evidence of the better known 'home informational bias'[9] as foreign institutions collectively lose EUR 20,809 million to domestic institutions and households in just 32 top Finnish stocks over my data period.

Could the trading policy giving rise to sustained long-term trading losses incurred by foreign delegated money managers simply represent rational actions by these agents acting fully in the interests of their principals, namely households? I can only answer this from the perspective of counterparty trading as I cannot rule out the possibility that foreign investors gained diversification benefits that might have outweighed trading losses. The noisy partially revealing rational expectations literature originating with Hellwig (1980), Kim and Verrecchia (1991, a, b), Wang (1993, 1994), Brennan and Cao (1996, 1997), Orosel (1998), Spiegel (1998), and Watanabe (2008) contends that such equilibria can exist even when one counterparty is far more informed than the other. In the Appendix B, I both test and reject this hypothesis for the various matched counterparties I consider. Each informed party appears to receive a private signal of expected fundamental value that differs significantly from the rational expectations equilibrium in which all past prices are fully discounted. The daily trading pattern of collective buys and sells is not compatible with rational expectations, further supporting my contention that delegated money managers suffer from severe agency problems. With rational expectations not only should stock prices follow a random walk without sequential prices being highly correlated and mean reverting but, in addition, trade magnitude and direction, i.e., order-flow, should be random and thus not strongly positively auto-correlated, as I find.

In practice, do private information and agency considerations matter when considering investment performance? Griffin, Harris, Shu, and Topaloglu (2011) conclude that the most "sophisticated market participants", largely hedge funds, "actively purchased technology stocks during the (high-tech) run-up and quickly reversed course in March 2000, driving the collapse". These investors presumably suffer from two agency issues is particular: First, they cannot directly access collective private information signals received by the many hundreds of thousands of household accounts in my sample who conduct their own

[9] See, for example, Coval and Moskowitz (1999), and for an application to real estate, Chinco and Mayer (2015).

trades and, second, they lost other people’s money, not their own. This is important, as there is natural attrition of households that lose their personal wealth via trading and may learn that they would be better off delegating but loss-making institutional investors may continue trading as long as they relatively outperform other institutional investors. Similarly, Edelen, Ince and Kadlec (2016) show that institutions have a strong tendency to buy stocks classified as overvalued. DeVault, Sias, and Starks (2016) subject the standard assumption that institutional investors’ represent “smart money” to close scrutiny by showing that to the contrary, institutions, not households, destabilize markets by irrational sentiment-based demand shocks.

I believe mine is the first study to focus deliberately on an “apples with apples” comparison over relevant time-periods without imposing mandated investor horizons and implied stock turnover rates that have limited or no applicability to these collective investor-types. This means I overcome the problem that two investor-type groups might have similar portfolio alphas based on factor models assuming a fixed investment horizon but in exceedingly volatile markets may earn entirely different realized trading profits due to one having better private market timing ability and information than the other. Since market timing is endogenous rather than mechanical and exogenous, and is also reliant on both the incentives and information base of the trader, any comparison of agent-type performance requires a performance measure that both recognizes and rewards stock-timing ability.

2.2 Literature Review

There has been a long history of findings based on the *C-T* portfolio approach that purports to show that, in terms of trading ability, households (i.e., individual investors) significantly underperform. The survey by Barber and Odean (2013) provides a summary of this *C-T* portfolio and related literature. Using the trading records of 10,000 accounts from a discount brokerage house over the seven-year period, 1987-1993, Odean (1999), with imposed horizons of four months, one year, and two years, examines the difference between equally-weighted *C-T* portfolio buy and sell returns to obtain a raw return difference of -23 basis points per month or 2.76 percent p.a.. Their methodology imposes forced uniform holding periods for all investor categories in the sense that positions are assumed to no longer be held after the applied set holding period. Apart from the problems induced by imposing counter-factual realizations, this *C-T* methodology suffers from an additional problem in that the buy and sell portfolios record the presence of trades but not their magnitude. Thus, a value-weighting approach along the lines of the present contribution possesses advantages over an equal-weighting approach.

Barber and Odean (2000) examine trading from 78,000 accounts for a discount brokerage over the six-year period ending in January 1997. They conclude that household accounts underperform the market, largely due to round-trip transaction costs that are assumed to be an incredible 4 percent. Broker fees and spread costs of this magnitude seem high for clients of discount brokers. In common with Odean (1999), they conclude that household investors are overconfident insofar as transaction costs incurred as a result of trading reduce returns below index returns that assume, counterfactually, that they can be matched without portfolio rebalancing. Neither study of discount broker client trades is in a position to know who the counterparties of these household trades are and thus how they relatively performed as they do not have comparable institutional trades and stock turnovers. Consequently, these studies do not tell us if institutional investor trading performance is any better or worse than this relatively limited household experience that can only be compared with an index that requires some costly trading to replicate.

If there truly is a dichotomy between my findings for Finnish households and that of some US individual clients of a discount broker, it could be due in part to differences in the educational systems. The educational attainments of Finnish students in test scores is the second highest in the OECD whereas the USA is at the OECD mean (OECD, 2010). Similarly, an OECD (2016) survey of 52,000 adults in 30 countries tested their financial knowledge and rated on how they behave, and feel, about money. France ranked highest overall, with a score of 14.9 out of a possible 21, followed closely by Finland.

Grinblatt and Keloharju (2000) analyze the first two years of detailed Finnish trading data when it became available, namely 1995-1996, to conclude that foreign institutional investors in Finnish stocks outperform what they term "unsophisticated" Finnish households. They only focus on a short six-month horizon to derive their results which unlikely to capture the performance of longer-horizon, largely household traders. Their methodology imposes forced holding periods on these two groups ranging from one day to six months. Swan and Westerholm (2016) replicate the precise methodology of Grinblatt and Keloharju (2000) but extend their sample by an additional eight years to find that Finnish households generally outperform Foreign Nominees for other than the two-year Grinblatt and Keloharju (2000) sample period. When I repeat their analysis for their two-year period with essentially identical data but without imposing fixed horizons I find, to the contrary, that households outperform their foreign investor counterpart. For the entirety of 1996 Finnish households outperform foreign nominees in trading Nokia with a modest cumulative gain of about Euros 3 million and a corresponding cumulative loss by foreign investors, such that by the end of Grinblatt and Keloharju's (2000) sample period these gains more than overcome household losses during 1995.

However, their most valuable finding from my perspective is that household trading is what they term "contrarian", meaning that they buy when prices are falling and sell when prices are rising. Since institutional investors may induce trends into asset price movements, contrarian households will appear to perform badly using the *C-T* methodology as it captures short-term price movements unfavorable to households. In the noisy, partially revealing, rational expectations model of Brennan and Cao (1996) contrarian trading is a natural consequence of informational advantage. Barber and Odean (2001) do not adopt a *C-T* approach. Rather, utilizing the same discount brokerage house data as Barber and Odean (2000), they use as their benchmark the household's own annual buy-and-hold return counterfactual return. Sizeable turnover fees amounting to a remarkable 4 percent for a round-trip more than absorb any gain from higher-yielding investments. The commission rate alone is 3 percent but this is puzzling as most discount brokers do not provide advice or charge commissions, but the common practice for their data period in the early 1990s may have been different. Moreover, lacking institutional data, no comparison is made with any other investor class.

Barber, Lee, Liu, and Odean (2009) analyze seven years of Taiwanese households and foreign investors commencing in 1995 using the *C-T* methodology and forced acquisition-disposal horizons ranging from one day to six months. Despite the inability of households to exercise timing ability due to the mandated horizons, the authors' conclude that households suffer material losses amounting to USD 32 billion over their sample period. In Figure 2.1 below I present contrary evidence which suggests that the contrarian trading strategy adopted by individual Taiwanese traders was highly profitable by the end of their sample period, despite losses made at some intermediate positions. For each day of the Barber, Lee, Liu, and Odean (2009) sample period I assume that households purchased a constant number of shares in the Index if the index fell the previous day and sell the same number of shares if the index rose the previous day. In contrast, Kaniel, Saar, and Titman (2008) conclude that individuals earn relatively high returns over fairly short horizons, consistent with liquidity provision.

Linnainmaa (2010) utilizes Finnish household trading data to conclude that these investors lose money around earnings announcements, experience poor post-trade returns, and are subject to the the "disposition effect"[10] because they place limit orders. Kelley and Tetlock (2013) utilize a large sample of individual trader data for the US to show that individual investors' order imbalances predict monthly returns without mean reversion and contribute to market efficiency. Kelley and Tetlock (2013) are the first to show that when one examines individual investors as a crowd, it appears that they generate a powerful signal of valuable information that affects the pricing of securities over the relatively short-term.

Barrot, Kaniel, and Sraer (2016) utilize an eight-year sample of individual trades from a French discount broker to investigate their performance as liquidity providers to institutional traders. While their findings are similar to Kelley and Tetlock (2013), and they find increased risk-bearing capacity when volatility is high, they conclude that these investors do not profit from liquidity provision because they tend to get "picked-off" and do not reverse their trades rapidly enough. In fact, the average number of days to reversal in their sample is very long at 309.7 and not too dissimilar to the slow turnover rates shown by Finnish households. Of course, all these indicators of poor short-term individual trader performance do not in any way conflict with the findings of Swan and Westerholm (2016) and the present paper that individuals are superior long-term traders. Linnainmaa's (2010) findings on the susceptibility of Finnish households to the disposition effect is a consequence of the contrarian nature of Finnish trading such that on average they buy when prices are low and sell when high – consistent with their high long-run profitability and the informed trading model shown in the Appendix B.

The noisy, partially revealing, rational expectations equilibrium models of Hellwig (1980) and Wang (1993) provide a platform for examining the effect of asymmetric information on both stock prices and trading behavior. These noisy rational models derive from a theory of equilibrium price formation in which only some traders receive an

[10]i.e., they sell winners and hold on to losers

informed signal and stock prices are not fully revealing. Traders who receive an informed signal will appear to be contrarian, as do the households I investigate, and traders devoid of private information will appear to be positive feedback traders, as are the institutional traders I investigate.

Kim and Verrecchia (1991, a, b), Wang (1993, 1994), Brennan and Cao (1996, 1997), Orosel (1998), Spiegel (1998), and Watanabe (2008) extend the rational expectations approach. Importantly, the model of Brennan and Cao (1996) can account for high volumes of trading as participants with information of differing precision adjust portfolios in response to news, with absolute price changes and trade volume positively associated. Following on from their 1996 model, Brennan and Cao (1997) show that if good (bad) news leads to a price rise (fall), then less informed foreign investors will upwardly (downwardly) revise their expectations by more than better informed domestic investors, leading to prices rising (falling) further and domestic investors selling (buying) more to (from) the foreign investors. Brennan and Cao (1997) argue that there is a dichotomy between foreign and domestic investors with the latter being more informed. I find much stronger evidence for the Brennan and Cao (1996, 1997) hypotheses based on the actual trading profits of all foreign institutional investors and domestic household and institutional traders on a daily basis over a lengthy 17 years data that was inaccessible to Brennan and Cao (1997).

However, there is an obvious downside to the use of these rational models in my context of trade between households and institutional investors as they cannot explain why relatively uninformed foreign institutional investors lose vast sums of depositor money in the longer term. These losses seem to exceed likely possible benefits earned by institutional investors from risk sharing gains but I cannot rule out this possibility. In recent years the Kyle (1985) model has become popular, perhaps because it assumes an apparently irrational group of “noise traders” that systematically lose money to informed traders, rather than postulating that both counterparties are fully rational.

In the Appendix B I suppose that due to the geographic locational advantage of Finnish households and institutions and world-class educational standards that these investor classes each receive a private signal of future share value, unlike their foreign institutional counterparts. I derive a simple contrarian trading rule derived from the autocorrelation in stock prices and in order-flow that explains the trading success of these two groups. My simple trading rule is shown to be incompatible with foreign investors possessing rational expectations, consistent with Kyle's (1985) noise trader model.

2.3 Holding-Period-Invariant Trader Methodology

The *C-T* approach has been widely applied in research on the performance of private investors (e.g., Odean 1999, Barber and Odean, 2000, 2002; Seasholes and Zhu, 2010; Ivkovic, Sialm, and Weisbenner, 2008; Kumar and Lee, 2006; and Barber, Lee, Liu, and Odean, 2009). Additionally, it has been applied to many other areas of finance including long-run stock performance, insider trading and the relative performance of mutual and hedge funds. The approach applied to groups of traders consists of two steps: In step 1 an aggregate portfolio of buy trades for the group is constructed on (say) a daily basis and then either the return or the excess return is computed over a given horizon such as one month or one year. Similarly, a portfolio of sells by the same group is constructed with the difference in return or excess return between the buy and sell portfolios over the same given horizon being recorded. Trading prowess is greater the more positive is the net difference in return. The method is then reapplied from scratch for the next month or year, depending on the assumed horizon. These aggregate period-by-period portfolio return differences are then regressed on a set of market factors with the intercept interpreted as the performance alpha.

If the comparison is between two agent-types then it would normally be assumed that each has the same exogenously-given investment horizon which is derived from some average turnover rate. An obvious weakness in this by now standard approach is that the holding period is far from constant and will in part reflect the very timing and trading skills that one wishes to model. Holding periods vary, in part because traders are not pre-programmed mechanical robots and better informed investors will display superior timing skills giving rise to endogenous variation in the holding period.

I proceed as follows: Since trading skill is most meaningful in comparison between two agent-types in the same market over identical periods, mark both agents' portfolio value to market on the initial day with sufficient holdings to ensure non-negative holdings in future. Initially include only net buys or sells between the two agent-types since this is the most relevant comparison. Trades made with third-parties without the two agents trading with one another may simply imply some commonality in belief (and trading direction) that is irrelevant to the initial comparison.

Suppose the signed net buys (trades) of agent-type A with type B that trades stock of the n stocks that are traded in common on at date t, $j \in (1, ..., t)$, are denoted by $x^A_{i,j}$, and for type B, $x^B_{i,j} = -x^A_{i,j}$, as the sum of the signed order flows must be zero. The type-A agent cumulative net buys for an individual stock in the trade portfolio until the close of business on the previous evening is denoted $X^A_{i,t-1} = \sum_{j=1}^{j=t-1} x^A_{i,j}$ and constitutes type-A agent's pre-existing trade portfolio. For simplicity, I focus on just the current period's continuously compounded return (i.e., the logarithm (Ln) of the price relative in stock i over the current period,$p_{i,t}$, as compared to the previous period), as given by $r_{i,t} = Ln\left(\frac{p_{i,t}+D_{i,t}}{p_{i,t-1}}\right)$, where $D_{i,t}$ represents the dividend and the bracketed term is the price relative. Henceforth, prices reflect reinvested dividends. I ignore transaction costs and other frictions for now. The total dollar (Euro) profit/loss,P^A_t, recorded for agent type-A for all stocks in the agent-type trade portfolio on date t is

$$P^A_t = \sum_{i=1}^{n} r_{i,t} p_{i,t-1} X^A_{i,t-1} \tag{2.1}$$

so that the entire pre-existing trade portfolio of each agent-type is marked to market according to the closing price at the end of each period (e.g., day). In essence, this methodology simply takes snapshots of the value of each investor-type's trade portfolio at (say) daily intervals but does not counterfactually assume regular realizations. In the absence of transaction costs the cumulative trade dollar profit/loss of one agent-type, that I dub the holding-period invariant (HPI) amount, is identical to that of the other after taking account of the sign difference:

$$HPF^A_t \equiv CP^A_t = \sum_{i=1}^{n} \sum_{j=2}^{j=t} r_{i,j} p_{i,j-1} X^A_{i,j-1} \equiv -CP^B_t \equiv -HPF^B_t = -\sum_{i=1}^{n} \sum_{j=2}^{j=t} r_{i,j} p_{i,j-1} X^B_{i,j-1}. \tag{2.2}$$

Since I assume that both parties face the same riskless time value of money and mine focus is on the difference in post-trade performance, I do not consider the trading return in excess of the riskless rate.

Accumulating each trader profit account over any interval provides an exact value of the net trading gain to agent-type A and exactly opposite gain/loss for agent-type B. Moreover, the sum of the trading profits over both parties is always zero, as it should be. Unlike the C-T methodology, the profit or loss as measured by HPI captures precisely the timing ability of each party to foresee future price movements without imposing arbitrary assumptions about endogenous trader horizons on either or both groups. In this framework, the profitable agent-type with the greatest foresight is the type that systematically buys (sells) followed by a positive (negative) return and the profits of the two types on their trade portfolios are always the mirror image of each other.

The only other study that I am aware of which also achieves a zero net daily trading profits summed over two investor groups trading with each other is by Barber, Lee, Liu, and Odean (2009). Like me, for each investor group they construct cumulative daily net buy and net sell portfolios with stocks marked to market each day but with the proviso that shares are included only for horizons of 1, 10, 25 and 140 days (i.e., six months). Hence, in effect each group is forced to limit its investment horizon to a specified and relatively short interval regardless of its actual horizon, unlike my approach which poses no limit on the horizon as it is entirely determined by the group's actual net trades. Limiting the horizon to relatively short intervals such as one day, the main focus of their study, will not meet the aim of evaluating the trading decisions of potentially informed investor groups with stock timing ability as any such timing ability is unlikely to correspond to a fixed, regular horizon such as one day. In fact, as it is well known, individuals are contrarian traders who buy when prices are falling and sell when prices are rising such that the next day, and even next six-month, return on their aggressive (market) orders must inevitably be negative, as they find.

Figure 2.1 replicates the movement in the average monthly index value for the Taiwanese market over their sample period with the dashed line representing the index movements and the solid line showing the Holding Period Invariant returns to an individual investor who buys (sells) a constant number of shares when the index, i.e., stock price, is falling (rising). Unlike Barber, Lee, Liu, and Odean (2009), no restrictions are placed on the trade horizon of each class of investor. The graph indicates that this contrarian strategy is highly profitable over their sample period with positive cumulative profits, questioning their methodology that purports to show individual trading is extremely loss-making when only short-term movements in the net trade portfolio are taken into account.

In their defense of either a one-day or relatively short-term horizon, Barber, Lee, Liu, and Odean (2009, p.620) consider evaluating cumulative counterparty trading over longer intervals than six months without forced short-term trading intervals as their primary

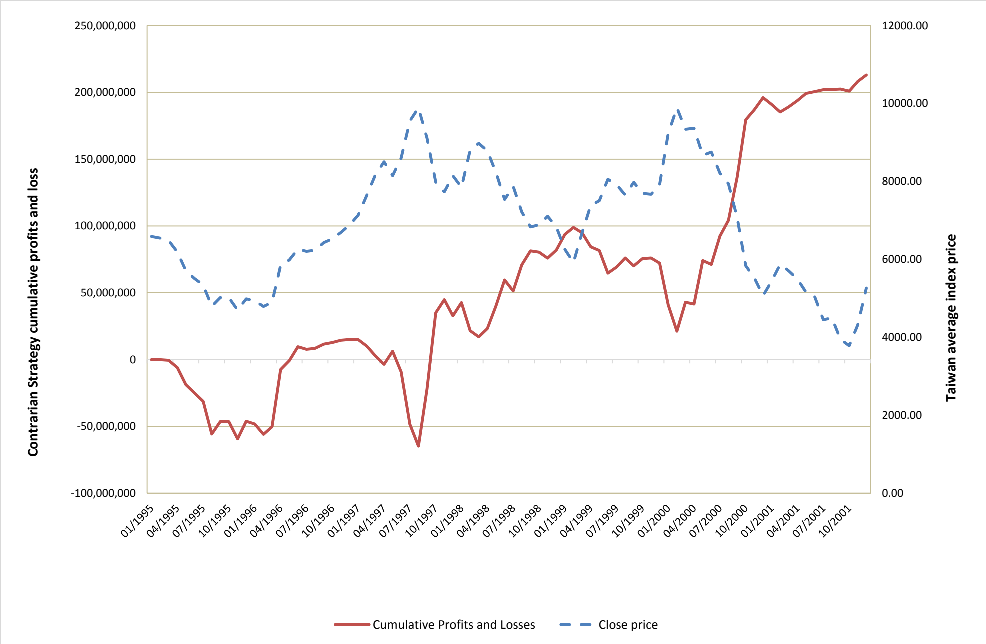


Figure 2.1 Taiwanese market cumulative Profits and Losses from a contrarian strategy, 1995-2001 inclusive

analytical method but reject it on the basis that there are well-known statistical problems associated with making comparisons over long periods. Below I propose and introduce a method for overcoming these statistical problems by using Monte Carlo simulation with a benchmark based on a random daily uninformed trading direction.

Adding in additional stocks does not change the nature of the argument, with the *C-T* approach promoting the idea that incorporating multiple stocks in a portfolio increases the robustness of that methodology and therefore also the HPI methodology. While, of course, it is possible to adjust *HPI* estimates to include only abnormal returns as does Barber, Lee, Liu, and Odean (2009), it is pointless if the aim is to simply compare trading prowess as identical adjustments are made to both the buyer and seller return. Even adjusting for transaction costs is largely unnecessary if both agent-types incur the same costs but the usual presumption is that households incur higher transaction costs per trade than do either domestic or foreign institutional investors. Conventionally, in the second stage of the *C-T* methodology, the returns computed over a specified horizon are regressed on market risk factors to obtain a risk-adjusted comparison of trading prowess. However, unless there is a benchmark that would need to be in common for both agent-types, it is not clear what purpose risk adjustment serves if the idea is to measure pure trading ability with the presumption that either each agent-type is risk-neutral or that there are negligible risk differences between investor types.

What benchmark should one adopt to assess both the economic and statistical significance of the trading ability of participants? The conventional approach in asset pricing is to introduce a market portfolio benchmark but, as Diacogiannis and Feldman (2013) and the associated literature cited therein point out, portfolios are never mean-variant efficient making inferences difficult if not impossible. Grinblatt and Titman (1993) propose an innovative method that bypasses the need for a conventional market benchmark and hence much of the controversy within the asset pricing literature. They compute the difference between the realized return on a particular portfolio and the expected return they would have achieved had the portfolio manager been uninformed.

I utilize this insight and make it applicable to my problem by carrying out Monte Carlo simulations. For any given sequence of daily trades over any given interval between two types of participants, here collective households and foreign nominee institutional investors, I can only observe one outcome corresponding to the realized wealth gain to one party and corresponding loss to the other on the trade portfolio. While *expost* it is clear that one investor-type achieved a better outcome then the other, the favorable outcome may simply have been due to chance rather than superior knowledge, information, and trading ability no matter how great the wealth gain to one party at the expense of the other. How can one tell? Using 10,000 trials and the actual trades in every stock traded on every day, I randomize the trade direction of the two participants to compute randomized wealth gains and corresponding losses that simulate informationless trading. By examining the proportion of times one investor category either achieves the same or better outcome purely by chance, I attach statistical probabilities to each actual outcome based on this random benchmark.[11]

According to Seasholes and Zhu (2010), the main benefit of aggregating each the entire trades of each agent-type within the *C-T* methodology is to take into account the cross-sectional correlation of stock returns that might otherwise bias the statistical significance of agent-type returns if a pooled cross-section time-series regression methodology were to be employed. When net buyer and net seller portfolios based on *C-T* are formed,

[11] I thank Michael Brennan for suggesting this extension of Grinblatt and Titman's (1993) insight.

and horizons imposed that are inconsistent with the trading data used to construct the buyer and seller portfolios, this introduces measurement errors that may bias findings towards one particular agent-type. Certainly, as a minimum, both sizeable and unnecessary measurement error is introduced. For example, with an imposed one year horizon, the error in measuring cumulative profit and loss for foreign nominee trades with households ranges from plus EUR 2,388 million to minus EUR 3,045 million (see Table 2.4 and Figure 2.8 below). These errors are sizeable. One can far more easily and reliably construct the actual trader profit or loss using the cumulative profit/loss on a mark-to-market HPI method described above without imposing possibly arbitrary and or contradictory holding periods and turnover rates on the aggregate trades of each agent-type.

The standard justification for adopting a specific holding period, whether it be (say) one day, one month, one year, or two years, is that the individual trade data displays some type of average turnover rate. However, these individual trades include trades within each agent-type, as well as between agent types, and at the level of the aggregate type there may be no meaningful turnover rate of fixed duration. For example, over the seventeen year period in Finland between January 1995 and 2011, inclusive, households collectively largely sell the main stock, Nokia, to foreign nominee institutional investors when the stock price is rising and buy when it is falling with these price movements most likely representing price pressure due to the order imbalances of foreign nominee investors. These price movements do not occur based on any mechanical pattern such as a horizon of a month or a year. Moreover, the findings of the current paper suggest that the household pattern of trading is based on fundamental information as to whether the stock is either under- or over-priced and, as such, is endogenous.

To explain in more detail how the *C-T* approach imposes implicit trade reversal at the specified horizon length, N, denote the net buy-sell number of shares bought and sold in stock i by the two trader types on date t as $x^A_{i,t} \equiv -x^B_{i,t}$ for the two trading types. For a horizon of N periods the buy and hold return commencing at period t is denoted by $r^N_{i,t} p_{i,t-1}$, where $r^N_{i,t} = Ln\left(\frac{p_{i,t}+D_{i,t}}{p_{i,t-N}}\right)$ is the continuously compounded “buy and hold” return over this period. The cumulative buy and hold return over the horizon N commencing at time t for agent-type A is identical to minus the same return for agent-type B:

$$CR^A_{t+N} = \sum\nolimits_{i=1}^{n} \sum\nolimits_{j=t}^{j=t+N} x^A_{i,j} r^N_{i,j} p_{i,j} \equiv -\sum\nolimits_{i=1}^{n} \sum\nolimits_{j=t}^{j=t+N} x^B_{i,j} r^N_{i,j} p_{i,j-1} = -\,CR^B_{t+N}. \qquad (2.3)$$

At time $t+N$, by the implicit assumption underlying the *C*-*T* approach, all trades undertaken N periods earlier at time t are reversed (i.e., expunged from the investor's portfolio) at the end of the horizon. Hence:

$$x_{i,t}^{A} \equiv -x_{i,t+N}^{A} \text{ and } -x_{i,t}^{B} \equiv x_{i,t+N}^{B}, \tag{2.4}$$

over the next horizon, and are then reversed again to yield a stable turnover rate with the entire portfolio turning over every N periods. Thus the portfolio performance within any given interval, N, depends entirely on trades made during that interval since earlier holdings that the trader-type actually retains have been counterfactually removed.

However, since it is unlikely that agent-type A and agent-type B will have identical turnover rates, or even relatively stable turnover rates at all, and thus the same horizon of periods, the *C*-*T* approach will only give the same profit/loss as the HPI method if equation (2.4) is precisely satisfied, i.e., the *C*-*T* turnover assumption is precisely satisfied. Thus, computing the cumulative return over the first buy and hold horizon, as in equation (2.3), and for each additional horizon, will only give the correct HPI solution in the unlikely event that the horizons of the two agent-types firstly exist, secondly are identical, and thirdly, that the horizon assumption made in the calculations is correct. By contrast, the HPI solution provides the exact answer, regardless of the horizon, or even in the absence of any horizon.

Due to Nordic countries such as Finland and Sweden reporting far much more disaggregated data on investors than is available from other countries, there is extensive information on household investor behavior which is unavailable from more opaque countries. Calvet, Campbell, and Sodini (2007) observe mutual fund holdings in Sweden at the individual level, as well as individual direct investment in shares, to report that many Swedish households are well-diversified and achieve high Sharpe ratios.

2.4 Data

2.4.1 Source of investor-level transactions

My data source is the well-established database from Euroclear Finland Ltd (formerly Finnish Central Securities Depository) that includes all transactions in the share depository for all 1.061 million investor accounts (classified into 994,937 households, 722 institutions, 96 foreign investor nominee accounts and 65,010 others) with holdings in 232 unique common stock listed on the Nasdaq OMX Helsinki Exchange, Finland. In this paper, I focus on the three main groups of investors: households, domestic institutional investors, and foreign investor nominee accounts, including all transactions for these accounts in Nokia and in 32 other major Finnish stocks, as of January 1, 1995, carrying the analysis through to December 31, 2011, a period of 17 years, inclusive.

Table 2.1[12] summarizes my basic household data over the 17 years of my study. On average, there are 493,272 household accounts of which only about 42 percent are active each year with one or more trades. Barrot, Kaniel, and Sraer (2016) report that 49 percent of individuals in their sample based on a French discount broker make at least one trade a year while Kumar and Lee (2006) report 45 percent for a major US discount broker. Hence the trading propensity for all Finnish households is slightly lower than that reported for the French and US discount brokers. Over the full period of the data, the value of these accounts has approximately doubled, with a commencement value of around EUR 16 billion. However, at the height of the Nokia bubble period in 1998 the value temporarily rose to a staggering EUR 63 billion. While the mean household portfolio value is about EUR 60.7 Thousand over the entire period, the median value is far lower at only EUR 4.3 Thousand, showing that the distribution of shareholder wealth is highly skewed. Over the period the mean number of stocks per household account has risen from only 1.9 to 3.4 with the median value remaining at one stock for most of the period, while recently increasing to a modest two stocks per household account. Consequently, with some exceptions pertaining to a small number of wealthy households possessing hundreds of stocks, there is little evidence from my dataset of any desire by the typical Finnish household investor to diversify and hence they appear willing to bear risk. Finally, and perhaps surprisingly, female-headed accounts make up a sizeable 34 percent of the total.

[12]The term “active trader” defined in Table 2.1 is only for the reader to gain an overall understanding of the Finnish households trading behaviours. In my *HPI* sample analysis, I have applied the sample selection criteria based on the discussions in Section 2.4. I also split my entire Finnish individual traders into active households and passive households. The details are presented in Section 2.7.

Table 2.1 Household Investor Summary Statistics, 1995-2011, Inclusive

The number of household (HH) accounts holding stocks is split into "Active" in column (1) and "Inactive" in column (2). "Active" means that the household conducted one or more share trades in that year. The total value of all household accounts, active and inactive, at the end of each year is displayed in EUR billions in the HH Value column (3), with the percentage change shown in column (4). The mean value of each account in EURs, regardless of its activity status, is displayed in column (5), the median value in column (6) and the standard deviation value in column (7). The mean number of stocks in each account is shown in column (8). While for space reasons, the median number is not shown, it nonetheless remains constant at 1 until 2010 when it increases to 2. The mean age of household investors is shown in column (9) and the percentage of female accounts is shown in column (10).

	Number HHs		Total HH Value		Portfolio Value			Stocks	Age	Women
Year	Active (000's) (1)	Inactive (000's) (2)	Level EUR B (3)	Change % (4)	Mean EUR (5)	Median EUR (6)	Std Dev EUR (7)	Mean No. (8)	Mean Years (9)	% (10)
1995	59.6	300	15.53	NA	43,183	5,167	356,817	1.9	44.5	42.9
1996	140.1	217	14.69	-5.5	41,142	4,928	355,891	1.8	49.1	33.2
1997	127.6	232.8	18.56	23.4	51,485	5,348	552,128	1.9	48.7	33.4
1998	176.5	193.1	63.14	122.4	170,829	6,916	1,522,015	1.9	47.2	35.9
1999	330.3	36.8	50.09	-23.2	136,470	5,988	524,904	2	46.8	41.6
2000	323.5	129	27.29	-60.7	60,299	4,144	591,732	2.2	46.6	36.4
2001	245.3	248.2	24.94	-9	50,531	3,440	393,755	2.3	48.3	31.4
2002	194.1	286.9	22.09	-12.1	45,934	3,369	322,457	2.3	48	31.9
2003	158.2	325.7	21.9	-0.9	45,256	3,440	276,301	2.3	49.1	32.5
2004	256	281.1	22.55	2.9	41,996	3,265	307,753	2.4	50.7	34.9
2005	251.4	300.1	24.67	9	44,729	3,440	363,654	2.5	49.9	33.3
2006	205.5	351	27.43	10.6	49,278	3,600	491,292	2.7	49.7	31.1
2007	194.4	359.8	28.79	4.8	51,948	3,679	616,411	2.6	50.1	31
2008	175.4	402.4	26.63	-7.8	46,088	3,707	470,556	2.9	49.1	29.6
2009	227.2	376.7	30.12	12.3	49,868	4,166	327,391	3.2	50.1	32.2
2010	216.1	407.7	33.39	10.3	53,531	4,514	466,267	3.4	48.7	29.3
2011	268.7	387.4	32.05	-4.1	48,843	4,255	493,200	3.4	49.1	31.5
Mean	208.8	284.5	28.46		60,670	4,315	496,031	2.5	48.6	33.7

In assessing the willingness of Finnish households to diversity or bear risk one needs to consider the limitations of my individual household data as it pertains to the individual shareholdings and thus does not assign mutual fund holdings to individuals. Moreover, representing the legal records of Finnish stock holdings, it does not include any foreign stock holdings, either individual stocks or mutual funds. I have no reason to think that Finnish households are any more or less diversified than are their Swedish neighbors for which there are comprehensive records of their entire individual portfolios based on official wealth statistics. Calvet, Campbell, and Sodini (2007) find that nearly two-thirds of Swedish households participate in financial markets and for those that participate about 60 percent consists of risky assets and the remainder cash. A substantial portion of these risky assets are delegated to mutual funds inclusive of foreign shares and that the majority of Swedish households are sufficiently diversified to outperform the Sharpe ratio of their own domestic stock index.

To describe entire cycles of boom and bust, I split up my entire data period into four sub-periods: the Grinblatt and Keloharju (2000) period of analysis consisting of just two years, 01/03/1995 - 12/31/1996; the high-tech boom and collapse period, 01/03/1997 - 07/03/2003; the pre-GFC boom to post the Lehman Brothers bust, 07/04/2003 - 03/06/2009, the post GFC period, 03/07/2009 - 12/30/2011; and I also analyze the entire 17-year period for which data is available, 01/03/1995 - 12/30/2011.[13]

2.4.2 Data steps

From my dataset I compute the daily buys and sells undertaken by every household individually and foreign nominee institutional investors, in every market that conducts trades in Finnish stocks over the seventeen years of my daily data. On eliminating on a daily basis trades between households, between domestic institutions, and between foreign nominees, I am left with the daily net buys and sells of the three groups, (i) households and foreign nominees; (ii) households and domestic institutions, and (iii) domestic institutions and foreign nominees. While many trades between these three groups can be matched at the level of individual trades, this is not possible for all trades. However, since I have the entire population of trades by households, domestic institutions, and foreign nominees’

[13] I perform various verifications in the Appendix A.1.1 to demonstrate that the raw dataset collected from Euroclear Finland Ltd is robust with respect to my results.

institutional investors, I solve for the unique allocation of trades that equates daily buys and sells between each of the three groups. For example, if the net holdings of foreign institutions in (say) Nokia increases by x shares on day t while domestic institutional holdings fell by y shares and households by z shares with a constant total stock of Nokia shares held collectively by these three shareholder categories, then foreigners purchased y shares from domestic institutions and z shares from households totaling x shares. Since the holdings of both classes of domestic investor diminished on this occasion, neither was a net buyer from the other.

The initial holdings of my three groups are inferred from backward induction by the requirement that the holdings of households and domestic mutual funds cannot be negative, given the daily sequences of matched buys and sells for each participant group and the marking to market of each investor groups entire portfolio on the last day of each event period as well as on the last day of the dataset.

Table 2.2 summarizes my three samples of *HPI* portfolio trades, 1995-2011, and the overall traded value of my three investor groups, households, domestic, and foreign institutions.

I select 32 leading Finnish firms based on three criteria. The first criterion is that the firms be leading firms from the sample of approximately 100 firms that survive and have an average market capitalization larger than EUR 100 million presented in Table A.1.1 sorted by average traded value per day during the entire sample period. The second criterion is that the firms be ranked in the top 50 for the proportion made up of foreign nominees' trade and their value traded from 1995 to 2011. The third criterion is that the number of trading days for the stock should be at least 250 trading days. I combine these three ranking filters with a limit of 32 firms. My method implies a "look ahead" bias in the choice of the 32 stocks to analyze, but this counts against my findings in that my stock sample is precisely chosen because foreign institutional investors chose to trade these relatively large stocks due to a self-selection process in which this investor class chose stocks they expected to outperform.[14]

The Finnish equity market behaves quite differently from other developed markets, such as U.S. stock market. Among the entire 232 Finnish stocks during the examined periods, there are only 126 Finnish stocks that meet the first two criteria: 1) trade more than

[14] I am grateful to Michael Brennan for alerting me to this potential problem.

250 trading days, and 2) have an average market capitalization of at least EUR 100 million. The remaining stocks are not as useful to be the focus of this study, because they are too small to attract sufficient foreign nominee interest. Among these 126 Finnish stocks, I also added a filter to pick the top 50 market share by foreign institutional investors. Finally, I have 32 leading stocks. The average trading volume of Nokia over the entire 17-year period (1995-2011) represents more than 50% of the average daily trading volume supplied by the 32 large Finnish stocks and 39% of the average daily trading volume supplied by the 126 leading Finnish stocks. In terms of the average daily market trading value and average market capitalization, Nokia alone makes up a similar percentage rate of approximately 50% among the 32 stocks and 40% of the 126 major Finnish stocks.[15] Nokia is also ranked as the top stock in foreign institutional investors’ average market share holdings among these 126 Finnish stocks. Hence, since Nokia dominates the Finnish market, I must give considerable weight to it in my analysis.

By the nature of my *HPI* methodology, there should be a sizeable level of participation by foreign institutional investors in the stocks that I investigate so as to avoid any bias in favour of Finnish households in my paired trading group framework. Hence, I should consider the data sample that captures the sizeable matched trades between each paired group. Otherwise, my findings may be biased toward the investor category that has undertaken less trading activity. Moreover, the *HPI* matched trading group will eventually end up with many zero-balance trades and perhaps too few paired trades to draw strong statically-significant conclusions if the sample is too unbalanced. Since I find that households are the superior traders, it is important to ensure that any biases are least favourable towards this group. Since, almost definitionally, institutional investors should relatively perform better in the larger stocks such as Nokia which they relatively prefer, it is important to ensure that bias due to endogenous choice by institutional investors, and which favours these losing investors, remains in my analysis. Nonetheless, for completeness, I have included the *HPI* trading performance results for the entire set of 232 Finnish stocks for Finnish household trades with Foreign Nominee institutional investors in Table 2.6 without introducing any specific sample selection criteria.[16] The results do not alter by much. Details concerning these stocks are presented in Table A.1.1.

[15] I present the summary of the top 100 stocks matched with three selection criteria in Table A.1.1.

[16] I thank Ron Kaniel for suggesting to test the entire 232 Finnish stocks to eliminate concerns on the sample selection bias.

Table 2.2 Summary Statistics of daily *HPI* Portfolio Trades and Trading Value in EUR (millions) by Households, Foreign Nominees and Domestic Financial Institutions from 1995 to 2011, respectively.

Descriptive Statistics	Household trades with Foreign Nominees		Household trades with Domestic Financial Institutions		Domestic Financial Institutions trades with Foreign Nominees	
	HPI Trades	Household Traded Value (EUR M)	*HPI* Trades	Domestic Institutions Traded Value (EUR M)	*HPI* Trades	Foreign Nominees Traded Value (EUR M)
Mean	30,006***	1.7931***	8,833***	1.2933***	42,436***	192.9717***
Median	2,953.70	0.2982	0	0.2024	1,200	17.2548
Maximum	11,948,399	300.50	2,203,411	337.62	13,533,875	49,440.74
Standard Deviation	119,434.34	5.4821	37,299.77	4.0729	139,947.41	874.5347
t-value	79.44	103.43	74.88	100.41	95.88	69.77
Number observations	99,979	99,979	99,979	99,979	99,979	99,979

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.5 Results

I focus on the largest Finnish stock, Nokia, within the group of 32 major Finnish firms and presents trading profits and losses of each agent type and their counterparts in Table 2.3 Panels A to C for Nokia.

Table 2.3 Cumulative Profits and Losses after Transaction Costs for Direct Trades between each trading pair group in Nokia

The cumulative Profits and Losses is at the end of day of each period and it is independent which means that every starting point of the cumulative Profits and Losses is zero. The significance of these cumulative profits and losses is tested by running a Monte Carlo simulation 10,000 times, where the daily direction taken by each of the investor categories in each stock is random. I thus employ an informationless benchmark. The result of this simulation provides the confidence interval I use to test the significance of the reported profits. Transaction cost per trade for households is EUR0.005 and EUR0.001 for foreign nominees, respectively.

Panel A Between Households and Foreign Nominees in Nokia

Periods	Households Cum. P&L (EUR M)	Foreign Nominees Cum. P&L (EUR M)
01/03/1995 - 12/30/1996	3.23	-3.68
01/03/1997 - 07/03/2003	2,663.55***	-2,665.00***
07/04/2003 - 03/06/2009	580.23*	-581.76*
03/07/2009 - 12/30/2011	-613.2	611.54
01/03/1995 - 12/30/2011	4,922.83*	-4,927.92***

Panel B Between Households and Domestic financial institutions in Nokia

Periods	Households Cum. P&L (EUR M)	Domestic Institutions Cum. P&L (EUR M)
01/03/1995 - 12/30/1996	-2.33	2.14
01/03/1997 - 07/03/2003	108.27***	-108.60***
07/04/2003 - 03/06/2009	132.99*	-133.33*
03/07/2009 - 12/30/2011	-60.64	60.26
01/03/1995 - 12/30/2011	353.70*	-354.94***

Panel C Between Domestic financial institutions and Foreign Nominees in Nokia

Periods	Domestic Institutions Cum. P&L (EUR M)	Foreign Nominees Cum. P&L (EUR M)
01/03/1995 - 12/30/1996	-13.96	12.56
01/03/1997 - 07/03/2003	7,275.58***	-7,277.85***
07/04/2003 - 03/06/2009	162.17*	-163.43*
03/07/2009 - 12/30/2011	-122.79	121.93
01/03/1995 - 12/30/2011	14,112.72***	-14,114.65***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Once the net trade flows in Nokia between the various agent-types, household and foreign nominees, households and domestic institutions, and domestic and foreign institutions, have been computed, the *HPI* methodology set out in equations (2.1) and (2.2) above is applied to trades between households and foreign nominees, trades between households and domestic institutional investors, and, finally, domestic institutional investors and foreign nominees in Table 2.3, Panels A to C, respectively.

These tables, as well as the remaining tables included, present the results when transaction costs are considered but they indicate that differences arising from transactions costs are not great. To account for transaction costs I apply realistic average brokerage costs that representative retail and institutional investors are expected to pay. Since it has been shown in the literature (e.g. Linnainmaa (2010)) that household investors are likely to use limit orders are executed on the initiation of other (institutional) traders I do not impose a bid-ask spread transaction cost component on household investor trades. I also do not impose a negative effective spread that would be a result of the above observation since a significant proportion of retail trades would still be executed using marketable limit orders that exhibit positive effective spreads. I also assume that household orders are not affected by market impact as their order size is typically below average trade size. I hence do not adjust for spread and market impact and apply a brokerage fee of 0.5 percent or 50 basis points for households, which corresponds to what an average online or active phone customer would pay in brokerage fees.

Institutional trades are likely to be impacted both by the bid-ask spread, typically the at the minimum tick size EUR 0.01 during most of the trading day, and by market impact. As these metrics are difficult to measure in a reliable way across a large sample of transactions and over a long time-period, and since it might put institutions at an unfair disadvantage vs. households in my comparison, I also do not adjust the institutional transaction costs for spread or market impact. For institutions, I apply a transaction cost of 0.1 percent or 10 basis points, which correspond to what an active large institution would pay in brokerage fees. Some of the literature on transaction costs tends to assume that the difference in transactions costs between households and institutions is even higher than the five-fold I apply. My argument is that in today’s highly liquid automated market, transaction costs are a relatively small factor that is unlikely to explain the results. In unreported work I simulate imposing very high transaction costs on households and extremely low transaction costs on institutions and this does not alter my main findings.

Figure 2.2 shows the daily cumulative net purchases of Nokia by households and foreign nominees over my entire sample period while Figure 2.3 displays the cumulative profit and loss for households and foreign nominees over the entire period. It can be seen that foreign nominee cumulative daily profit almost perfectly tracks the Nokia stock price over the entire period. This is because foreign nominees almost perfectly follow the trend in the price of Nokia over the entire period, consistent with the noisy rational expectations literature, e.g., Brennan and Cao (1996), in which foreign investors are relatively uninformed.[17] Figures 2.4 to 2.7 shown in the Appendix graph the cumulative daily profit and loss for households and foreign nominees in Nokia over my periods of analysis, together with the Nokia stock price.

2.5.1 Entire Period: January 3, 1995 to December 30, 2011

Figure 2.2 shows that, since approximately 2008 when the price of Nokia began to fall, households have been net buyers of Nokia from foreign nominees but over much of the earlier period households have been net sellers, especially when Nokia was rising in price. Nokia, having risen rapidly in value from a little over a EUR to about EUR 63 in April 2000, fell to about EUR 3.5 by the end of 2011. It is especially in this latter period that Figure 2.3 and Table 2.3 Panel A shows that after transaction costs, households collectively made significant trading gains at the expense of foreign nominees that totaled EUR 4,922.8 million even after deducting the "loss" of EUR 580 million made during the last two years of the 17-year period. The net loss to foreign nominees was EUR –4,927.9 million for institutions with the EUR 5 million difference due to differential transaction costs. Hence transaction costs, while not a deciding factor, affect the profits of households more than for institutions due to the five times higher costs paid by households.

[17] In personal correspondence, Masahiro Watanabe argues against this interpretation on the grounds that relatively uninformed investors would not trade in the apparently aggressive style used by foreign nominees. However, given that foreign nominees are trading in the world market for Nokia and the Finnish economy is negligible in size relative to the world economy, it is not surprising that foreign nominees dominate the Finnish market for Nokia and appear highly aggressive even though they appear to lack information.

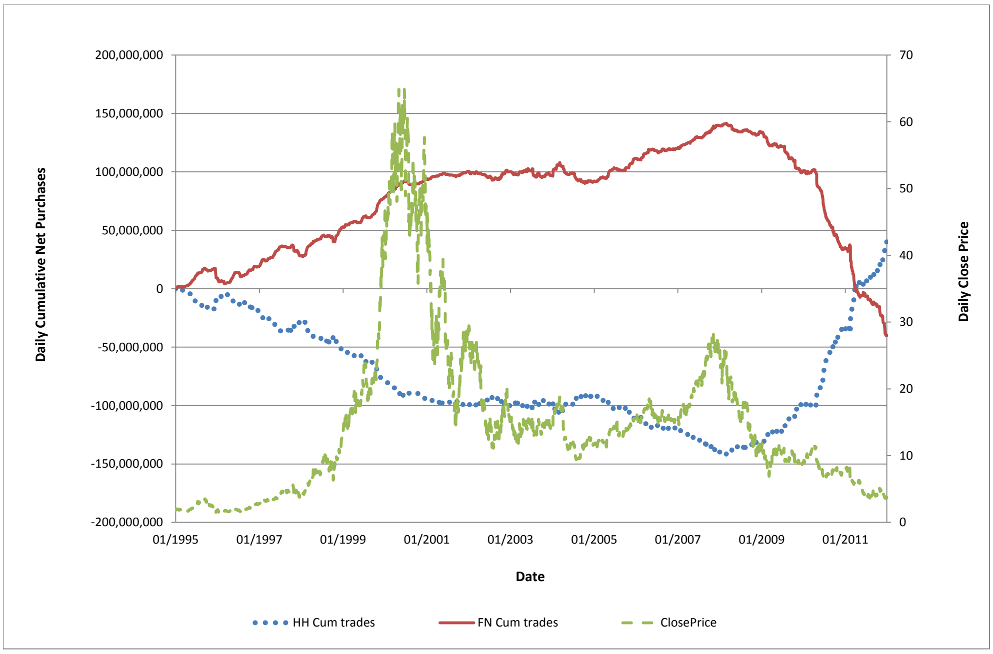


Figure 2.2 Daily cumulative net purchases for Household and Foreign Nominees on Nokia and Nokia’s Closing Price, January 3, 1995 to December 30, 2011 - Entire Period

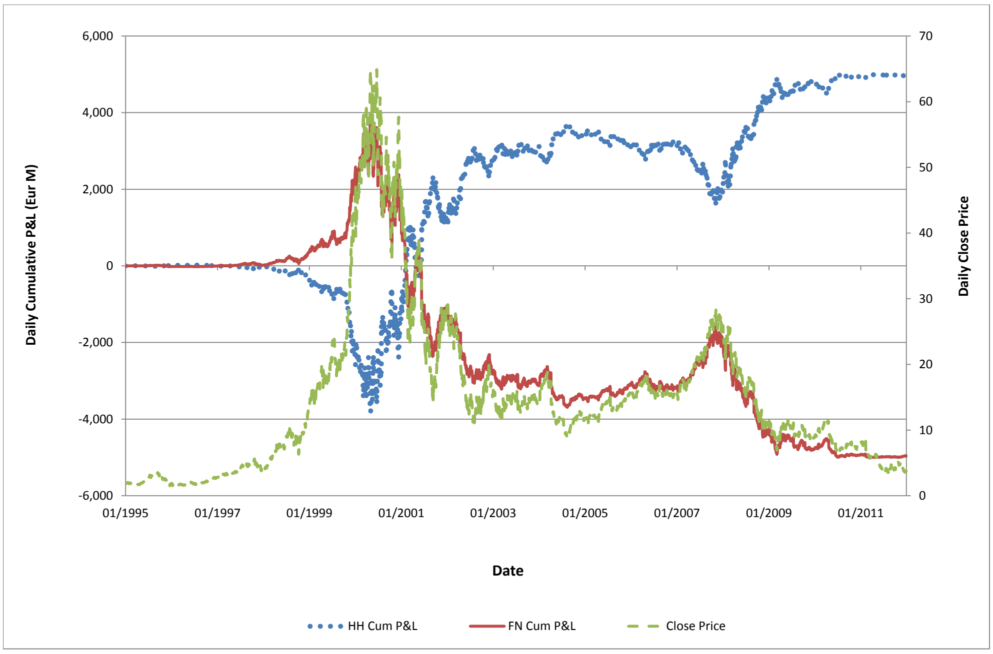


Figure 2.3 Cumulative daily Profits and Losses for Household and Foreign Nominees on Nokia and Nokia’s Closing Price, January 3, 1995 to December 30, 2011 - Entire Period

2.5.2 Sub-Period 1: January 3, 1995 to December 30, 1996

Grinblatt and Keloharju (2000) conclude from trading evidence based on an assumed six-month trading horizon over this period in the major industrial stocks that foreign nominee institutional investors “significantly outperform” and households “underperform” such that foreign investors appear “sophisticated” and “smart” (to use their terminology) compared with households. Apart from the assumption of a fixed horizon common to all investors, they construct buy ratios for individual trades inducing a possible cross-sectional bias in their statistical findings. An inspection of cumulative profit and loss in Figure 2.4 shows that households lost significantly with respect to their trades in Nokia with foreign nominees over the first year, 1995, but more than made up for these losses during 1996 to finish with a EUR 3.23 million profit gain for households and a corresponding loss for foreign nominees of 3.68, as shown in Table 2.3 Panel A above, where P&L is measured net of transaction costs.

Figure 2.4 Cumulative daily Profits and Losses for Household and Foreign Nominees on Nokia and Nokia’s Closing Price, January 3, 1995 to December 30, 1996 - Grinblatt and Keloharju (2000) Evaluation Period

2.5.3 Sub-Period 2: January 3, 1997 to July 3, 2003

Households did not commence significant trading with foreign nominees until halfway through the period in January 2001 when Nokia had almost reached its peak. Households continued to sell for another two years before commencing modest purchases. Over this period, Figure 2.5 shows they continued to reap large gains at the expense of foreign nominees, ending up with significant accumulated profits of EUR 2,664 million at the expense of foreign nominees at the end of the high-tech bubble period on their net trade portfolio, as shown by Table 2.3 Panel A. Since households gain largely due to superior trade timing ability that is fully reflected in the HPI methodology, the imposition of mechanical investment horizons, as in the *C-T* methodology, severely adversely affects the measured trading performance of households.

Could the apparent informational advantage of households be due simply to “luck” as a result of portfolio rebalancing as they divested Nokia to gain diversification benefits once Nokia became a world stock?[18] This represents an implausible scenario as individual Finnish households typically held only one stock for most of my sample period with little indication of seeking diversification benefits within my dataset. I test the “luck” hypothesis by computing the internal rate of return (IRR) to households by simply buying and never selling until the end. The “BuyOnly” IRR yields a return of minus 25 percent instead of the plus 42.84 percent of their actual IRR over the entire period (see below). The failure of this “buy and hold” methodology to approximate the actual IRR is not surprising as such a “BuyOnly” IRR methodology represents an extreme form of the *C-T* methodology with the household actual sales ignored, other than the notional sales at the end of the period.

2.5.4 Sub-Period 3: July 4, 2003 to March 6, 2009

In the post high-tech boom period that was prior to the GFC collapse, households purchased the leading stock, Nokia, from foreign nominees until November of 2004, after which they continued to sell for the next three years until December 2007 when they commenced purchasing again. Their cumulative trades are almost precisely the mirror image of Nokia’s price movements over this period while, of course, foreign nominee cumulative trades almost exactly match Nokia price movements in the opposite direction. Thus households buy Nokia when it is a recent loser, i.e. its price is falling and they hold

[18]Michael Brennan raised this point in correspondence and proposed the “BuyOnly” IRR tests.

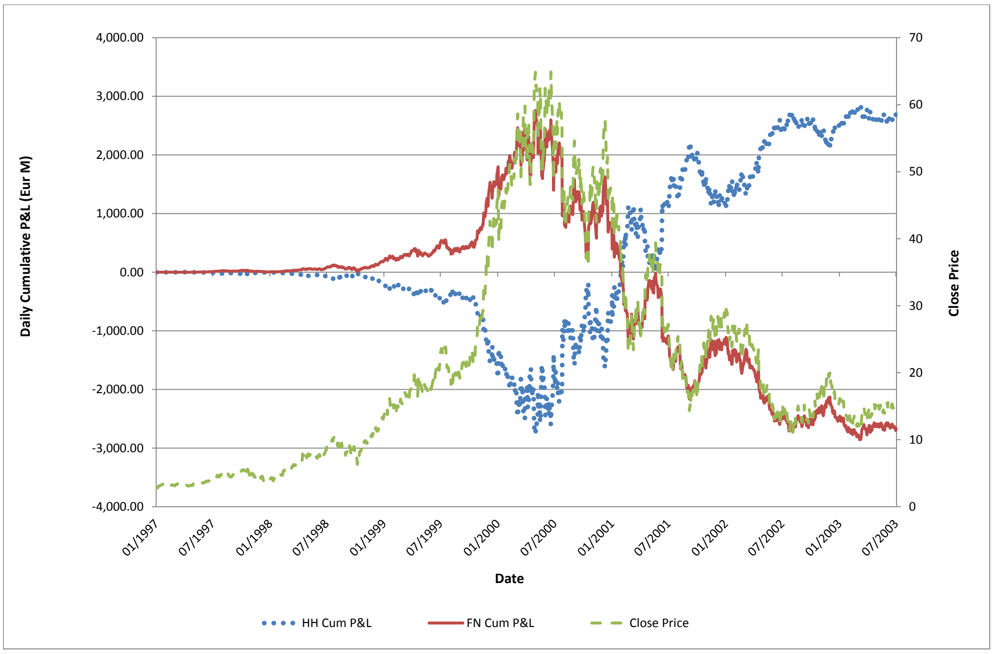


Figure 2.5 Cumulative daily Profits and Losses for Household and Foreign Nominees on Nokia and Nokia's Closing Price, January 3, 1997 to July 3, 2003 - the High-Tech Bubble Period

on to their existing inventory, and sell Nokia when it is a recent winner, i.e., when its price is rising. Much of the extensive literature on the 'disposition effect" surveyed by Barber and Odean (2013) might infer that household investors in Nokia are subject to this psychological problem when in fact they appear to be successful traders or speculators. Figure 2.6 shows that households made significant accumulated losses as they heavily sold Nokia until it reached its peak but more than recouped these losses once the full force of the GFC collapse was evident. In fact, Table 2.3 Panel A shows that households significantly profited by EUR 580.2 million net of transaction costs, at the expense of foreign nominees, by the end of the GFC bubble period.

2.5.5 Sub-Period 4: March 7, 2009 to December 30, 2011

Households continued to purchase from foreign nominees over this entire period while Nokia continued to fall in price. Figure 2.7 and Table 2.3 Panel A shows that, within this data period, this acquisition strategy is yet to pay off with a significant accumulated loss of

Figure 2.6 Cumulative daily Profits and Losses for Household and Foreign Nominees on Nokia and Nokia’s Closing Price, July 4, 2003, to March 6, 2009

EUR 613.2 million but events past the cut-off date suggest that this has nonetheless proved to be a winning strategy.

2.5.6 The magnitude of the measurement error induced by Calendar-Time Portfolios

The *C-T* portfolio profit and loss for horizons ranging from one month to one year is computed using the buy and hold formula given by equations (2.3) and (2.4) above. In Table 2.4 and Figure 2.8, the error in measuring cumulative profit and loss for foreign nominee direct trades with households ranges from plus EUR 2,388 million to minus EUR 3,045 million. These errors are more severe, the longer is the imposed investor horizon. Figure 2.8 show that the *C-T* approach correctly indicates the direction of the trading profit change only 51 percent of the time. Such is the magnitude of the errors in variables problem induced by the use of the *C-T* methodology that trading portfolio alpha regression estimates found after controlling for market risk factors become highly questionable. These regressions are typically carried out in the second stage of *C-T* applications.

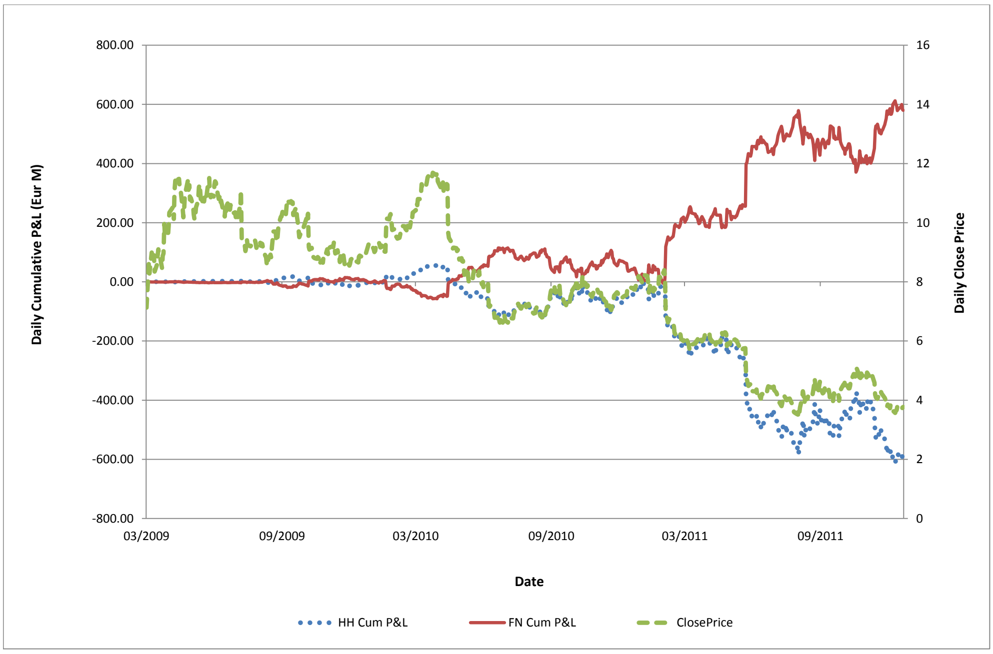


Figure 2.7 Cumulative daily Profits and Losses for Household and Foreign Nominees on Nokia and Nokia's Closing Price, March 7, 2009, to December 30, 2011

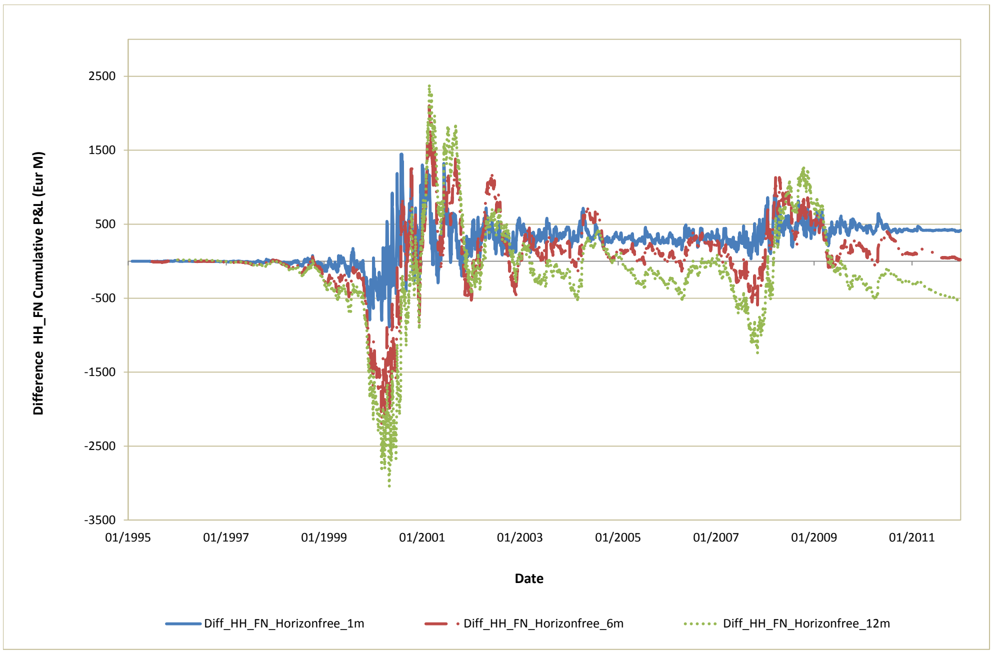
Table 2.4 Calendar-Time Portfolio Rebalancing every one month, six months and 12 months respectively, for each trading group from January, 1995 to December, 2011

	One Month		Six Months		12 Months	
	Households Cum. P&L (EUR M)	Foreign Nominees Cum. P&L (EUR M)	Households Cum. P&L (EUR M)	Foreign Nominees Cum. P&L (EUR M)	Households Cum. P&L (EUR M)	Foreign Nominees Cum. P&L (EUR M)
Nokia	4,121.68	-4,124.64	4,759.97	-4,762.20	5,791.20	-5793.23
Inclusive of Nokia	4,803.93	-4,814.20	5,430.65	-5,437.61	6,007.89	-6013.63
Exclusive of Nokia	682.26	-689.56	670.68	-675.41	216.69	-220.39
	Households Cum. P&L (EUR M)	Domestic Institutions Cum. P&L (EUR M)	Households Cum. P&L (EUR M)	Domestic Institutions Cum. P&L (EUR M)	Households Cum. P&L (EUR M)	Domestic Institutions Cum. P&L (EUR M)
Nokia	283.58	-284.21	353.88	-354.27	456.11	-456.39
Inclusive of Nokia	526.48	-529.47	500.94	-502.76	427.05	-428.46
Exclusive of Nokia	242.9	-245.26	147.06	-148.49	-29.07	27.93
	Domestic Institutions Cum. P&L (EUR M)	Foreign Nominees Cum. P&L (EUR M)	Domestic Institutions Cum. P&L (EUR M)	Foreign Nominees Cum. P&L (EUR M)	Domestic Institutions Cum. P&L (EUR M)	Foreign Nominees Cum. P&L (EUR M)
Nokia	12,000.26	-12,003.20	13,068.39	-13,070.77	15,208.67	-15,210.93
Inclusive of Nokia	12,824.4	-12,836.89	14,327.75	-14,335.63	16,286.30	-16,292.72
Exclusive of Nokia	824.14	-833.7	1,259.36	-1,264.86	1,077.63	-1,081.78

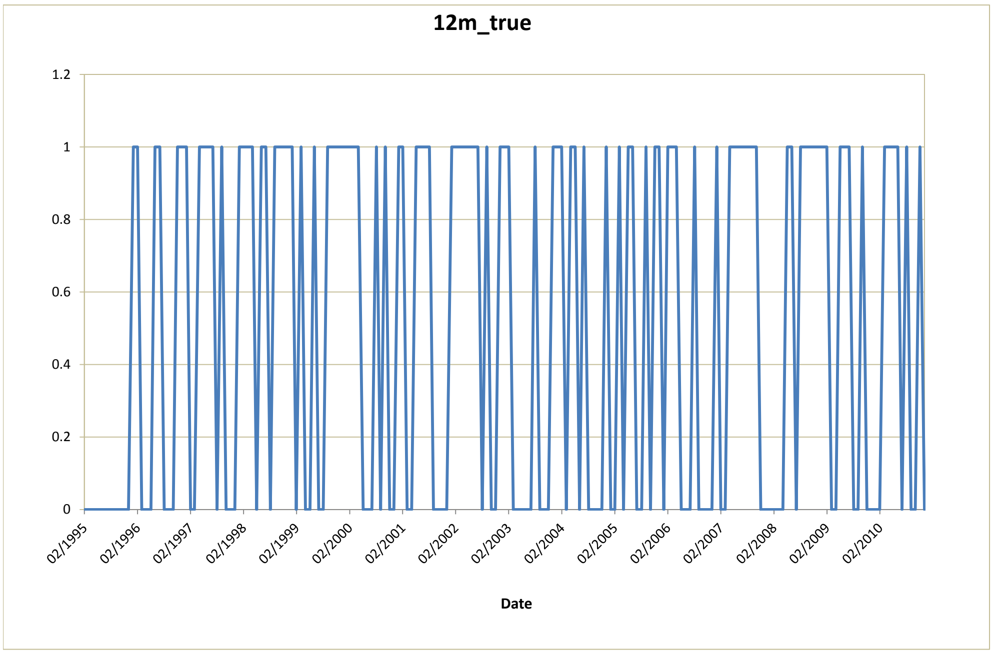
2.5.7 Extension to 32 major Finnish stocks and entire 232 Finnish stocks

In Table 2.5 Panels A to C I extend my findings for Nokia for my three investor groups and four time periods plus the entire sample period to my main sample of 32 major Finnish stocks, inclusive of and excluding Nokia. My findings are very similar to my earlier results just for Nokia. Households outperform both institutional investor groups and domestic institutions outperform foreign nominees. However, the magnitude of the additional trading profit earned by including an additional 31 major Finnish stocks is not great because these remaining stocks are much smaller than Nokia and were not subject to such extreme valuation fluctuations as was Nokia. These tables also report the profit measured after transaction cost per Euro traded. For households inclusive of Nokia these profit rates range from 3 percent to 16 percent but are much lower if Nokia is excluded. For domestic institutions trading with Foreign Nominees the net profit rate might appear low at only 3 percent yet, such is traded volume, profits aggregate to many billions of Euros over my trading period.

To eliminate any concerns over sample selection bias, I extend my *HPI* analysis to the entire 232 Finnish stocks from 1995 to 2011 and the results are presented in the Table 2.6. I still find that households display significant superior trading ability against both foreign nominees and domestic institutions, respectively, but with a slightly lower trading profitability rate for each matched trading pair. In the comparison with institutional investors, domestic institutions also earn less trading advantage over foreign nominees in the aggregated 232 Finnish stocks *HPI* trading portfolio compared with the aggregated *HPI* portfolio constructed by the large 32 Finnish stocks. The most likely explanation is that the relative lack of foreign institutional interest in smaller stocks means less trend following and fewer sizeable profit opportunities for both domestic households and institutional investors. To put it differently, less foreign institutional interest translates into better pricing and thus fewer domestic profit opportunities.



(a) The Daily Difference in Cumulative Profits and Losses for the direct trades between Households and Foreign Nominees, as measured by Horizon Free method and *C-T* method for horizons of 1 month, 6 months, and 12 months, 1995-2011.



(b) The numbers of times that the one-year Calendar-Time *C-T* portfolio provides a correct direction for actual Profits and Losses changes, 1995-2011 (100 out of 196 direction changes, or 51%).

Figure 2.8 Errors introduced by the use of the *C-T* Methodology

Table 2.5 Cumulative Profits and Losses after Transaction Costs for Direct Trades between each trading pair group in Large Finnish Stocks (32 stocks, inclusive of and exclusive of Nokia, respectively)

The significance of these cumulative profits and losses is tested by running a Monte Carlo simulation 10,000 times, where the daily direction taken by each of the investor categories in each stock is random. I thus employ an informationless benchmark. The result of this simulation provides the confidence interval I use to test the significance of the reported profits. Transaction cost per trade for households is EUR0.005 and EUR0.001 for foreign nominees, respectively. Total trading value is computed as the sum of daily total trading value in two groups from 1995 to 2011.

Panel A Between Households and Foreign Nominees

Periods	Households Cum. P&L inclusive of Nokia (EUR M)	Foreign Nominees Cum. P&L inclusive of Nokia (EUR M)	Households Cum. P&L exclusive of Nokia (EUR M)	Foreign Nominees Cum. P&L exclusive of Nokia (EUR M)
01/03/1995 - 12/30/1996	-5.98	5.37	-9.21	9.05
01/03/1997 - 07/03/2003	2,969.51***	-2,972.96***	305.97***	-307.95***
07/04/2003 - 03/06/2009	664.88	-682.58	94.65	-100.82
03/07/2009 - 12/30/2011	-622.00	615.74	-8.79	4.20
01/03/1995 - 12/30/2011	5,636.15***	-5,654.15***	713.32***	-726.23***
Ratio of *HPI* trading profits to total trading value	16%	-16%	3%	-3%

Continued

Panel B Between Households and Domestic financial institutions

Periods	Households Cum. P&L inclusive of Nokia (EUR M)	Domestic Institutions Cum. P&L inclusive of Nokia (EUR M)	Households Cum. P&L exclusive of Nokia (EUR M)	Domestic Institutions Cum. P&L exclusive of Nokia (EUR M)
01/03/1995 - 12/30/1996	-5.71	5.46	-3.38	3.31
01/03/1997 - 07/03/2003	221.56***	-222.56***	113.29***	-113.96***
07/04/2003 - 03/06/2009	114.46	-116.54	-18.52	16.80
03/07/2009 - 12/30/2011	-8.85	6.88	51.78	-53.38
01/03/1995 - 12/30/2011	565.31***	-570.61***	211.61***	-215.67***
Ratio of *HPI* trading profits to total trading value	5%	-5%	3%	-3%

Panel C Between Domestic financial institutions and Foreign Nominees

Periods	Domestic Institutions Cum. P&L inclusive of Nokia (EUR M)	Foreign Nominees Cum. P&L inclusive of Nokia (EUR M)	Domestic Institutions Cum. P&L exclusive of Nokia (EUR M)	Foreign Nominees Cum. P&L exclusive of Nokia (EUR M)
01/03/1995 - 12/30/1996	-37.68	35.57	-23.72	23.00
01/03/1997 - 07/03/2003	7,447.48***	-7,455.12***	171.90***	-177.27***
07/04/2003 - 03/06/2009	655.67	-665.67	493.5	-502.26
03/07/2009 - 12/30/2011	-166.11	160.43	-43.33	38.50
01/03/1995 - 12/30/2011	15,200.98***	-15,209.46***	1,088.25***	-1,094.81***
Ratio of H*PI* trading profits to total trading value	29%	-29%	3%	-3%

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6 Cumulative Profits and Losses after Transaction Costs for Direct Trades between each trading pair group in 232 Finnish Stocks inclusive of and exclusive of Nokia, respectively

The significance of these cumulative profits and losses is tested by running a Monte Carlo simulation 10,000 times, where the daily direction taken by each of the investor categories in each stock is random. I thus employ an informationless benchmark. The result of this simulation provides the confidence interval I use to test the significance of the reported profits. Transaction cost per trade for households is EUR0.005 and EUR0.001 for foreign nominees, respectively. Total trading value is computed as the sum of daily total trading value in two groups from 1995 to 2011.

Panel A Between Households and Foreign Nominees

Periods	Households Cum. P&L inclusive of Nokia (EUR M)	Foreign Nominees Cum. P&L inclusive of Nokia (EUR M)	Households Cum. P&L exclusive of Nokia (EUR M)	Foreign Nominees Cum. P&L exclusive of Nokia (EUR M)
01/03/1995 - 12/30/1996	-33.56	32.44	-36.79	36.12
01/03/1997 - 07/03/2003	3,434.77***	-3,442.14***	771.22***	-777.14***
07/04/2003 - 03/06/2009	879.5	-892.44	299.27	-310.68
03/07/2009 - 12/30/2011	-689.47	679.07	-76.27	67.52
01/03/1995 - 12/30/2011	5,876.32***	-5,908.16***	953.49***	-980.24***
Ratio of *HPI* trading profits to total trading value	12.2%	-12.3%	2.5%	-2.6%

Continued

Panel B Between Households and Domestic financial institutions

Periods	Households Cum. P&L inclusive of Nokia (EUR M)	Domestic Institutions Cum. P&L inclusive of Nokia (EUR M)	Households Cum. P&L exclusive of Nokia (EUR M)	Domestic Institutions Cum. P&L exclusive of Nokia (EUR M)
01/03/1995 - 12/30/1996	-12.28	11.78	-9.96	9.63
01/03/1997 - 07/03/2003	238.35***	-240.79***	130.03***	-130.03***
07/04/2003 - 03/06/2009	31.37	-34.80	-101.62	98.53
03/07/2009 - 12/30/2011	-36.51	33.61	24.13	-26.65
01/03/1995 - 12/30/2011	265.02***	-274.30***	88.68***	-80.64***
Ratio of H*PI* trading profits to total trading value	1.9%	-1.9%	-0.8%	0.7%

Panel C Between Domestic financial institutions and Foreign Nominees

Periods	Domestic Institutions Cum. P&L inclusive of Nokia (EUR M)	Foreign Nominees Cum. P&L inclusive of Nokia (EUR M)	Domestic Institutions Cum. P&L exclusive of Nokia (EUR M)	Foreign Nominees Cum. P&L exclusive of Nokia (EUR M)
01/03/1995 - 12/30/1996	-80.54	77.01	-67.52	65.38
01/03/1997 - 07/03/2003	7,606.44***	-7,619.03***	329.35***	-339.66***
07/04/2003 - 03/06/2009	1,000.44	-1,014.36	837.43	-850.10
03/07/2009 - 12/30/2011	-154.65	147.03	-32.00	25.23
01/03/1995 - 12/30/2011	15,111.45***	-15,149.12***	998.73***	-1,030.61***
Ratio of H*PI* trading profits to total trading value	22%	-22%	1.8%	-1.8%

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.5.8 Conventional investment performance proxy – Internal rate of return (IRR)

As a robustness check, I also perform internal rate of return (IRR) calculations without imposing any horizon assumptions other than the start and end dates of the projects to evaluate household, domestic institutional and foreign nominees trading ability. IRR takes an NPV "investment view" of expected financial results. This means, essentially, that the magnitudes and timing of cash flow returns are compared to cash flow costs. IRR analysis begins with a cash flow stream, the series of net cash flow outflow figures required for the investment with a positive realization of the portfolio at the end. I computed the HPI portfolio initial values of each agent-type, as described above, and marked to market on day 0 as its own initial investment outlay. I then take the daily value of stock purchases as additional investment outlay with sales representing a cash benefit over each one-day period from 3rd January 1995 to 30th December 2011. On the final day, the value of the portfolio is marked to market as the cash realization.

My continuously compounded IRR formula is standard, (e.g., as in SAS's IRR solve routine):

$$\sum_{j=1}^{j=k} NPV_j = \sum\nolimits_{j=1}^{j=k} \left[-IHV_{j,t=0} + \sum\nolimits_{j,t=1}^{j,t=n-1} \left(Daily\ NCF_{j,t} \right) e^{-rt} + FHV_{j,n} e^{-rn} \right] = 0, \quad (2.5)$$

where NPV is the net present value of the portfolio of the k stocks with $k = 32$ *or* 31 when there are multiple stocks, $IHV_{j,t=0}$ is the opening initial holding value of the jth stock in the portfolio representing the initial investment outlay, t is the designated day commencing at day 0 and finishing at $t = n - 1$, $Daily\ NCF_{j,t}$ is the daily Net Cash Flow consisting of the EUR value of sells for the jth stock in the portfolio when a sell occurs and is negative for purchases representing investment outlays, $FHV_{j,n}$ is the final realized holding value of the jth stock in the portfolio on the last day, day $t = n$, and e^{-rt} is discount factor with r the continuously compounded daily rate of return that is converted to its annual equivalent based on 250 trading days per year.

The “Buy Only” IRR is represented by:

$$\sum_{j=1}^{j=k} NPV_j = \sum\nolimits_{j=1}^{k} \left[-IHV_{j,t=0} - \sum\nolimits_{j,t=1}^{j,t=n-1} \left(Daily\ Purchases_{j,t} \right) e^{-rt} + FHV_{j,n} e^{-rn} \right] = 0, \tag{2.6}$$

where the only difference is that sales are ignored until the end-date with *Daily Purchases$_t$* representing the negative cash outlay each day a stock purchase occurs.

Table 2.7 Panel A displays the IRR results for Nokia alone over the four periods described above and for the entire seventeen-year period. The households’ *HPI* investment portfolio yields a unique 42.84 percent annualized continuous compounded internal rate of return, compared with a – 42.84 percent internal rate of return made by foreign nominee institutional investors over the entire seventeen years’ period. For a few stocks other than Nokia there was evidence of multiple roots and for these stocks the root recommended by the SAS routine was chosen. The counterfactual household “BuyOnly” IRR is massively lower at -25.15 percent p.a., indicating that it is necessary to include the exact timing of asset sales, as well as purchases, as the regular IRR method does. The "BuyOnly" IRR is but a crude extension of the conventional “buy and hold” *C-T* methodology, with my findings indicating that it severely distorts performance measurement. The remaining rows show that there is a huge variation in the IRR over the four shorter periods. For the most recent interval from March 2009 to December 2011 all IRR’s are either negative or are not defined due to falling prices.

Table 2.7 Panel B extends the IRR analysis to the full sample of a portfolio of the 32 (31) designated stocks, with the entire portfolio treated in the same way as the IRR for a single stock. In the interests of space, only the entire sample period results are shown. The table indicates that the IRR earned by households in trading with foreign nominees in the 31 stocks sampled earned a lower IRR of 19.1 percent p.a., which is about half the magnitude for Nokia alone. The final row in Table 2.5 Panel A shows that this return corresponds to a trading profit rate on trades of 16 percent. Thus, relatively large trading profit rates translate into quite high IRRs, given the magnitude of trading.

Table 2.7 Summary of Continuously Compounded Internal Rate of Return (IRR) of daily *HPI* Trading

Panel A: Summary of Continuously Compounded Internal Rate of Return (IRR) and "BuyOnly" IRR for Various Periods using daily *HPI* Trading for Nokia for Trades within the Three Groups.The term 'NA' indicates that SAS function cannot provide a valid root due to the nature of the different values of cash flows and the IRR is annualized based on 250 trading days per year. "BuyOnly" IRR indicates that sell trades are ignored until the portfolio is realized on the last day.

	Households with Foreign Nominees	Households with Domestic Financial Institutions	Domestic Financial Institutions with Foreign Nominees
01/03/1995-12/30/1996			
IRR	34.49%	1.34%	28.16%
BuyOnlyIRR	35.38%	30.79%	27.72%
01/03/1997-07/03/2003			
IRR	77.57%	55.18%	79.29%
BuyOnlyIRR	-6.12%	-6.03%	-3.17%
07/04/2003-03/06/2009			
IRR	2.41%	7.37%	1.98%
BuyOnlyIRR	-33.50%	-32.30%	-44.05%
03/07/2009-12/30/2011			
IRR	NA	NA	-38.09%
BuyOnlyIRR	-50.15%	-52.80%	-45.72%
01/03/1995-12/30/2011			
IRR	42.84%	13.18%	51.79%
BuyOnlyIRR	-25.15%	-20.42%	-18.19%

Panel B: Summary of Continuously Compounded Internal Rate of Return (IRR) of daily *HPI* Trading for 32 stocks (inclusive of Nokia) and 31 stocks (exclusive of Nokia) for Trades within the Three Groups from 1995 to 2011, respectively.IRR presents the continuously compounded internal rate of return for 32 (31) stocks with each group treated as a single investor in the entire portfolio of stocks each day. "BuyOnly" IRR is computed using the same single investor methodology as for the conventional IRR except that sell trades are ignored until the portfolio is realized on the last day.

	Households with Foreign Nominees		Households with Domestic Financial Institutions		Domestic Financial Institutions with Foreign Nominees	
	Inclusive of Nokia	Exclusive of Nokia	Inclusive of Nokia	Exclusive of Nokia	Inclusive of Nokia	Exclusive of Nokia
Number of Stocks	32	31	32	31	32	31
IRR	19.10%	6.87%	7.63%	7.15%	27.40%	6.94%
Buys Only IRR	-4.04%	0.56%	-2.97%	0.58%	-1.93%	0.18%

2.6 Householder Informational Advantage

The exceedingly high returns earned by households trading with either domestic or foreign institutional investors over the 17-year period, or for that matter, domestic institutions with foreign, suggests that they trade on the basis of private information. But what could be the source of this private informational advantage? One possibility is that households living in the greater Helsinki area are de facto insider traders as Nokia and other major companies are headquartered there and Nokia employees could pass on price sensitive information to neighboring households. A number of empirical studies find that information is more readily transmitted over short rather than long geographic distances. For example, Hau (2001) document that location matters in generating trading profits. Coval and Moskowitz (2001) find evidence of local informational advantages while Hong, Kubik and Stein (2005) find that word of mouth is used to share information by mutual fund managers in close geographic proximity. If this is the case then I should find that when greater Helsinki households are pitted against households in the remainder of the country in a trading battle for supremacy that the former dominate.

Table 2.8 Sub-periods cumulative Profits and Losses after transaction costs for direct trades between each trading pair in Large Finnish stocks (Nokia alone, 32 stocks, inclusive of and exclusive of Nokia, respectively)

I follow the turning points of CCI shown in Figure 2.9 to break down my entire sample period into three sub-periods, i.e., January, 1995 to November, 2001; December, 2001 to December 2008; January, 2009 to December 2011. This alterative way in splitting seventeen year-period into three sub-periods is a robustness check that I use endogenous variable to estimate Finland economy movements. CCI has been proven that a powerful indicator to represent the whole economy. The table shows *HPI* portfolio daily cumulative profits and losses (EUR million) in four different pairs of trading groups, i.e., Column (1) and Column (2) present Greater Helsinki households in the comparison of the rest Finnish households. Column (3) through Column (8) shows the trading performance between Households in direct trading with Foreign Nominees, Households in direct trading with Domestic Institutions and Domestic Institutions in direct trading with Foreign Nominees, respectively. *** represents statistically significant at 0.01 probability level.

Periods(Trough to Trough)	Cumulative P&L (EUR M)							
	Households with Greater Helsinki(1)	Other Households(2)	Households(3)	Foreign Nominees(4)	Households(5)	Domestic Institutions(6)	Domestic Institutions(7)	Foreign Nominees(8)
Nokia								
01/03/1995 - 11/30/2001	36.18***	-36.29***	1,355.53***	-1,357.01***	41.06***	-41.51***	4,103.44***	-4,106.75***
12/03/2001 - 12/31/2008	18.9	-18.97	495.42	-497.28	73.33	-73.73	324.06	-325.63
01/01/2009 - 12/30/2011	6.02	-6.06	-693.91	692.16	-66.64	66.25	-159.77	158.86
01/03/1995 - 12/30/2011	187.52***	-187.74***	4,922.53***	-4,927.63***	353.65***	-354.89***	14,112.94***	-14,113.91***
Inclusive of Nokia								
01/03/1995 - 11/30/2001	37.09***	-37.41***	1,590.74***	-1,593.70***	122.52***	-123.48***	4,074.82***	-4,082.49***
12/03/2001 - 12/31/2008	32.46	-33.04	546.34	-554.62	-17.29	15.03	1,001.50	-1,013.20
01/01/2009 - 12/30/2011	10.75	-11.24	-598.25	591.5	-12.23	10.16	-201.26	195.18
01/03/1995 - 12/30/2011	198.86***	-200.25***	5,614.61***	-5,632.61***	558.14***	-563.44***	15,194.10***	-15,202.58***
Exclusive of Nokia								
01/03/1995 - 11/30/2001	0.92***	-1.12	235.21***	-236.69***	81.45***	-81.97***	-28.62***	24.25***
12/03/2001 - 12/31/2008	13.56	-14.08	50.92	-57.34	-90.63	88.76	677.44	-687.57
01/01/2009 - 12/30/2011	4.73	-5.18	95.66	-100.67	54.41	-56.09	-41.5	36.32
01/03/1995 - 12/30/2011	11.34***	-12.52***	692.08***	-704.98***	204.49***	-208.55***	1,082.12***	-1,088.68***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

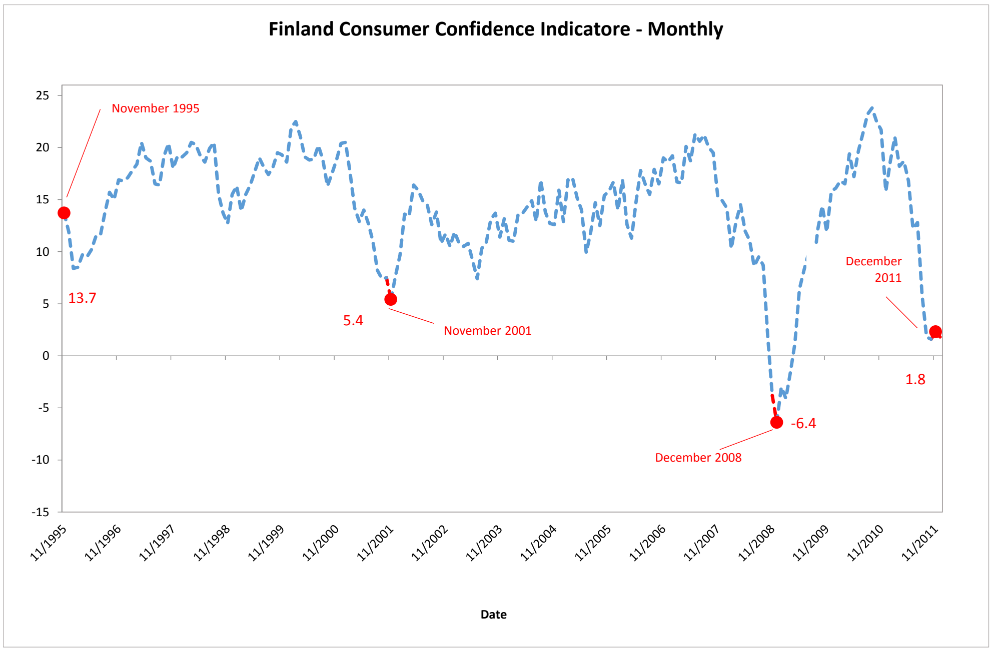


Figure 2.9 Finland Consumer Confidence Indicator (CCI) as an exogenous variable reflecting economic environments – Monthly

Since my database includes the local postcode addresses of the over one million Finnish trading accounts and these households trade with each other as well as with domestic and foreign institutions, columns (1) and (2) of Table 2.8 test the hypothesis that households located close to Nokia headquarters possess better information on which to trade than do households located elsewhere in the country. Table 2.8, showing the cumulative profits for each trading group in millions of Euros, is split into three periods spanning the 17 years of the database based on the lowest points in the Finnish Consumer Confidence Index (CCI) displayed in Figure 2.9. These business cycle turning points differ from the stock price index turning points used in the previous tables. Yes, indeed, the first two columns confirm the hypothesis that Helsinki households trade with their non-Helsinki based on superior information. The table indicates that Helsinki households profited by 198.86 million Euros in trades with their non-Helsinki counterparts over the 17 years of my data in 32 large Finnish stocks inclusive of Nokia. Not surprisingly, the bulk of the profits were made in Nokia. The remaining columns basically confirm the previous findings based on stock price index movements that households are overall the most informed traders, followed by domestic institutions and, finally, foreign institutions. Branikas, Hong and Xu (2016) document the effect of households location choices on portfolio choices, however, this is not the case in my Finnish households sample, clearly they do not have the ability to determine the location they were born.

In Table 2.9 I pit the two identified household trading groups, Helsinki and the remainder, individually against both domestic institutional and foreign investors to test the hypothesis that Finnish households are collectively better informed and thus superior traders even when not in receipt of insider information due to the close proximity of Nokia headquarters. Panel A is based on the intervals specified by the CCI and Panel B, the stock price index. Both the Helsinki and remainder groups dominate foreign investors with the two groups respectively earning EUR 3,506 and 2,349 million trading profit based on the 32 largest stocks inclusive of Nokia at the expense of their geographically very distant counterparties over the full 17 years of the database. The Helsinki households remain superior traders when pitted against their domestic institutional rivals with a profit of EUR 600 million but for the remaining households it is lineball with domestic institutions gaining approximately EUR 100 million but losing approximately the same amount on non-Nokia stocks. Since most domestic institutional investors are located in Helsinki, the remaining households suffering a geographic informational disadvantage do well to draw lineball. I conclude that Finnish households overall appear to have better access to information than do either domestic or foreign institutional investors.

Table 2.9 *HPI* trading performance in different location

Panel A: This panel shows the *HPI* trading performance between Greater Helsinki households with Foreign Nominees, Other households with Foreign Nominees, Greater Helsinki households with Domestic Institutions, Other households with Domestic Institutions, in each sub-period (Based on CCI).

Periods (Trough to Trough)	Cumulative P&L (EUR M)							
	Greater Helsinki House-holds (1)	Foreign Nomi-nees (2)	Other House-holds (3)	Foreign Nomi-nees (4)	Greater Helsinki House-holds (5)	Domestic Institu-tions (6)	Other House-holds (7)	Domestic Institu-tions (8)
Nokia								
01/03/1995 - 11/30/2001	768.24***	-769.46***	607.40***	-608.80***	85.84***	-86.27***	-35.15	34.63
12/03/2001 - 12/31/2008	268.98***	-270.49***	238.68***	-240.44***	52.53	-52.99	31.44	-31.91
01/01/2009 - 12/30/2011	-209.39	208.52	-395.73	394.14	-27.48	27.15	-39.03	38.53
01/03/1995 - 12/30/2011	3,068.99***	-3,072.60***	2,130.68***	-2135.43***	457.29***	-458.50***	-100.84	99.35
Ratio of profits to total trading value	64.04%	-64.11%	36.01%	-36.09%	32.24%	-32.33%	-6.01%	5.92%
Ratio of profits to total trading volume	8.52	-8.53	4.49	4.50	3.79	-3.80	-0.28	0.28
Inclusive of Nokia								
01/03/1995 - 11/30/2001	928.77***	-931.21***	681.67***	-684.75***	145.04***	-145.97***	3.53	-4.71
12/03/2001 - 12/31/2008	345.21	-351.59	190.42	-199.12	12.18	-14.49	-52.9	50
01/01/2009 - 12/30/2011	-171.19	167.65	-386.5	380.04	-2.28	0.57	-4.96	2.34
01/03/1995 - 12/30/2011	3,506.54***	-3,518.89***	2,349.17***	-2,367.43***	599.87	-604.82	-3.07	-3.63
Ratio of profits to total trading value	24.16%	-24.25%	11.60%	-11.69%	10.82%	-10.91%	-0.04%	-0.05%
Ratio of profits to total trading volume	2.84	-2.85	1.29	1.30	1.21	-1.22	-0.00	-0.00
Exclusive of Nokia								
01/03/1995 - 11/30/2001	160.52***	-161.74***	74.26***	-75.95***	59.20***	-59.71***	38.68	-39.33
12/03/2001 - 12/31/2008	76.24	-81.11	-48.26	41.32	-40.35	38.49	-84.35	81.92
01/01/2009 - 12/30/2011	38.2	-40.86	9.23	-14.1	25.2	-26.58	34.07	-36.19
01/03/1995 - 12/30/2011	437.54	-446.3	218.49	-232	142.57	-146.32	97.77	-102.98
Ratio of profits to total trading value	4.50%	-4.59%	1.52%	-1.62%	3.45%	-3.54%	1.75%	-1.84%
Ratio of profits to total trading volume	0.50	-0.51	0.16	-0.17	0.38	-0.39	0.06	-0.06

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: This panel shows the *HPI* trading performance between Greater Helsinki households with Foreign Nominees, Other households with Foreign Nominees, Greater Helsinki households with Domestic Institutions, Other households with Domestic Institutions, in each sub-period (Based on historical index movement, the same as in the tables above).

Periods (Trough to Trough)	Cumulative P&L (EUR M)							
	Greater Helsinki Households (1)	Foreign Nominees (2)	Other Households (3)	Foreign Nominees (4)	Greater Helsinki Households (5)	Domestic Institutions (6)	Other Households (7)	Domestic Institutions (8)
Nokia								
01/03/1995 - 07/03/2003	1,739.34***	-1,740.89***	1,321.71***	-1,323.51***	236.92***	-237.42***	-65.05	64.46
07/04/2003 - 03/06/2009	301.07	-302.3	312.73	-314.18	85	-85.39	65.99**	-66.40**
03/07/2009 - 12/30/2011	-178.71	177.89	-344.19	342.69	-25.04	24.72	-39.03	38.53
01/03/1995 - 12/30/2011	3,068.99***	-3,072.60***	2,130.68***	-2135.43***	457.29***	-458.50***	-100.84	99.35
Ratio of profits to total trading value	64.04%	64.11%	36.01%	-36.09%	32.24%	-32.33%	-6.01%	5.92%
Ratio of profits to total trading volume	8.52	-8.53	4.49	4.50	3.79	-3.80	-0.28	0.28
Inclusive of Nokia								
01/03/1995 - 07/03/2003	1,985.16***	-1,988.39***	1,428.16***	-1432.41***	322.20***	-323.42***	-11.03	9.51
07/04/2003 - 03/06/2009	415.88	-421.78	272.9	-280.99	88.68	-90.79	16.2	-18.87
03/07/2009 - 12/30/2011	-177.2	173.98	-405.67	399.78	-1.8	0.18	-4.96	2.34
01/03/1995 - 12/30/2011	3,506.54***	-3,518.89***	2,349.17***	-2,367.43***	599.87	-604.82	-3.07	-3.63
Ratio of profits to total trading value	24.16%	-24.25%	11.60%	-11.69%	10.82%	-10.91%	-0.04%	-0.05%
Ratio of profits to total trading volume	2.84	-2.85	1.29	1.30	1.21	-1.22	-0.00	-0.00
Exclusive of Nokia								
01/03/1995 - 07/03/2003	245.82***	-247.50***	106.44***	-108.91***	85.27***	-86.00***	54.02	-54.95
07/04/2003 - 03/06/2009	114.81	-119.48	-39.83	33.19	3.68	-5.4	-49.79	47.53
03/07/2009 - 12/30/2011	1.5	-3.91	-61.48	57.1	23.25	-24.54	34.07	-36.19
01/03/1995 - 12/30/2011	437.54	-446.3	218.49	-232	142.57	-146.32	97.77	-102.98
Ratio of profits to total trading value	4.50%	-4.59%	1.52%	-1.62%	3.45%	-3.54%	1.75%	-1.84%
Ratio of profits to total trading volume	0.50	-0.51	0.16	-0.17	0.38	-0.39	0.06	-0.06

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel C: This panel shows the *HPI* trading performance between Greater Helsinki Domestic Institutions with Other Domestic Institutions, Greater Helsinki households with Greater Helsinki Domestic Institutions, Other households with Other Domestic Institutions, in each sub-period (Based on Finland Consumer Confidence Indicator).

Periods (Trough to Trough)	Cumulative P&L (EUR M)					
	Greater Helsinki Domestic Institutions (1)	Other Domestic Institutions (2)	Greater Helsinki Households (3)	Greater Helsinki Domestic Institutions (4)	Other Households (5)	Other Domestic Institutions (6)
Nokia						
01/03/1995 - 11/30/2001	7.36***	-7.42***	85.95**	-86.39**	2.36**	-2.39**
12/03/2001 - 12/31/2008	1.75	-1.77	52.46**	-52.91**	-0.75	0.73
01/01/2009 - 12/30/2011	2.70***	-2.72***	-46.04	45.65	-1.53	1.51
01/03/1995 - 12/30/2011	51.22	-51.32	437.08**	-438.36**	25.14**	-25.21**
Ratio of profits to total trading value	46.92%	-47.01%	29.54%	-29.63%	37.83%	-37.93%
Ratio of profits to total trading volume	4.68	-4.69	3.41	-3.42	3.71	-3.71
Inclusive of Nokia						
01/03/1995 - 11/30/2001	12.94	-13.14	145.21**	-146.22**	5.31	-5.41
12/03/2001 - 12/31/2008	11.1	-11.29	-13.73	11.22	0.61	-0.73
01/01/2009 - 12/30/2011	8.94	-9.12	-28.6	26.42	4.91	-5.03
01/03/1995 - 12/30/2011	62.29	-62.86	557.18**	-562.89**	40.86	-41.22
Ratio of profits to total trading value	12.42%	-12.53%	9.05%	-9.14%	12.75%	-0.12.87%
Ratio of profits to total trading volume	1.09	-1.10	0.98	-0.99	1.15	-1.16
Exclusive of Nokia						
01/03/1995 - 11/30/2001	5.59	-5.72	59.25**	-59.83**	2.95	-3.02
12/03/2001 - 12/31/2008	9.36	-9.52	-66.19	64.14	1.35	-1.46
01/01/2009 - 12/30/2011	6.25	-6.4	17.44	-19.23	6.44	-6.54
01/03/1995 - 12/30/2011	11.08	-11.54	120.1	-124.53	15.72	-16.01
Ratio of profits to total trading value	2.82%	-2.94%	2.57%	-2.66%	6.19%	-6.31%
Ratio of profits to total trading volume	0.24	-0.25	0.27	-0.28	0.55	-0.56

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel D: This panel shows the *HPI* trading performance between Greater Helsinki Domestic Institutions with Other Domestic Institutions, Greater Helsinki households with Greater Helsinki Domestic Institutions, Other households with Other Domestic Institutions, in each sub-period (Based on historical index movement, the same as in the tables above)

Periods (Trough to Trough)	Cumulative Profits and Losses (EUR M)					
	Greater Helsinki Domestic Institutions (1)	Other Domestic Institutions (2)	Greater Helsinki Households (3)	Greater Helsinki Domestic Institutions (4)	Other Households (5)	Other Domestic Institutions (6)
Nokia						
01/03/1995 - 07/03/2003	23.33***	-23.40***	236.45**	-236.96**	14.41**	-14.45**
07/04/2003 - 03/06/2009	2.12	-2.14	85.69**	-86.09**	-0.05	0.037
03/07/2009 - 12/30/2011	2.77	-2.78	-43.61	43.22	-1.43	1.41
01/03/1995 - 12/30/2011	51.22***	-51.32***	437.08**	-438.36**	25.14**	-25.21**
Ratio of profits to total trading value	46.92%	-47.01%	29.54%	-29.63%	37.83%	-37.93%
Ratio of profits to total trading volume	4.68	-4.69	3.41	-3.42	3.71	-3.72
Inclusive of Nokia						
01/03/1995 - 07/03/2003	24.66	-24.89	322.70**	-324.02**	17.85**	-17.97**
07/04/2003 - 03/06/2009	15.69	-15.87	68.09	-70.38	4.98	-5.11
03/07/2009 - 12/30/2011	8.05	-8.22	-28.26	26.18	4.7	-4.82
01/03/1995 - 12/30/2011	62.29	-62.86	557.18**	-562.89**	40.86	-41.22
Ratio of profits to total trading value	12.42%	-12.53%	9.05%	-9.14%	12.75%	-12.87%
Ratio of profits to total trading volume	1.09	-1.10	0.98	-0.99	1.15	-1.16
Exclusive of Nokia						
01/03/1995 - 07/03/2003	1.33	-1.49	86.25**	-87.06**	3.44	-3.52
07/04/2003 - 03/06/2009	13.57	-13.72	-17.61	15.71	5.04	-5.14
03/07/2009 - 12/30/2011	5.28	-5.43	15.35	-17.04	6.13	-6.23
01/03/1995 - 12/30/2011	11.08	-11.54	120.1	-124.53	15.72	-16.01
Ratio of profits to total trading value	2.82%	-2.94%	2.57%	-2.66%	6.19%	-6.31%
Ratio of profits to total trading volume	0.24	-0.25	0.27	-0.28	0.55	-0.56

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.7 Robustness Check

Barrot, Kaniel, and Sraer (2016, pp.160-162) examine the ability of a sample of individual investors from a French discount broker to learn how to earn trading profits from liquidity provision based on their contrarian trading strategy. They find that traders that are less picked-off and reverse their trades more rapidly are more likely to survive while less experienced traders are more likely to suffer attrition. This finding raises the possibility that my results above showing the superior trading ability of Finnish households could be upward-biased or my findings reversed since there is both attrition in my sample of household traders and the entry of new traders. Since my methodology excludes trades between households, could I be missing the losses of households that suffer attrition if they sell out to newly entering households? To find out I redo my analysis presented in Panels A and B of Table 2.5 above and this time confine it to just those households who actively participated at the beginning of my sample period commencing in 1995 and thus exclude newly entering households. In Table 2.10 I report these new results to show that actually the initial household investors do a great deal better than the entire sample inclusive of the new entrants. For example, the profit rate for households trading with foreign nominees inclusive of Nokia is 29 percent over the entire sample period compared to only 0.16 for the entire sample, as shown in Table 2.5. I thus reject the conjecture that the exceptional performance of Finnish household traders in my sample is due to bias introduced by the attrition of poor traders and the entry of new traders.

Barber and Odean (2013) claim that many individual investors seem to trade too much with a perverse security selection ability. This finding raises the question that whether active Finnish individual traders and passive Finnish individual trades perform differently when they direct trade with either foreign nominees and domestic institutional investors. Hence, given the entire 17-year examine period, I split households into two categories, i.e., active households and passive households. For each individual household account, the individual trader is defined as the active trader if making at least 100 trades and trading more often than once a month, otherwise, the individual trader is defined as the passive trader. Over the 994,937 households, the active households category contains approximately 30,000 active individual traders. I redo my analysis presented in Table 2.5 above as a result of the households trading frequency by constructing two *HPI* trading pair groups, active households and foreign nominees, and passive households and foreign nominees. The results are presented in Table 2.11 Panel A and Panel B, respectively, showing that active individual traders do worse than passive individual traders when they directly trade with foreign institutional investors.[19] Foreign nominees are statistically significantly dominated by both active households and passive households, but active individual traders show relatively less trading advantage over passive traders in the face of foreign nominees given the same examined period and same sample. Over the entire 17-year period, in the direct trades with foreign nominees, active households gain a profitability rate 7% over the 28 Finnish stocks which is lower than the profitability rate made by passive households 31%. For Nokia alone, passive households earn a superior 41% profitability rate compared with the active household’s rate of 29%. But note that active households still massively outperform Foreign Nominee institutional investors. Hence, while it may be true that some individual investors trade too often and to their relative detriment, it is not true that highly active households under-perform institutional investors. The so called “overconfidence”, “boys will be boys”, phenomena claimed by Barber and Odean (2001) is largely due to their assumption of a huge almost 4% round-trip trading cost for households utilizing a “discount broker”. Normally, discount brokers not offering advice charge almost negligible fees.

[19] I do not include the similar table to show the difference when they trade with domestic institutions due to the lesser amount data available to capture the statistical significance of *HPI* trades.

Table 2.10 Cumulative Profits and Losses after Transaction Costs for Direct Trades between each Trading Pair when Restricted to just the Initial 1995 Set of Households

Sample	Period(Trough to Trough)	Cumulative P&L (EUR M)			
Category		Households (1)	Foreign Nominees (2)	Households (5)	Domestic Institutions (6)
Nokia					
	01/03/1995 - 12/30/1996	-0.09	-0.55	-2.93	2.66
	01/01/1997 - 07/03/2003	2,357.57***	-2,359.23***	206.73***	-207.14***
	07/04/2003 - 03/06/2009	317.67	-318.88	110.16	-110.53
	03/07/2009 - 12/30/2011	-193.74	192.80	-40.8	40.50
	01/03/1995 - 12/30/2011	4,782.59***	-4,787.03***	570.41***	-571.83***
Inclusive of Nokia (28 stocks)					
	01/03/1995 - 12/30/1996	-8.10	7.18	-6.38	5.98
	01/01/1997 - 07/03/2003	2,538.72***	-2,543.04***	280.42***	-281.88***
	07/04/2003 - 03/06/2009	526.88	-534.00	48.47	-50.90
	03/07/2009 - 12/30/2011	-214.85	210.10	-36.19	33.98
	01/03/1995 - 12/30/2011	5,426.53***	-5,443.65***	698.71***	-705.22***
Ratio of *HPI* trading profits to total trading value from 1995 to 2011		29%	-29%	10%	-10%
Exclusive of Nokia (27 stocks)					
	01/03/1995 - 12/30/1996	-8.01	7.73	-3.45	3.32
	01/01/1997 - 07/03/2003	181.15	-183.81	73.68***	-74.73***
	07/04/2003 - 03/06/2009	209.21	-215.12	-61.69	59.63
	03/07/2009 - 12/30/2011	-21.11	17.29	4.69	-6.52
	01/03/1995 - 12/30/2011	643.95	-656.62	128.30***	-133.39***
Ratio of *HPI* trading profits to total trading value from 1995 to 2011		5%	-5%	2%	-2%

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.11 *HPI* trading performance between active households and foreign nominees, and between passive households and foreign nominees, respectively

Panel A: This panel shows the *HPI* trading performance between active households and foreign nominees, in each sub-period (Based on historical index movement, the same as in the tables above)

Periods	Households Cum. P&L Nokia (EUR M)	Foreign Nominees Cum. P&L Nokia(EUR M)	Households Cum. P&L inclusive of Nokia(EUR M)	Foreign Nominees Cum. P&L inclusive of Nokia(EUR M)	Households Cum. P&L exclusive of Nokia(EUR M)	Foreign Nominees Cum. P&L exclusive of Nokia(EUR M)
	(1)	(2)	(3)	(4)	(5)	(6)
01/03/1995 - 12/30/1996	1.52	-1.9	-2.29	1.72	-3.81	3.62
01/03/1997 - 07/03/2003	974.22***	-975.51***	1,017.42***	-1,021.4***	43.21	-45.89
07/04/2003 - 03/06/2009	218.48	-220.23	117.80	-128.73	-100.68	91.51
03/07/2009 - 12/30/2011	-277.06	275.46	-297.12	288.71	-20.06	13.25
01/03/1995 - 12/30/2011	1,783.5***	-1,788.53***	1,880.97***	-1,904.87***	97.47***	-116.34***
Ratio of trading profits to total trading value 1995 to 2011	29%	-29%	7%	-7%	2%	-2%

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: This panel shows the *HPI* trading performance between passive households and foreign nominees, in each sub-period (Based on historical index movement, the same as in the tables above)

Periods	Households Cum. P&L Nokia (EUR M)	Foreign Nominees Cum. P&L Nokia(EUR M)	Households Cum. P&L inclusive of Nokia(EUR M)	Foreign Nominees Cum. P&L inclusive of Nokia(EUR M)	Households Cum. P&L exclusive of Nokia(EUR M)	Foreign Nominees Cum. P&L exclusive of Nokia(EUR M)
	(1)	(2)	(3)	(4)	(5)	(6)
01/03/1995 - 12/30/1996	-0.72	0.38	-5.84	5.36	-5.12	4.98
01/03/1997 - 07/03/2003	1,461.76***	-1,462.69***	1,644.77***	-1,646.9***	183.01***	-184.21***
07/04/2003 - 03/06/2009	338.91	-339.67	479.44	-483.18	140.53	-143.51
03/07/2009 - 12/30/2011	-308.09	306.9	-376.54	372.48	-68.45	65.59
01/03/1995 - 12/30/2011	2,965.27***	-2,968.5***	3,464.72***	-3,475.15***	499.45***	-506.65***
Ratio of trading profits to total trading value 1995 to 2011	41%	-41%	31%	-31%	7%	-7%

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.8 Conclusion

In this paper I develop and apply to the all households, domestic institutions, and foreign nominee institutional investors in Nokia and 32 other major Finnish stocks a new methodology I dub the holding-period-invariant portfolio method. This is in contrast to the conventional *C-T* portfolio methodology that had its origins in important contributions made by Jaffe (1974) and Mandelker (1974) approximately forty years ago. I also adopt an extensive seventeen-year window of matched daily trades by each investor group based on the daily portfolios of all Finnish investors in Finnish stocks, all households and all domestic institutional investors.

The conventional *C-T* portfolio approach owes its justification to the presence of cross-sectional dependence in the trades of individual participants and hence the aggregation of individual trades to the level of a single investor-type. However, this method then unnecessarily assumes that all investors mechanically turn over their entire portfolio at a specified interval corresponding to an assumed horizon. I show that this methodology leads to bias and considerable errors and even an inability to correctly indicate the direction of the trading profit change. By contrast, my methodology is free of such error and bias, enabling it to recognize the endogenous nature of investment timing decisions made by the million or so individual households in my dataset.

I find that the direct trade portfolio of households with foreign institutional investors in Nokia results in a gain to households of EUR 4,923 million over the seventeen years of my dataset. This represents a striking internal rate of continuously compounded return of 42.84 percent p.a.. If the Calendar-Time "Buy and Hold" equivalent of the IRR, that I dub the "BuyOnly" IRR, is used instead the return falls to minus 25 percent p.a.., indicating severe methodological error. While domestic institutions lost out to households in direct trading, these institutional investors gained an even larger reward of EUR 14,113 million, or an IRR of 51.79 percent p.a.., in their trades with foreign nominees, 1995-2011.

The trading advantage of households over both domestic and foreign institutional investors is unlikely to be due purely to a locational home advantage as households share their advantage with local institutions. Hence the household trading gain of a fairly modest EUR 354 million in Nokia at the expense of local institutional investors (IRR 13.18 p.a.) appears dependent on the absence of agency issues with the concomitant better risk-reward incentives possessed by households and ability to better exploit any personal or 'inside' information. Consistent with this view, I find that households located geographically near Nokia headquarters dominate more distant households and that both groups dominate foreign investors such that even households geographically distant from Nokia headquarters and potentially insider-trading employees are still more informed than foreign investors. The better performance of both household groups and domestic institutions over foreign institutions with a combined gain of EUR 20,809 million suggests that there remains an overall 'home-bias' informational advantage.

As Hayek (1945) pointed out, the only way that individuals possessing valuable private information can effectively exploit such information is for them to act on it themselves. Delegation to others is impossible, putting the agents of relatively less informed households – namely institutional investors – at a disadvantage. Friedman (1953) famously predicted the demise of destabilizing speculative activity due to inevitable losses. However, his prediction failed to account for agency issues endemic with professional money managers and their loss of other people's money.

Chapter 3

The Gender Face-Off: Do Females Traders Come Out On-Top

"Women of the Street" 2015, "Market bubbles may be a male phenomenon, and if so, then investment returns could be improved if your money was managed by a woman." It is female, not male, who are the superior investors and that we would all be wealthier and more financially secure if we learned to invest "like a lady."

3.1 Introduction

Does gender matter when investing in the equity market? As data quality used in evaluating individual investors' trading performance in research is predominantly poor in comparison to institutional investors, in this paper I utilize a remarkably comprehensive data set that allows us to provide new and improved insight into the Finnish individual's trading behavior over the 17 year period, 1995-2011, on a daily basis. Specifically, I adopt an approach dubbed the "holding-period-invariant" (*HPI*) portfolio methodology firstly introduced by Lu, Swan and Westerholm (2016) to investigate whether gender difference affect households' investment decisions.

With limited aims in this study, I only focus on trades between counterparties such as female investors with male investors, female investors with non-female, i.e., males plus all institutional investors plus all other categories of investor, and male investors with non-male, i.e., female and all non-female investors, respectively. I am not concerned with the performance of their overall stock portfolios. Furthermore, I lack resources from data providers to access every household's derivatives accounts, together with their income information, although I do know age and geographic location,[1] as well as gender and each individual's daily trades and daily equity portfolio for every day for 17 years. I also know family names and can identify spouses, including the spouses of designated insider traders.[2] Thus I do not claim to offer a comprehensive treatment of the overall performance of each investor type but rather emphasize the differences in both knowledge and timing ability that are reflected in matched counterparty trades over extended time periods.

An extensive academic literature documents that gender matters in a number of different domains, including consumption, labor market, investment and corporate governance (e.g. compensation of top executives). In particular, recent finance literature has claimed that male and female investors differ in terms of risk aversion, overconfidence and mutual trust,

[1] Hau (2001) document that location matters in generating trading profits.

[2] I follow the procedures described in Berkman, Koch, and Westerholm (2014) to identify Finnish insider female and male investors' account over the period 2000 to 2011.

with these dimensions impacting financial decision making and performance. For instance, several studies have documented that female investors seem to be more risk averse than male investors, hold less volatile portfolios, and expect lower returns (e.g., Sunden and Surette (1998), Agnew, Balduzzi, and Sunden (2003), Eckel and Grossman (2008), Croson and Gneezy (2009), Bertrand (2011), as well as Niederle (2014). Male investors invest more often and more aggressively than female investors when facing financial opportunities (Deaux and Farris (1977), Barber and Odean (2001), and Dorn and Huberman (2005)). Other argues that male investors are more overconfident than female investors (e.g., Barber and Odean (2001), and Niederle and Vesterlund (2007, 2011)), but Dorn and Huberman (2005) find in a survey of investors matched up with their actual trading accounts that two proxies for overconfidence fail to explain cross-sectional variation in trade intensity. Self-reported less risk averse respondents and less experienced investors' trade a great deal more. Niessen-Ruenzi and Ruenzi (2015) find evidence that investors are reluctant to invest in female-managed U.S. equity mutual funds but these flows are not driven by differences in past performance, or fund characteristics other than gender. Hence they put down these differences as evidence of prejudice. Bose, Ladley and Li (2016) model testosterone differences within a trading model.

Recent research into the brain using experimental findings together with brain imaging by Bruguier, Quartz, and Bossaerts (2010) has found an association between the "theory of the mind" and trader intuition, including the ability to detect informed traders in the crowd. "Theory of the mind" refers to an ability to read either benevolence or malevolence, e.g., the presence of an informed trading opponent, into patterns in one's surroundings and is different from mathematical reasoning skills. Walker (2005) and the literature she cites finds that females, here 3-to 5-year old children, are more competent at theory of the mind tasks than are similar males. Rueckert and Naybar (2008) find that females perform better on a test for empathy than do males while pointing out that empathy is similar in concept to the "theory of the mind". Similarly, Derntl et al. (2010) find that females utilise more emotion-related areas of the brain relative to males. Thus while Bruguier, Quartz, and Bossaerts (2010) had too small a sample to be able to detect trading differences between males and females, there is extensive evidence supporting the idea that females are better at theory of the mind tasks.

There is also a large literature on exposure to the male steroid hormone, testosterone, and a second hormone, cortisol, with both hormones associated with highly stressful and competitive environments such as trading floors. In experiments conducted on a large (550) cohort of University of Chicago MBAs Sapienza, Zingales, and Maestripieri (2009) find that higher prenatal exposure to testosterone and higher circulating testosterone are associated with less aversion to risk. MBA graduates high in testosterone and low in risk aversion were more likely to choose risky finance careers. Bossaerts et al. (2010) find that testosterone significantly decreases trust amongst unfamiliar individuals and thus increases social vigilance which enhances preparation for very competitive environments such as the trading floor. However, my subjects, being individual traders, do not trade on a competitive trading floor but rather trade from home where females may be less at a disadvantage. Cueva et al. (2015) find that naturally occurring cortisol predicts subsequent risk-taking and price instability in an experimental situation and that administered doses of both hormones shifts investments toward riskier assets. More recently, Nave et al. (2017) found that men given doses of testosterone performed more poorly on a test designed to measure cognitive reflection than a group give a placebo and conclude that testosterone makes men less likely to question their impulses.

Only recently has the conversation turned to whether there is a “gender advantage” in investing (Jones (2015)). While portfolio diversification is one of the major elements of investing, there has been no attempt to create diversity among those who manger money – either professionally or personally. Thus the current study tests the hypothesis that female and male investors trading behavior differs in an environment away from the trading floor, which is important for both academic researchers and practitioners alike.

Compared with previous literature, this paper makes four main contributions. First, it adds to the exiting literature on differences between female and male investors in a new setting by utilizing *HPI* methodology to investigate the effect of gender in equity markets. *HPI* methodology contrasts with the conventional Calendar-Time *C-T* methodology that figures prominently in the survey by Barber and Odean (2013). The existing literature is based largely on *C-T* portfolios, or related methods, which impose specified investor horizons. At the end of each horizon, be it a day, week, month, or six months, the portfolio is realized and the entire process begins over again irrespective of, or in contradiction to, the actual trades that are generally known to the researcher. Thus if an investor buys a share when the stock is falling in price and the price continues to fall over the next day, week, or month, but then rises dramatically prior to the sale at a huge profit, the *C-T* methodology characterises that as a loss if the specified turnover period was less than a month. All actual completed round-trip trades are ignored, even though the researcher possesses the entire sequence.

To my best knowledge, the present study is the first to perform "apples to apples" comparisons over relevant time-periods without imposing mandated investors horizons that have limited or no applicability to these collectively male and female investors. This means I overcome the problem that two investor-type groups might have similar portfolio alphas based on factor models assuming a fixed investment horizon but in exceedingly volatile markets may earn entirely different realized trading profits due to one having better private market timing ability and information than the other. Since market timing is endogenous and reliant on both the incentives and information base of the trader, any comparison of agent-type performance requires a performance measure that both recognizes and rewards stock-timing ability.

Second, my data sourced from Euroclear Finland Ltd is used as it enables study of the whole universe of stock exchange trades for one country, regardless of the actual location of trading around the globe, for example, in Helsinki or in the United States. The data set includes details of all trades made in Finnish stocks, whether conducted on the Helsinki stock exchange directly, or elsewhere, from January 1995 through December 2011 over a seventeen year-period on a daily basis. Such a comprehensive data set has not previously been used to study the role of gender based all transactions (all 1.016 million investor accounts) and it is far superior to any other database used in investigating gender difference in individuals' trading behavior.

Third, the present study also adds to the existing literature on portfolio performance benchmark analysis. I utilize the spirit of Grinblatt and Titman (1993)[3] to carry out a random portfolio benchmark to access both the economic and statistical significance of the trading ability of participants. The conventional approach in asset pricing is to introduce a market portfolio benchmark but, as Diacogiannis and Feldman (2013) and the associated

[3]Grinblatt and Titman (1993) propose an innovative method that bypasses the need for a conventional market benchmark and hence much of the controversy within the asset pricing literature. They compute the difference between the realized return on a particular portfolio and the expected return they would have achieved had the portfolio manager been uninformed confirm the statistical significance of these findings at the 0.001 probability level based on 10,000 Monte Carlo simulations utilizing a random trading direction benchmark.

literature cited point out, portfolios are never mean-variant efficient making inferences difficult within CAPM or similar frameworks (Bossaerts and Plott (2004); Asparouhova, Bossaerts and Plott (2003); Bossaerts and Yang (2015)). If two investor groups have not similarly invested in the Fama-French factor portfolios, then Fama-French factor portfolios are not suitable for serving as a benchmark to compare the participants' relative trading performance.

My analysis aims to capture a sufficiently long time period through several complete market cycles of boom and bust which has not been analyzed in detail by previous research with a similar focus. This is because that such a comprehensive data set has not been available to researchers until now. Specifically, to make valid comparisons of long-term trading performance between investor categories, it requires at least one entire cycle, otherwise short-term trend followers will normally dominate with contrarian traders falsely seen to be systematic losers. My analysis include time-windows split into three carefully selected sub-periods to capture the full business cycle of boom and bust: 1) January 3, 1995 to July 3, 2003, is an extended hi-tech bubble period of a "bull" followed by a "bear" market. 2) July 4, 2003 to March 6, 2009, is the boom prior to the financial crisis including the subsequent collapse following the demise of Lehman Brothers, and 3) March 7, 2009 to December 30, 2011, is the post financial crisis recovery. Finally, I analyze the entire period, 1995 to 2011, inclusive. Thus my period of analysis includes two "bull-bear" sequences plus the post financial crisis of 2007/2008 environment. I also replicate my analysis using periods defined as the troughs in the Finnish Consumer Confidence Index (CCI) with quite similar results.

Lu, Swan and Westerholm (2016) has documented that the so called "home bias" ceases to be a bias as it defines "home informational superiority". That is, households located close to Nokia have a clear trading advantage over both domestic and foreign institutions. Thus, finally, in the present study, I further explore whether home informational advantage existed in female investors and male investors, respectively. I pit male investors and female investors located close to Nokia in a trading battle with male investors and female investors in the remained of the country, the more geographically advantaged male investors and female investors prove to be superior. Moreover, female investors located close to Nokia have a clear and very superior trading advantage over male investors located close to Nokia. That is, females located in the greater Helsinki region close to Nokia headquarters and the headquarters of other major companies seem to have a particular informational advantage over similarly located males, as well as males located in the remainder of the country.

Berkman, Koch, and Westerholm (2014) demonstrate that the trading accounts of children in Finland seem to be dominated by guardians that are highly informed and thus likely to be connected to insider traders. This important finding raises a distinct possibility that male designated insiders and other male insider traders could likewise be using their spouse's accounts to conduct potentially illegal trades that might explain the superiority of the Helsinki region female traders that I document. To investigate this possibility further, I use two special pieces of knowledge, the geographic location of every male and female trader and their family names to match traders to my database of designated corporate insiders. After removing the spouses of designated insider traders account, I do find the remaining female traders still dominate males. Berkman, Koch and Westerholm (2014) focus on the short-term insider information utilized by genuine insider traders. By contrast, my females are mostly very long-term contrarian traders who lose money for many months at a time on their bold trades, they could not conceivably be genuine insider traders, or even represent the spouse of the insider, since almost invariably insiders are privy to short-lived inside information that needs to be exploited immediately.

Since I find that local investors in the greater Helsinki area near company headquarters, and particularly females, outperform all other groups, the question arises: what provides this local trader advantage if not due to conventional insider informational access? Chhaochharia, Kumar, and Niessen-Ruenzi (2012) propose that local investors better monitor management but this does not explain the relatively poorer trading performance of males in this region. Branikas, Hong, and Xu (2016) attribute local gains to endogenous locational choice but that is not what is going on here. What my findings indicate is that local knowledge that is largely semi-public in nature is more beneficial to females than to males. For example, during the huge gyrations in the price of Nokia over the period 1998-2003, locals would have known that it was "business as usual" with this being particulary useful knowledge to the more contrarian, less susceptible to herding mentality, females.

As an indication that the long-term performance differences are not trivial, I find that female investors trading directly with male investors outperform by EUR 195 million in just one stock alone (Nokia) over a 17-year period. This represents a remarkable internal rate of return (IRR) of 43.16 percent p.a. for female investors trading with male investors. Had female investors simply bought over the entire period with realization only at the end, the counterfactual "BuyOnly" IRR would have been exceedingly lower with a loss-making return of -13.04 percent p.a.. This indicates the grossly misleading nature of "buy and hold" portfolio analyses that ignore the actual timing of trades. Furthermore, female investors also outperform non-female investors inclusive of institutional investors and other categories by EUR 1,407 million, generating a similar IRR of 46.28 percent p.a., and male investors outperform non-male investors by a massive EUR 2,329 million over the same period with a lower IRR of 43.76 percent p.a. that exceeds the household performance with the same counterparty.[4]

One might ask how it is it possible that, simultaneously, females outperform non-females and males outperform non-males inclusive of females? The answer is that institutional investors, together with "government" and other residual share categories, make up the majority counterparties to both females and males. Moreover, just as Lu, Swan, and Westerholm (2016) showed that households, irrespective of gender, outperformed both domestic and foreign institutions, here I show that both females and males, each considered as separate categories, outperform their institutional and all residual counterparts collectively. These are not only novel but also important findings as they indicate that the superior trading ability of females over males does not detract from the ability of males to outperform all institutional and residual category investors while females also continue to outperform all institutional and residual category investors consistent with their overall superiority. Focusing only on trades between different categories of counterparties, trading becomes a zero sum game in my analysis. Hence a negative return almost identical in magnitude[5] applies to the counterparties.

The organization of the paper is as follows. Section 3.2 outlines the literature in the relevant field. Section 3.3 details the methodology employed. Section 3.4 presents the Finnish data and constructs the main variables. Section 3.5 presents the sample statistics and empirical results. In Section 3.6 I document female investors trading strategy. Section 3.7 concludes. The Appendix presents details on *HPI* portfolio and *C-T* portfolio construction and estimation methodology.

[4]The reason that these numbers for Nokia are so large is not just Nokia's huge size, but more importantly, its performance as one of the world's greatest "bubble" stocks, rising in value by over 50 fold during the "hi-tech bubble" period prior to its collapse.

[5]The reason there can be minor differences is because of differential transaction costs.

3.2 Literature Review

This section contains four approaches in reviewing previous literature: 1) Individual investors' investment decisions. Because of the limited availability of datasets for researchers, previous literature mainly covered individual investors in United States [6], Finland[7], Sweden[8], Korean[9], Chinese Mainland[10] and Taiwan[11], but ranged from developed countries to emerging economies; 2) Given the popularity of investigations into individual investors trading ability, recent studies shed further light on subgroups of individuals. There is a great curiosity as to whether variations exit within individual investor categories. I concentrate on gender bias in the present study, but after controlling for age, geographic characteristics and insider corporate accounts; 3) I also briefly outline the gender effect in the field of corporate governance. This is another growing popular area to compare any sex discrepancy in the individuals' investment decisions; and 4) The use of *C-T* portfolio approach in measuring investors' trading performance.

3.2.1 First approach in the literature: Individual investors' investment decisions and trading behavior

Individual investors are increasingly provided with similar opportunities to make significant investment decisions. In general, individual investors have been assumed less sophisticated, trading too much, holding onto losers too long, buying stocks with corporate announcements, trading with stale limit orders, and many other instances of suboptimal behavior.

Barber and Odean (2000) argue that individual investors' trading performance was hazardous to their wealth but do not report an apples-with-apples comparison with institutional investors. For their discount broker for the early period, 1991-1996, spread plus commission costs amounted to a sizeable 4 percent on a round-trip basis with a turnover rate similar to mutual funds. Hence, if there were any under-performance of households

[6] See e.g., Odean (1999); Barber and Odean (2000); Kaniel, Saar and Titman (2008); Hvidkjaer (2008); Griffin et al. (2011); Kelley and Tetlock (2013).
[7] See e.g., Grinblatt and Keloharju (2000); Grinblatt, Keloharju and Linnainmaa (2012); Grant, Mills and Westerholm (2013); Swan and Westerholm (2016).
[8] See e.g., Campbell (2006), Calvet, Campbell, and Sodini (2007, 2009); Calvet and Sodini (2014)); Betermier, Calvet and Sodini (2016).
[9] See e.g., Choe, Kho, and Stulz (1999); Park, Chung and Kim (2015).
[10] See e.g., Hong, Jiang, Wang and Zhao (2014).
[11] See e.g., Barber, Lee, Liu, and Odean (2009); Gao and Lin (2015).

relative to institutional investors over this period, it was most likely due to higher commissions paid by households as spread costs were similar. Grinblatt and Keloharju (2000) claimed that individual investors in Finland performed poorly compared to institutional investors, but Lu, Swan and Westerholm (2016) reverse their findings over their data period with an improved methodology. Furthermore, it has been argued by many researchers that individual investors tend to realise gains too early and at the same time fail to realise losing positions. Such a bias is referred as the "disposition effect" and, as I subsequently argue, is difficult to reconcile with the superior trading performance of Finnish households.

Recent researches have shown that significant categories of individual investors perform better than institutions in the short run and particularly during periods of high volatility (Kaniel, Saar and Titman (2008), Griffin (2011), Kelley and Tetlock (2013)) and in the long run (Grinblatt, Keloharju and Linnainmaa (2012) and Lu, Swan and Westerholm (2016)). Barber, Odean and Zhu (2009) show that retail order imbalances forecast cross-sectional US stock returns a year later. Kelley and Tetlock (2013) state that individual investors' stock order imbalances predict monthly returns through a large sample of individual trader data for the US. In addition, Finnish individual investors often outperform domestic Finnish institutions (Grant, Mills and Westerholm (2013)). Lu, Swan and Westerholm (2016) employ the same Finnish data but covering a longer sample period from 1995 through 2011, showed that contrarian individual investors in Finland outperform both domestic and foreign institutions. For individual investor group alone, Keppo, Shumway and Weagley (2015) document that individual investors who successfully time the Finnish market in the first half of the sample are more likely to successfully time in the second half.

3.2.2 Second approach in the literature: Gender's effect on individual's investment decisions

According to Bruce (1995), 80-90 percent of females will be responsible for their finances at some point in their lives. I believe this percentage value will increase gradually, corresponding to more attention being paid to females' investment decisions from academic researchers and industry practitioners. That is because there is a growing body of empirical literature investigated the gender effect on investment decisions. In general, males seem to have more financial knowledge and wealth and they are more confident in their investing decisions with more risk tolerance. Nonetheless, the evidence on performance and behavior differences between female and male is mixed.

From the perspective of the theory of value and growth investing, one recent study by Betermier, Calvet and Sodini (2016) concludes that male investors are more likely to invest in growth stocks whereas female investors prefer value investing. These baseline patterns are robust to control for the length of risky asset market participation and other measures of financial sophistication.

Leung et. al (2015) found that an increasing number of Finnish individual investors trade using discount-retail brokers. These decisions against the use of professional advice could be due to cost saving consideration or because they believe their trading ability through their own knowledge is better than professional broker analysts' recommendations. Leung et. al (2015) also conclude that male investors trade more than female investors and higher wealth or income level is a positive driver within the male investors' decisions in choosing Discount-Retail brokers. This could be evidence that risk taking increases with wealth and those male investors have more confidence in their own decision-making process when they make their investment decisions.

Beyond the finance literature, previous studies from psychology indicate that females experience emotions more strongly than do males (Harshman and Paivio (1987)). The stronger emotional experience can affect the utility of a risk choice. In particular, female show more intense nervousness and fear than male in anticipation of negative outcomes (e.g., Brody and Hall (2000)). If negative outcomes are experienced more severely by females than males, they will naturally be more risk averse when facing a risky situation. In identical situations, Bolla et. al (2004) has shown that male and females who solve the same decision-making task involving a gambling task are different, with the males out-performing, because their brain mechanisms differ. Grossman, Michele and Wood (1993) point out that female tend to feel fear while male tend to feel anger. They are more likely to be afraid of losing, relative to male and hence evaluate a given gamble as being more risky, and will act in a more risk-averse way.

Several explanations have been proposed in indicating different risk attitudes across genders. The most basic explanation comes with biological roots. Kuhnen and Chiao (2009), Sapienza et al. (2009), Cesarini and et al. (2010), Cronqvist and Siegel (2014), and Cronqvist et al. (2015) explore the effect of seasonal affective disorder (SAD) on risk attitudes and empirical regularities in financial markets also speak to these differences, because females are affected by SAD more than males.

There is also an important literature on the effects of testosterone and other steroids on trader success or otherwise. Coates and Herbert (2008) find that if trader's profitability is high on a particular day then their testosterone level is significantly higher on that day. Moreover, if their testosterone level at 11:00 am was high then the day's trading profitability was also a full standard deviation higher. These were very short-lived highly risky trades of up to 1 billion pounds. The relationship was even stronger for experienced high-frequency traders. Coates, Gurnell, and Sarnyai (2010), in their survey, point out that higher pre-natal testosterone is also associated with more profitable short-term, high-intensity trading but could be reversed for longer holding periods with fewer physical demands.[12] My findings in this paper indicate that females appear to be superior traders when managing their own funds using an apparent contrarian trading strategy over the longer-term. Here the female's low testosterone levels relative to males may be an advantage in this trading environment that differs so markedly from that pioneered by Coates and Herbert (2008).

3.2.3 Third approach in the literature: Gender's effect in the field of corporate governance

Kumar (2010) finds that female stock analysts issue bolder and more accurate forecasts which he attributes to discouragement towards females entering the profession and thus to self-selection with only the most talented females entering the field. However, the main evidence he finds consistent with self-selection based on talent relates to a higher female relative to male forecast accuracy, the lower is female concentration. A female innate advantage in forecasting of stock returns is quite consistent with what I find: female trading superiority utilizing their own money in a non-competitive home environment with no obvious entry restrictions or discouragement to participation. Equally, both males and females should consider delegation if they don't feel sufficiently confident to manage their own portfolio. Kumar (2010) also finds that, while fewer females enter the analyst profession, those that do tend to be promoted faster, presumably due to their greater ability. This is more evidence of innate differences rather than self-selection. Moreover, the far

[12]See Kamstra, Kramer, and Levi (2003) for the first empirical evidence and Kamstra et al. (2014) for the first theoretical interpretation of these regularities.

bolder and hence more contrarian forecasts made by females indicates a feminine distaste for herding. Similarly, females dominate stock trading largely because of their strongly contrarian trades. The author also finds that females have a greater propensity to issue bold positive forecasts, indicative of greater optimism but optimism can be due to more than self-selection. The abiding problem with Kumar's (2010) self-selection argument is not because it is weak, but rather because it is too strong. There is hardly a single area of professional endeavor in which males are not in the majority. Think of academia, CEOs, corporate boards, and most professions. Judging by the self-selection argument, there should be overwhelming evidence of female superiority in all these areas as there is for female analysts. There is not. Why is it that in both self-trading and as analysts females make bolder (contrarian) trades and make bolder (contrarian) forecasts? Could this be due to differences in brain function rather than to self-selection? In both cases female predictions are superior. In one case they make higher profits for their clients in the other they make higher profits for themselves. HL Mencken (1918, p.37) noted these differences between men and women one hundred years ago: "The one character that distinguishes man from the other higher vertebrate, indeed, is his excessive timorousness, his easy yielding to alarms, his incapacity for adventure without a crowd behind him."

Levi, Li and Zhang (2010) show that in the case of female CEOs, the bid premium over the pre-announcement target share price is much smaller when compared to M&A deals with male counterparts. Huang and Kisgen (2013) find that acquisitions made by female CFO firms have significantly higher announcement returns and argues that females appear to undertake greater scrutiny and exhibit less hubris in acquisition decisions. Additionally, female CFOs issue debt less frequently, and debt and equity issuances are associated with higher announcement returns. Gayle, Golan and Miller (2012) find female are paid more and their pay is tied more closely to the firm's performance. There is also evidence for close cooperation between female directors and executives if both are in a minority position (Matsa and Miller (2011)). Finally, Adams and Ferreira (2009) show that female directors have a significant impact on board inputs and firm outcomes but do not find evidence of female superiority.

3.2.4 Fourth approach in the literature: Calendar-Time (*C-T*) portfolio methodology, the choice of performance measurement

There has been a long history of findings based on the *C-T* portfolio approach and widely applied to many areas of finance including private investors trading performance, long-run stock performance, and insider trading and the relative performance of mutual and hedge funds. The survey by Barber and Odean (2013) provides a summary of this *C-T* portfolio and related literature. Using the trading records of 10 thousand accounts from a discount brokerage house over the seven-year period, 1987-1993, Odean (1999), with imposed horizons of four months, one year, and two years, examines the difference between equally-weighted *C-T* portfolio buy and sell returns to obtain a raw return difference of -23 basis points per month or 2.76 percent p.a.. Their methodology imposes forced uniform holding periods for all investor categories in the sense that positions are assumed to no longer be held after the applied set holding period. Apart from the problems induced by imposing counter-factual realizations, this *C-T* methodology suffers from an additional problem in that the buy and sell portfolios record the presence of trades but not their magnitude. Thus, a value-weighting approach along the lines of the present contribution possesses advantages over an equal-weighting approach.

3.3 Holding-Period-Invariant Trader Methodology

The conventional wisdom of measuring trading performance in asset-pricing is to suppose that the individual trade data displays some type of average turnover rate, but there may be no meaningful turnover rate of fixed duration. For example, over the seventeen year-period in the Finnish market between January 1995 and 2011, inclusive, female investors largely sell the leading 28 firms to male investors when stock price is rising and buy when it is falling. These price movements do not occur based on any mechanical pattern such as a fixed, in calendar-time, horizon.

I now describe the *C-T* portfolio approach for two groups of traders: An aggregate portfolio of buy trades for the group is constructed on a daily basis and then either the return, or the excess return, is computed over a given horizon such as one month or six months. Similarly, a portfolio of sells by the same group is constructed with the difference in return or excess return between the buy and sell portfolios over the same given horizon being recorded. Trading prowess is greater the more positive is the net difference in return. The method is then reapplied from scratch for the next month or six months, depending on the assumed horizon. These aggregate period-by-period portfolio return differences are then regressed on a set of market factors with the intercept interpreted as the performance alpha.

According to *HPI* methodology that was first implemented in Lu, Swan and Westerholm (2016), I proceed as follows: (1) I first aggregate all trades made by the investor group, stock, and day. (2) Since trading skill is most meaningful in comparison between two agent-types in the same market over identical periods, mark both agents' portfolio value to market on the initial day with sufficient holdings to ensure non-negative holdings in future. (3) Initially include only net buys or sells (the balanced trades between two agent-types) between the two agent-types since this is the most relevant comparison.[13] (4) Since trades made with third-parties without the two agents trading with one another may simply imply some commonality in belief (and trading direction) that is irrelevant to the initial comparison, these trades are eliminated. (5) For each signed pairs of two agents, such as aggregated male investors and aggregated female investors, I compute daily balanced trades (net buys in common) of agent-type A with type B in every stock and then accumulate type-A net buys for an individual stock in the trade portfolio until the close of business on the previous evening to constitute type-A agent's pre-existing trade portfolio. Hence the corresponding type-B pre-existing trade portfolio equals the negative type-A agent's pre-existing trade portfolio. The sum of the cumulative net buys between type-A and type-B agents must be zero. (6) For simplicity, I focus on just the current period's continuously compounded return. I assume both agents reinvest dividends. Henceforth, the entire pre-existing trade portfolio of each agent-type is marked to market according to the closing price at the end of each period. In the absence of transaction costs [14] the cumulative trade dollar profit/loss of one agent-type, that I dub the holding-period invariant (*HPI*) amount, is identical to that of the other after taking account of the sign difference. Since I assume that both parties face the same riskless time value of money and my focus is on the difference in post-trade performance, I do not consider the trading return in excess of the

[13] For example, on the same day, I assume both agent-types trading in stock C. In the first situation: if agent-type A buys five shares of stock C and agent-type B sells 10 shares of stocks C, then in the *HPI* trading portfolio, net buys of agent-type A is 5 with corresponding -5 recorded as net buys for agent-type B. In the second situation: if both agent-types have the same trade direction, buying or selling, the net buys for both agent-type is 0.

[14] In Section 3.5 empirical results, I consider transaction costs.

riskless rate. (7) Finally, I accumulate each trader profit account over any specified interval to provide an exact value of the net trading gain to agent-type *A* and exactly opposite gain/loss for agent-type *B*. Moreover, the sum of the trading profits over both parties is always zero, as it should be. Unlike the *C-T* methodology, the profit or loss as measured by *HPI* captures precisely the timing ability of each party to foresee future price movements without imposing arbitrary assumptions about endogenous trader horizons on either or both groups. In this framework, the profitable agent-type with the greatest foresight is the type that systematically buys (sells) followed by a positive (negative) return and the profits of the two types on their trade portfolios are always the mirror image of each other. The details of the mathematical algebra presentations for *HPI* methodology and *C-T* approach are shown in Chapter 2 Section 2.3.

If the comparison is between two agent-types then it would normally be assumed that each has the same exogenously-given investment horizon which is derived from some average turnover rate. An obvious weakness in this by now standard approach is that the holding period is far from constant and will in part reflect the very timing and trading skills that one wishes to model. Holding periods vary, in part because traders are not pre-programmed mechanical robots and better informed investors will display superior timing skills giving rise to endogenous variation in the holding period.

Similarly with Lu, Swan and Westerholm (2016), I utilize the insight of Grinblatt and Titman (1993) to carry out Monte Carlo simulations to attach the economic and statistical significance for my results. For any given sequence of daily trades over any given interval between two types of institutions, here female and male investors, female and non-female investors, male and non-male investors, respectively, I am able to observe one outcome corresponding to the realized wealth gain to one party and corresponding loss to the other on the trade portfolio. However, it is possible that one-investor type achieved a favourable outcome due to their good luck rather than superior trading skills, no matter how great the wealth gain to one party at the expense of the other. I perform Monte Carlo simulations using 10,000 trails and the actual trades in every stock traded on every day but randomize the trade direction of the two types of investors to compute randomized wealth gains and corresponding losses that simulate informationless trading. By examining the proportion of times one investor category either achieves the same or better outcome purely by chance, I attach statistical probabilities to each actual outcome based on this random benchmark.

The main advantage of aggregating the entire individual trades of each agent-type within the *C-T* methodology is to take into account the cross-sectional correlation of stock returns that might otherwise bias the statistical significance of agent-type returns if a pooled cross-section time-series regression methodology were to be utilized (Seasholes and Zhu (2010)). Since the net buyer and net seller portfolios constructed by employing *C-T* methodology with imposed horizons is not aligned with the actual trading (transaction) data used to form the buyer and seller portfolios, this gives rise to measurement errors that may bias findings towards one particular participant. Whereas, *HPI* methodology can be easily applied to construct net buyer and net seller portfolios by cumulating actual realized daily profit/loss on a mark-to-market without imposing arbitrary or even contradictory holding periods and turnover rates on the aggregate trades of each agent-type.

3.4 Data

3.4.1 Source of investor-level transactions

My main data set combines data on Finnish individual investors' transactions with data on market returns from Compustat Global. The original transaction data contains all transactions in Finnish stocks during the sample period (1995–2011 inclusive) from Euroclear Finland Ltd. The book entry system holds the official record of the shareholdings and all trades and consistent of information on investor identity (gender, age, geographic location, some educational attainments), date, stock, transaction type, price and volume. I extend the datasets used in Seru, Shumway and Stoffman (2010), Grinblatt and Keloharju (2000, 2001a, 2001b) and Kaustia and Knüpfer (2002) to cover 17 years of trading from January 1, 1995 to December 31, 2011. For each transaction, I am provided the number of shares, the transaction price, a security identifier, investor identifier code and information about the investor. Each investor account has been assigned an anonymous number for privacy. Hence, it is possible to construct the precise composition and analyse a particular investor trading portfolio at any given date.

The vital advantage of this data set is that it allows the classification of all transactions by the investor type. Hence, the book entry system records the compulsory registration for every investor on the NASDAQ OMX Helsinki (OMXH) and allocates a unique investor type identification code of each investor. All Trades can be sorted by investor type and portfolios can be constructed based on each unique identified code. My interest of this study only focuses on the subset of transactions by individual investors (retail household investors). More importantly, for each account the gender and age information are available from the Finnish trading system. Furthermore, the information about the geographic characteristics of each individual investor is available from their post code.

Table 3.1 summarizes my basic household data over the 17 years of my study. On average, there are 493,272 household accounts of which only about 42 percent are active each year with one or more trades. Over the full period of the data, the value of these accounts has approximately doubled, with a commencement value of around EUR 16 billion. However, at the height of the Nokia bubble period in 1998 the value temporarily rose to a staggering EUR 63 billion. While the mean household portfolio value is about EUR 60.7 thousand over the entire period, the median value is far lower at only EUR 4.3 thousand, showing that the distribution of shareholder wealth is highly skewed. Over the period the mean number of stocks per household account has risen from only 1.9 to 3.4 with the median value remaining at one stock for most of the period, while recently increasing to a modest two stocks per household account. Consequently, with some exceptions pertaining to a small number of wealthy households possessing hundreds of stocks, there is little evidence from my data set of any desire by the typical Finnish household investor to diversify and hence they appear willing to bear risk. Finally, and perhaps surprisingly, female-headed accounts make up a sizeable 34 percent of the total.

Table 3.1 Household Investor Summary Statistics, 1995-2011, Inclusive

The number of household (HH) accounts holding stocks is split into “Active” in column (1) and “Inactive” in column (2). “Active” means that the household conducted one or more share trades in that year. The total value of all household accounts, active and inactive, at the end of each year is displayed in EUR billions in the HH Value column (3), with the percentage change shown in column (4). The mean value of each account in EURs, regardless of its activity status, is displayed in column (5), the median value in column (6) and the standard deviation value in column (7). The mean number of stocks in each account is shown in column (8). While for space reasons, the median number is not shown, it nonetheless remains constant at 1 until 2010 when it increases to 2. The mean age of household investors is shown in column (9) and the percentage of female accounts is shown in column (10).

	Number HHs		Total HH Value		Portfolio Value			Stocks	Age	Women
Year	Active (000’s) (1)	Inactive (000’s) (2)	Level EUR B (3)	Change % (4)	Mean EUR (5)	Median EUR (6)	Std Dev EUR (7)	Mean No. (8)	Mean Years (9)	% (10)
1995	59.6	300	15.53	NA	43,183	5,167	356,817	1.9	44.5	42.9
1996	140.1	217	14.69	-5.5	41,142	4,928	355,891	1.8	49.1	33.2
1997	127.6	232.8	18.56	23.4	51,485	5,348	552,128	1.9	48.7	33.4
1998	176.5	193.1	63.14	122.4	170,829	6,916	1,522,015	1.9	47.2	35.9
1999	330.3	36.8	50.09	-23.2	136,470	5,988	524,904	2	46.8	41.6
2000	323.5	129	27.29	-60.7	60,299	4,144	591,732	2.2	46.6	36.4
2001	245.3	248.2	24.94	-9	50,531	3,440	393,755	2.3	48.3	31.4
2002	194.1	286.9	22.09	-12.1	45,934	3,369	322,457	2.3	48	31.9
2003	158.2	325.7	21.9	-0.9	45,256	3,440	276,301	2.3	49.1	32.5
2004	256	281.1	22.55	2.9	41,996	3,265	307,753	2.4	50.7	34.9
2005	251.4	300.1	24.67	9	44,729	3,440	363,654	2.5	49.9	33.3
2006	205.5	351	27.43	10.6	49,278	3,600	491,292	2.7	49.7	31.1
2007	194.4	359.8	28.79	4.8	51,948	3,679	616,411	2.6	50.1	31
2008	175.4	402.4	26.63	-7.8	46,088	3,707	470,556	2.9	49.1	29.6
2009	227.2	376.7	30.12	12.3	49,868	4,166	327,391	3.2	50.1	32.2
2010	216.1	407.7	33.39	10.3	53,531	4,514	466,267	3.4	48.7	29.3
2011	268.7	387.4	32.05	-4.1	48,843	4,255	493,200	3.4	49.1	31.5
Mean	208.8	284.5	28.46		60,670	4,315	496,031	2.5	48.6	33.7

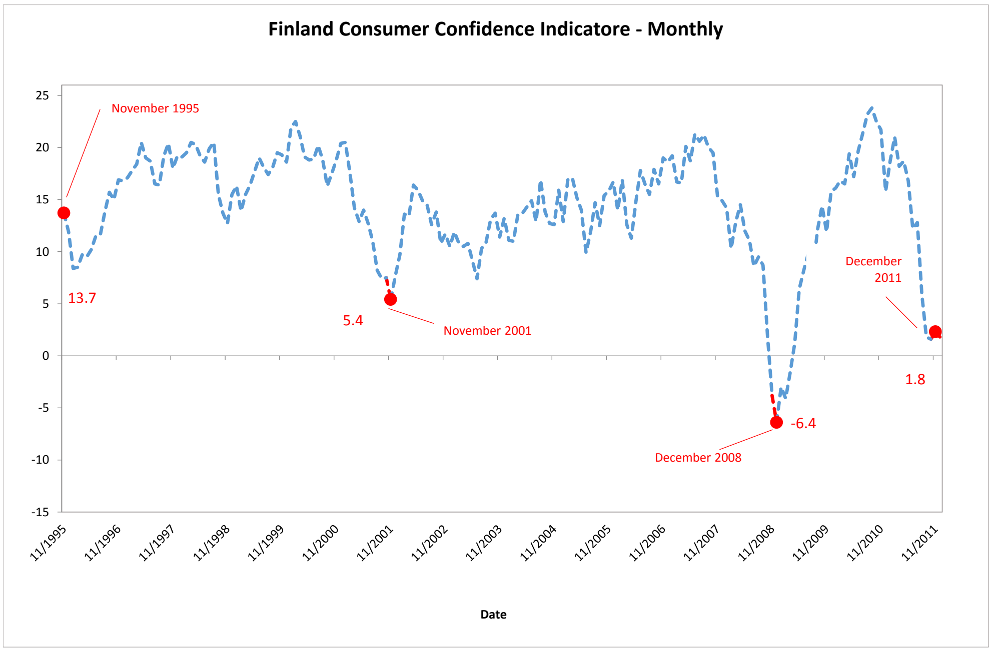


Figure 3.1 Finland Consumer Confidence Indicator (CCI) as an exogenous variable reflecting economic environments – Monthly

To describe entire boom-and-bust cycles, I split up my data period into three sub-periods: the high-tech boom and collapse period (01/03/1995–07/03/2003); the pre-GFC boom to the Lehman Brothers collapse (07/04/2003–03/06/2009); and the post-GFC period (03/07/2009–12/30/2011). I also analyze the entire 17 year period for which data is available (01/03/1995–12/30/2011).[15] As a robustness check, I also employ Finland Consumer Confidence Indicator (CCI) as the endogenous variable to reflect the economic environment from 1995 to 2011. That is because the CCI has been widely accepted as an important indicator of the macroeconomic business cycle. I extract monthly CCI from the Bank of Finland and break down the period into three sub-periods from trough to trough, i.e, January 1995 to November 2001; December 2001 to December 2008; January 2009 to December 2011. The Figure 3.1 displays monthly CCI time series back to November, 1995.[16]

[15] I perform various verifications to demonstrate that the raw data set collected from Euroclear Finland Ltd. is robust with respect to my results.

[16] The earliest day I am able to observe for monthly CCI is November 1995.

3.4.2 Data steps

From my data set, I compute the daily buys and sells undertaken by every male, female, non-male, and non-female household individually in every market that conducts trades in Finnish stocks over the 17 years of my daily data. On eliminating on a daily basis trades between male and female households, between male and non-male investors (i.e., females and all institutional investors), and between female and non-female investors (i.e., males and all institutional investors), I am left with the daily net buys and sells of the three groups: (i) male and female; (ii) male and non-male, and (iii) female and non-female. While many trades between these three groups can be matched at the level of individual trades, this is not possible for all trades. However, since I have the entire population of trades by male, female, non-male, and non-female investors, the initial holdings of my four groups are inferred from backward induction by the requirement that the holdings of each group cannot be negative, given the daily sequences of matched buys and sells for each participant group and the marking to market of each investor group's entire portfolio on the last day of each event period as well as on the last day of the data set. Table 3.2 summarizes my three samples of *HPI* portfolio trades (1995–2011) and the overall traded value of my three paired investor groups, male with female, male with non-male and female with non-female investors, respectively.

Table 3.2 Summary Statistics of daily *HPI* Portfolio Trades and Trading Value in EUR (millions) by female investors and male investors from 1995 to 2011, respectively.

		Female direct trade with Male	Female direct trade with Non-Female	Male direct trade with Non-Male
HPI trades				
	Mean	844.57***	3,884.43***	20,126.12***
	Median	0	0	688
	Maximum	301,310	3,495,222	7,722,542
	Standard Deviatiox n	4,080.53	20,728.52	92,508.36
	t-value	62.84	57.37	66.62
	Number observations	92,188	93,759	93,759
HPI traded value (EUR)				
	Mean	9,398.40***	47,055.45***	230,181.25***
	Median	0	0	5,540.94
	Maximum	4,341,877.10	69,030,634.50	105,080,210.80
	Standard Deviation	50,085.08	344,843.96	1,079,207.23
	t-value	56.97	41.78	65.31
	Number observations	92,188	93,759	93,759

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I pick 28 leading Finnish firms based on three criteria. The first one is the leading firms from the sample of approximately 30 firms that survive and have an average market capitalization larger than 100 million EUR, sorted by average traded value per day during the entire sample period. The second one is the ranked top 50 of the proportion made up of male households' trade and their value traded from 1995 to 2011. The third criterion is that the number of trading days for the stock should be at least 250 trading days. I then combine these three ranking filters with a limit of 28 firms. My method implies a "look ahead" bias in the choice of the 28 stocks to analyze but counts against my findings in that my stock sample is precisely chosen on the grounds that male investors chose to trade these relatively large stocks due to a self-selection process in which this investor class chose these stocks in which they expected to outperform.[17] I need to choose the sample stocks traded more actively by male to capture the sizeable *HPI* trades in each pair of trading group.[18] It is not meaningful to examine the *HPI* trading performance between female and male for the stocks that male did not trade much over the examined sample period. Details concerning these stocks are presented in Table C.1.1

3.5 Results

I focus on the largest Finnish stock, Nokia, within the group of 28 major Finnish firms and presents trading profits and losses of each agent type and their counterparts in Tables 3.3 Panel A to Panel B and Tables 3.4 Panel A to Panel D.

[17] I am grateful to Michael Brennan for alerting us to this potential problem.
[18] I have discussed the stock selection issues in depth in Chapter 2.

Table 3.3 Cumulative Profits and Losses after Transaction Costs for Direct Trades between Males and Females, Males and Non-Males, Females and Non-Females in Large Finnish stocks (28 stocks, inclusive of and exclusive of Nokia), respectively

Panel A: Sub-periods analysis based on Historical Index Movements

The cumulative Profits and Losses is at the end of day of each period and the cumulative Profits and Losses of each period is independent which means that every starting point of the cumulative Profits and Losses is zero. The significance of these cumulative profits and losses is tested by running a Monte Carlo simulation 10,000 times, where the daily direction taken by each of the investor categories in each stock is random. I thus employ an informationless benchmark. The result of this simulation provides the confidence interval I use to test the significance of the reported profits. Transaction cost per trade for households is EUR0.005. Total trading value is computed as the sum of daily total trading value in two groups from 1995 to 2011. *** represents statistically significant at 0.001 probability level.

	Period (Trough to Trough)	Cumulative P&L (EUR M)					
Category		Males (1)	Females (2)	Males (3)	Non-Males (4)	Females (5)	Non-Females (6)
Nokia	01/03/1995 - 07/03/2003	-96.46***	96.37***	1,481.45***	-1,483.90***	821.36***	-821.99***
	07/04/2003 - 03/06/2009	-25.69***	25.66***	283.27***	-285.47***	150.89***	-151.23***
	03/07/2009 - 12/30/2011	0.12	-0.15	-285.86	284.62	-52.21	52.03
	01/03/1995 - 12/30/2011	-194.82***	194.67***	2,329.36***	-2,335.25***	1407.31***	-1408.46***
Inclusive of Nokia (28 stocks)	01/03/1995 - 07/03/2003	-98.59***	98.34***	1,655.07***	-1,660.89***	905.04***	-906.47***
	07/04/2003 - 03/06/2009	-31.62***	31.31***	549.39***	-557.77***	312.58***	-314.06***
	03/07/2009 - 12/30/2011	3.04	-3.26	-380.52	375.68	-71.55	70.82
	01/03/1995 - 12/30/2011	-194.94***	194.17***	2,664.62***	-2,683.49***	1654.24***	-1657.88***
Ratio of HPI trading profits to total trading value from 1995 to 2011		-22.50%	22.41%	12.35%	-12.43%	37.50%	-37.58%
Exclusive of Nokia (27 stocks)	01/03/1995 - 07/03/2003	-2.13***	1.97***	173.63***	-176.99***	83.68***	-84.47***
	07/04/2003 - 03/06/2009	-5.93	5.66	266.12	-272.3	161.69***	-162.83***
	03/07/2009 - 12/30/2011	2.92	-3.11	-94.67	91.06	-19.34	18.79
	01/03/1995 - 12/30/2011	-0.12	-0.5	335.26***	-348.23***	246.93***	-249.42***
Ratio of HPI trading profits to total trading value from 1995 to 2011		-1.94%	-8.09%	2.40%	-2.49%	9.02%	-9.12%

* $p < 0.10$, ** $p < 0.01$, *** $p < 0.001$

Panel B: Sub-periods analysis based on Finland Consumer Confidence Indicator (CCI)

The cumulative Profits and Losses is at the end of day of each period and the cumulative Profits and Losses of each period is independent which means that every starting point of the cumulative Profits and Losses is zero. The significance of these cumulative profits and losses is tested by running a Monte Carlo simulation 10,000 times, where the daily direction taken by each of the investor categories in each stock is random. I thus employ an informationless benchmark. The result of this simulation provides the confidence interval I use to test the significance of the reported profits. Transaction cost per trade for households is EUR0.005. Total trading value is computed as the sum of daily total trading value in two groups from 1995 to 2011. *** represents statistically significant at 0.001 probability level.

	Period (Trough to Trough)	Cumulative P&L (EUR M)					
Category		Males (1)	Females (2)	Males (3)	Non-Males (4)	Females (5)	Non-Females (6)
Nokia	01/03/1995 - 11/30/2001	-39.89***	39.80***	722.66***	-724.51***	440.92***	-441.44***
	12/03/2001 - 12/31/2008	-18.93***	18.89***	201.81***	-204.53***	122.53***	-122.97***
	01/03/2009 - 12/30/2011	-0.51	0.47	-285.86	284.62	-58.41	58.22
	01/03/1995 - 12/30/2011	-194.82***	194.67***	2,329.36***	-2,335.25***	1407.31***	-1408.46***
Inclusive of Nokia (28 stocks)	01/03/1995 - 11/30/2001	-40.90***	40.69***	842.85***	-847.04***	482.44***	-483.58***
	12/03/2001 - 12/31/2008	-25.03***	24.70***	376.08***	-385.49***	253.40***	-255.15***
	01/03/2009 - 12/30/2011	2.38	-2.62	-380.52	375.68	-75.97	75.21
	01/03/1995 - 12/30/2011	-194.94***	194.17***	2,664.62***	-2,683.49***	1654.24***	-1657.88***
Ratio of HPI trading profits to total trading value from 1995 to 2011		-22.50%	22.41%	12.35%	-12.43%	37.50%	-37.58%
Exclusive of Nokia (27 stocks)	01/03/1995 - 11/30/2001	-1.02***	0.88***	120.19***	-122.53***	41.52***	-42.14***
	12/03/2001 - 12/31/2008	-6.1	5.81	174.26***	-180.96***	130.87***	-132.18***
	01/03/2009 - 12/30/2011	2.89	-3.09	-94.67	91.06	-17.56	16.99
	01/03/1995 - 12/30/2011	-0.12	-0.5	335.26***	-348.23***	246.93***	-249.42***
Ratio of HPI trading profits to total trading value from 1995 to 2011		-1.94%	-8.09%	2.40%	-2.49%	9.02%	-9.12%

* $p < 0.10$, ** $p < 0.01$, *** $p < 0.001$

Table 3.4 Cumulative Profits and Losses after Transaction Costs for Direct Trades between Males and Foreign Nominees, between Females and Foreign Nominees, between Males and Domestic Institutions, between Females and Domestic Institutions in Large Finnish stocks (28 stocks, inclusive of and exclusive of Nokia), respectively

Panel A: Between Male and Foreign Nominees and Between Female and Foreign Nominees

The cumulative Profits and Losses is at the end of day of each period and the cumulative Profits and Losses of each period is independent which means that every starting point of the cumulative Profits and Losses is zero. The significance of these cumulative profits and losses is tested by running a Monte Carlo simulation 10,000 times, where the daily direction taken by each of the investor categories in each stock is random. I thus employ an informationless benchmark. The result of this simulation provides the confidence interval I use to test the significance of the reported profits. Transaction cost per trade for households is EUR0.005. Total trading value is computed as the sum of daily total trading value in two groups from 1995 to 2011. *** represents statistically significant at 0.001 probability level.

	Period(Trough to Trough)	Cumulative P&L(EUR M)			
Category		Males	Foreign Nominees	Females	Foreign Nominees
		(1)	(2)	(3)	(4)
Nokia	01/03/1995 - 07/03/2003	2,148.98***	-2,151.43***	1,135.82***	-1,136.57***
	07/04/2003 - 03/06/2009	403.43	-405.64	207.38	-207.79
	03/07/2009 - 12/30/2011	-515.54	513.15	-82.86	82.47
	01/03/1995 - 12/30/2011	3,535.16***	-3,542.21***	2,023.28***	-2,024.82***
Inclusive of Nokia (28 stocks)	01/03/1995 - 07/03/2003	2,365.42***	-2,371.29***	1,285.05***	-1,286.69***
	07/04/2003 - 03/06/2009	444.02	-456.7	396.09	-398.61
	03/07/2009 - 12/30/2011	-582.4	572.05	-98.72	96.83
	01/03/1995 - 12/30/2011	3,828.04***	-3,856.79***	2,395.88***	-2,401.93***
Ratio of HPI trading profits to total trading value from 1995 to 2011		12.1%	-12.2%	33.38%	-33.46%
Exclusive of Nokia (27 stocks)	01/03/1995 - 07/03/2003	216.44***	-219.85***	149.23***	-150.12***
	07/04/2003 - 03/06/2009	40.59	-51.06	188.71	-190.83
	03/07/2009 - 12/30/2011	-66.86	58.9	-15.86	14.36
	01/03/1995 - 12/30/2011	292.88***	-314.58***	372.6***	-377.11***
Ratio of HPI trading profits to total trading value from 1995 to 2011		1.27%	-1.37%	7.36%	-7.45%

Panel B: Between Male and Domestic Institutions and Between Female and Domestic Institutions

The cumulative Profits and Losses is at the end of day of each period and the cumulative Profits and Losses of each period is independent which means that every starting point of the cumulative Profits and Losses is zero. The significance of these cumulative profits and losses is tested by running a Monte Carlo simulation 10,000 times, where the daily direction taken by each of the investor categories in each stock is random. I thus employ an informationless benchmark. The result of this simulation provides the confidence interval I use to test the significance of the reported profits. Transaction cost per trade for households is EUR0.005. Total trading value is computed as the sum of daily total trading value in two groups from 1995 to 2011. *** represents statistically significant at 0.001 probability level.

	Period(Trough to Trough)	Cumulative P&L(EUR M)			
Category		Males (1)	Domestic Institutions (2)	Females (3)	Domestic Institutions (4)
Nokia	01/03/1995 - 07/03/2003	-78.52	77.86	188.28	-188.55
	07/04/2003 - 03/06/2009	35.80	-36.24	91.00	-91.16
	03/07/2009 - 12/30/2011	-29.348	28.86	-1.48	1.47
	01/03/1995 - 12/30/2011	-137.45	135.85	416.52***	-416.97***
Inclusive of Nokia (28 stocks)	01/03/1995 - 07/03/2003	-10.55	8.61	241.35	-241.83
	07/04/2003 - 03/06/2009	-57.69	54.46	111.17	-111.96
	03/07/2009 - 12/30/2011	-9.33	6.09	-2.44	2.32
	01/03/1995 - 12/30/2011	-138.185***	129.84***	482.72***	-484.11***
Ratio of HPI trading profits to total trading value from 1995 to 2011		-1.59%	1.50%	29.24%	-29.32%
Exclusive of Nokia (27 stocks)	01/03/1995 - 07/03/2003	67.9	-69.25	53.07	-53.27
	07/04/2003 - 03/06/2009	-93.49	90.70	20.17	-20.79
	03/07/2009 - 12/30/2011	20.02	-22.77	-0.96	0.85
	01/03/1995 - 12/30/2011	-0.73	-6.01	66.20	-67.14
Ratio of HPI trading profits to total trading value from 1995 to 2011		-0.01%	-0.09%	6.31%	-6.40%

First, I compute the daily net trade flows in Nokia between various agent-types, male and female, male and non-male, female and non-female. Then, I apply my *HPI* portfolio approach in equation (2.1) and equation (2.2) shown in Chapter 2 to net trade flows of each trading group. I compute *HPI* trading portfolio between male and female, male and non-male, and female and non-female in Table 3.3 Panel A to Panel B, respectively. By extending the trading performance comparison analysis between Finnish households and institutional investors in Chapter 2, I further explore whether gender difference exist in the individual investor category when they direct trade with either foreign nominees and domestic institutional investors. Hence, I construct four new independent *HPI* trading pair groups, i.e., male versus foreign nominees and female versus foreign nominees, and male versus domestic institutions and female versus domestic institutions. The corresponding trading performance results are shown in Table 3.4 Panel A and Panel B, respectively.

These tables, together with remaining tables, show the results after taking into account transaction costs. However, the differences arising from transactions costs are not at all significant. To account for transaction costs I apply the same rules discussed in Lu, Swan and Westerholm (2016). I do not impose a bid-ask spread transaction cost component. In addition, I assume both male and female investor orders are not affected by market impact as their order size is typically below average trade size. Hence I apply a brokerage fee of 0.5 percent or 50 basis points for both male and female investors and a lower 20 basis points for institutional investors. Thus, in the following sections, I show male investors outperform non-male investors and female investors outperform non-female investors before transaction costs.

Figure 3.2 (a) to (b) show a time-series variation in the proportion of buy and sell trades (traded value in EUR) in Nokia and 27 stocks (exclusive of Nokia) that are initiated by male investors and female investors from January 1995 through December 2011. Figure 3.2 (a) shows that the proportion of trade value (in EUR) in Nokia initiated by male investors has increased while the proportion of trades initiated by female investors has declined during the sample period, reflecting increasing ownership by male investors. Figure 3.2 (b) displays the similar trend for the entire period in other 27 major stocks. These results are in line with the increasing male investor ownership in the U.S. (Barber and Odean (2001)). With the interest in per male and per female investor trading preference over the entire sample period, I compute the average monthly euro traded by male and female investors for the 28 stocks.

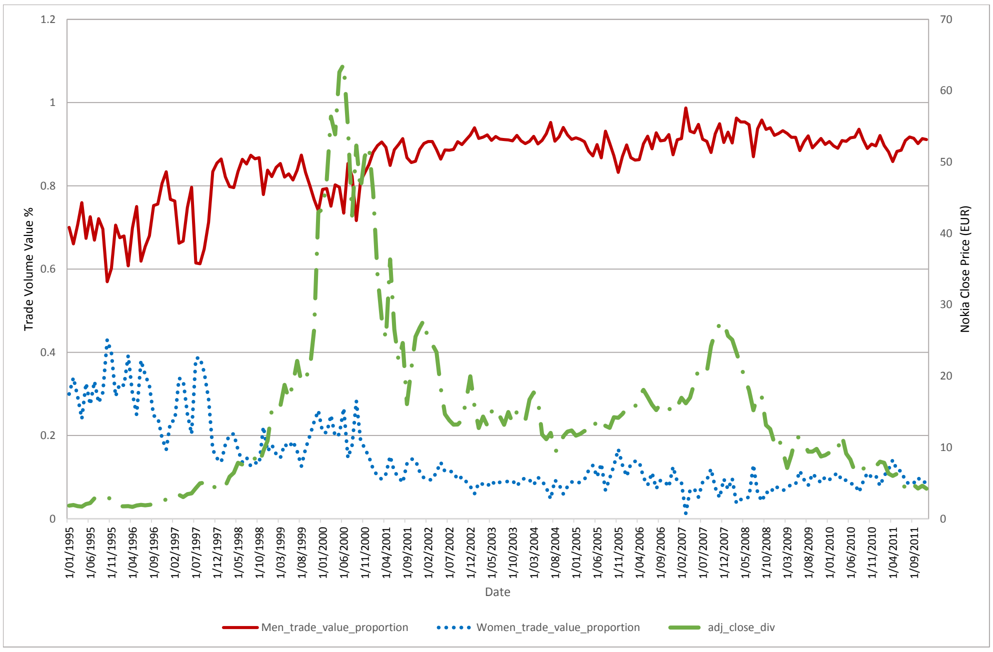
I aggregate my daily absolute value of buys and sells per stock-day into monthly observations (i.e., per month of male and female investors). I then compute the average traded value per male and per female investor by (1) calculating monthly traded value (in euro) of each stock and dividing by total number of male and female investors within the same month of each stock.[19] Figure 3.2 (c) clearly shows that, on average, male investors trade much more than do individual female investors from 1995 to 2011. Particularly, during each financial crisis period, male investors significantly increase their trading activities relative to normal market environments. Furthermore, the gap between male investors' and female investors' average trading value tend to increase associated with each recession. The gap reached its peak in September 2007.

Figure 3.3 presents the daily cumulative net purchases of Nokia by male and female investors over entire sample period while Figure 3.4 displays the cumulative profits and losses for male and female investors correspondingly. For both graphs, the daily Nokia closing price time series is shown on the right-hand side axis. It can be seen that male investors' cumulative daily profit almost perfectly tracks the Nokia stock price from 1995 to 2011. This is because male investors perfectly follow the trend in the price of Nokia from 1995 to 2011 and is thus positive-feedback traders with females being contrarian or negative feedback traders. Figure 3.3 to 3.7 plot the cumulative daily profits and losses for male and female investors in Nokia covering four periods of analysis.

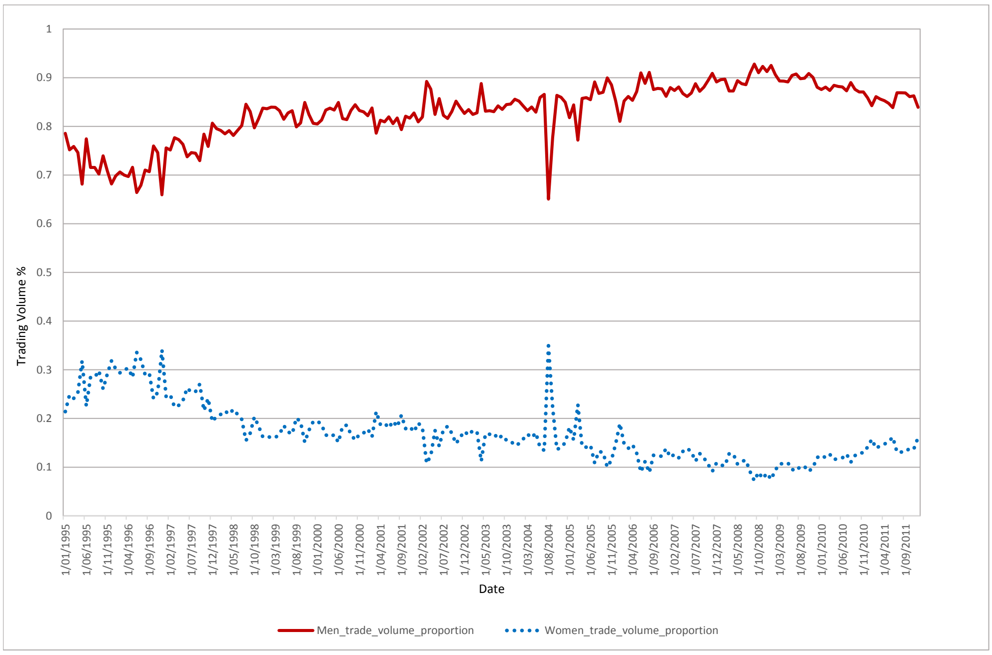
3.5.1 Entire Period: January 3, 1995 to December 30, 2011

Figure 3.3 shows that, since approximately 2008, when the price of Nokia began to fall, female investors have been net buyers of Nokia from male investors but over much of the earlier period, female investors have been net sellers, especially when the Nokia price was rising. Nokia, having risen rapidly in value from a little over EUR 1 to about EUR 63 in April 2000, fell to about EUR 3.5 by the end of 2011. It is especially in this latter period that Figure 3.4 and Table 3.3 Panel A show that after transaction costs, female investors collectively made significant trading gains at the expense of male investors, totaling EUR 194.64 million even after deducting the "loss" of EUR 0.39 million over the last two years

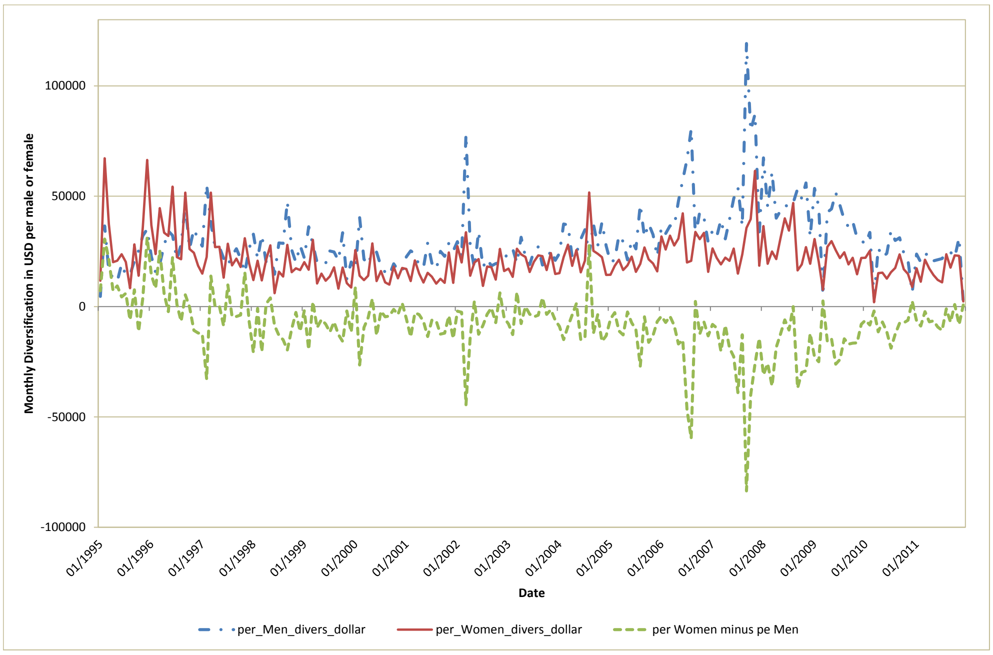
[19] My data set contains information related to numbers of male and female investors per stock per day.



(a) Proportion of trading value in Nokia, Male and Female.



(b) Proportion of trading value for 27 stocks (exclusive of Nokia), Male and Female.



(c) Monthly Euros traded per male and female investor in 28 stocks (inclusive of Nokia)

Figure 3.2 Summary of Trading Activity for Male and Female investors

of the 17-year period that would have largely been recovered when Nokia sold its phone interests to Microsoft.

3.5.2 Period 1: January 3, 1995 to July 3, 2003

Female investors did not commence significant trading with male investors until January 1999. Since the price of Nokia reached its peak around March 2000, female investors continued to sell for another two years before commencing modest purchases. Over this period, Figure 3.5 shows they continued to reap large gains at the expense of male investors, ending up with significant accumulated profits of EUR 96.37 million at the expense of male investors at the end of the high-tech bubble period on their net trade portfolio, as shown by Table 3.3 Panel A. Since female investors gain largely due to superior trade timing ability, as is fully reflected in the *HPI* methodology, the imposition of mechanical investment horizons, as in the *C-T* methodology, severely adversely affects the measured trading performance of female investors.

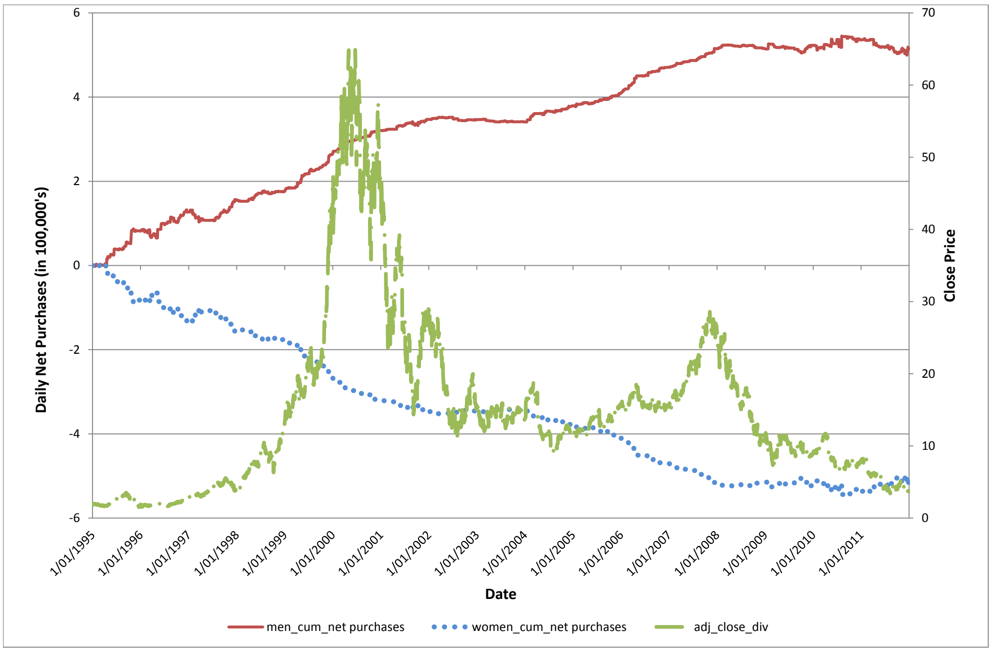


Figure 3.3 Daily cumulative net purchases for Female and Male (in 100,000's), January 3, 1995 to December 30, 2011 - Entire Period

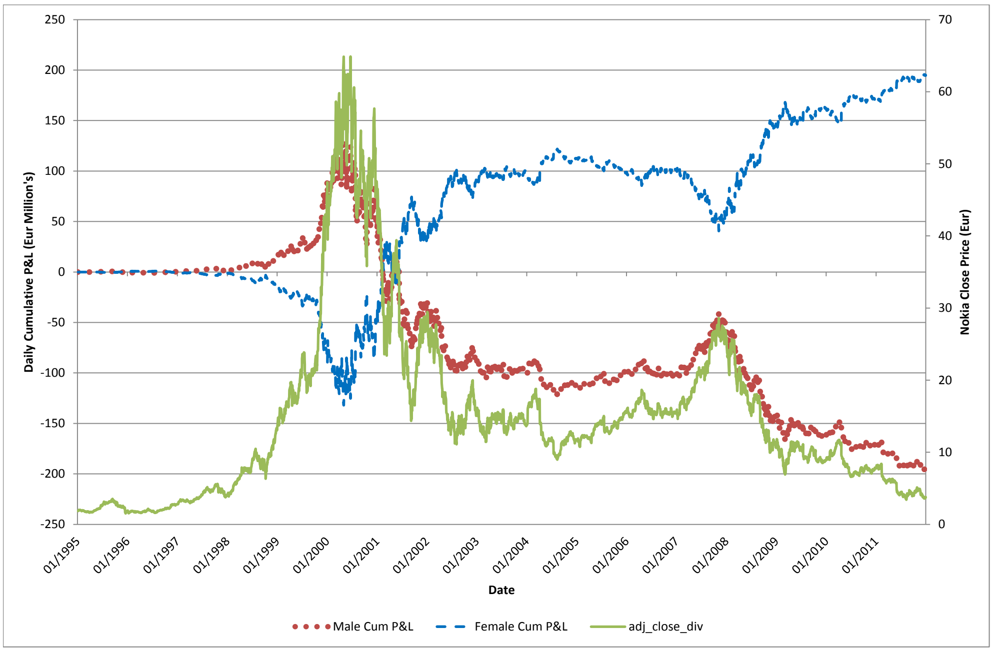


Figure 3.4 Cumulative daily Profits and Losses for Female and Male on Nokia and Nokia's Closing Price, January 3, 1995 to December 30, 2011 - Entire Period

Figure 3.5 Cumulative daily Profits and Losses for Female and Male on Nokia and Nokia's Closing Price, January 3, 1995 to July 3, 2003 - the High-Tech Bubble Period

3.5.3 Period 2: July 4, 2003 to March 6, 2009

In the time interval between post hi-tech boom period and the GFC collapse, female investors purchased the leading stock, Nokia, from male investors until December 2005, after which they continued to sell for the next two years until December 2007 when they commenced purchasing again. Their cumulative trades are almost precisely the mirror image of Nokia's price movements over this period. However, its counterparty, male investors presented as trend followers, almost exactly match Nokia price movements in the opposition over this period. Hence, female investors take buying actions when Nokia price fell off, i.e., when its price is failing and they hold on to their existing inventory, and sell out their shares of Nokia when it is a recent winner, i.e., when its price is rising. Much of the extensive literature on the "disposition effect" surveyed by Shefrin and Statman (1985) might infer that female investors in Nokia are subject to this psychological problem when in fact they appear to be successful traders or speculators despite this supposed problem. It would seem that informed contrarian trading, which involves buying and hanging on to losers until they come good, is mistaken for the "disposition effect". In fact, Grinblatt and

Keloharju (2001) utilize two years of my more extensive 17 years of Finnish trading data to show that Finnish investors seem reluctant to sell stocks once they have incurred a sizeable loss. However, as Grinblatt and Keloharju (2001, p.590) point out, this disposition effect "could just as easily be interpreted as contrarian behavior with respect to past returns". These very intuitive female investors in Finland exhibit an apparent contrarian strategy far more so than any other group and do in a highly profitable manner.

Figure 3.6 shows that female investors made significant accumulated losses as they heavily sold Nokia until it reached its peak but more than recouped these losses once the full force of the GFC collapse was evident. In fact, Table 3.3 Panel A shows that households significantly profited by EUR 25.66 million net of transaction costs, at the expense of male investors, by the end of the GFC bubble period.

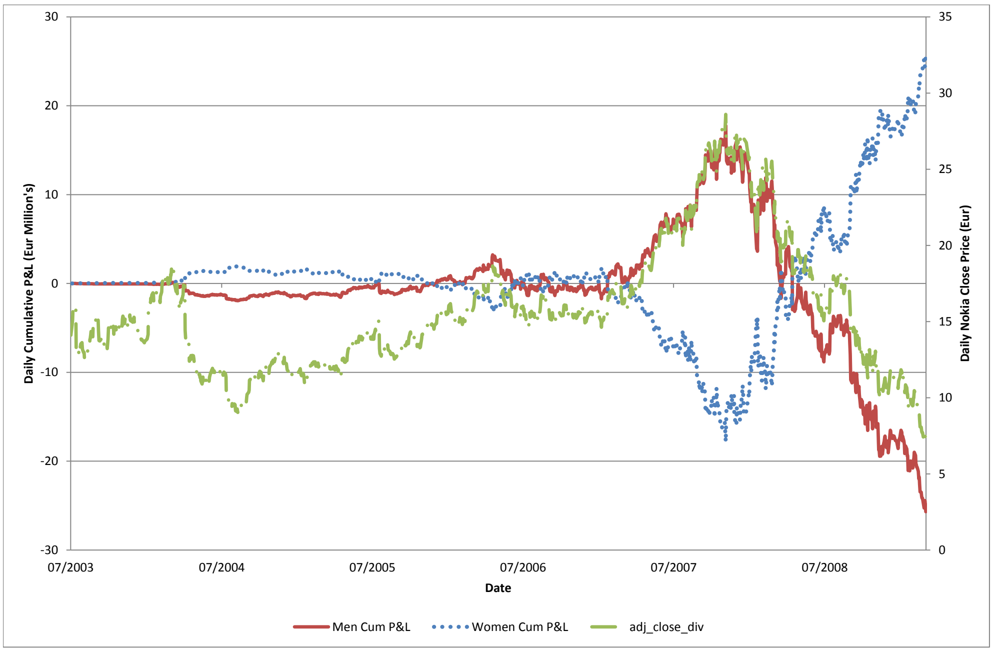


Figure 3.6 Cumulative daily Profits and Losses for Female and Male on Nokia and Nokia's Closing Price, July 4, 2003, to March 6, 2009

3.5.4 Period 3: March 9, 2009 to December 30, 2011

Over this entire period, female investors act as trend followers until March 2010 and then employ a contrarian trading strategy of buying when Nokia's price is dropping and selling when its price is rising up to March 2011. Since then, female investors changed their trading behavior to match up with Nokia price movements to the end of period. Figure 3.7 and Table 3.3 Panel A show that, within this data period, this acquisition strategy is yet to pay off with a significant accumulated loss of EUR 0.15 million but events past the cut-off date suggest that this has nonetheless proved to be a winning strategy.

One may have the suspicion that the apparent distinct informational advantage of female investors occurred simply because of "luck." Perhaps female investors rebalanced their portfolio to gain diversification benefits by buying Nokia, and the remarkable fact that Nokia became global stock was just luck. This represents an implausible scenario, as Finnish female investors typically held only one stock for most of my sample period, with little indication of seeking diversification benefits within my data set. I test the "luck" hypothesis by computing the internal rate of return (IRR) to female investors by simply buying and never selling until the end. The "BuyOnly" IRR yields a return of minus 13.04 percent instead of the plus 43.16 percent of their actual IRR over the entire period (see below). The failure of this "buy and hold" methodology to approximate the actual IRR is not surprising, as such a "BuyOnly" IRR methodology represents an extreme form of the *C-T* methodology, with the female investors actual sales ignored other than the notional sales at the end of the period.

3.5.5 Extension to 28 major Finnish stocks

In Table 3.3 Panel B I extend my analysis of Nokia for my four investor groups and three time periods plus the entire sample period to my main sample of 28 major Finnish stocks, inclusive of and excluding Nokia. My findings are very similar to my earlier results for Nokia alone. Female investors outperform both male and non-female investors. Male investors also outperform non-male investors, with the latter group dominated by institutional investors. However, the magnitude of the additional trading profit earned by including an additional 27 major Finnish stocks is not great because these remaining stocks are much smaller than Nokia's and were not subject to the same extreme valuation fluctuations. These tables also report the profit measured after transaction cost per euro traded. For female investors' direct trades with male investors and non-female investors inclusive of Nokia, these profit rates range from 22.41 percent to 37.5 percent but are much lower if Nokia is excluded.

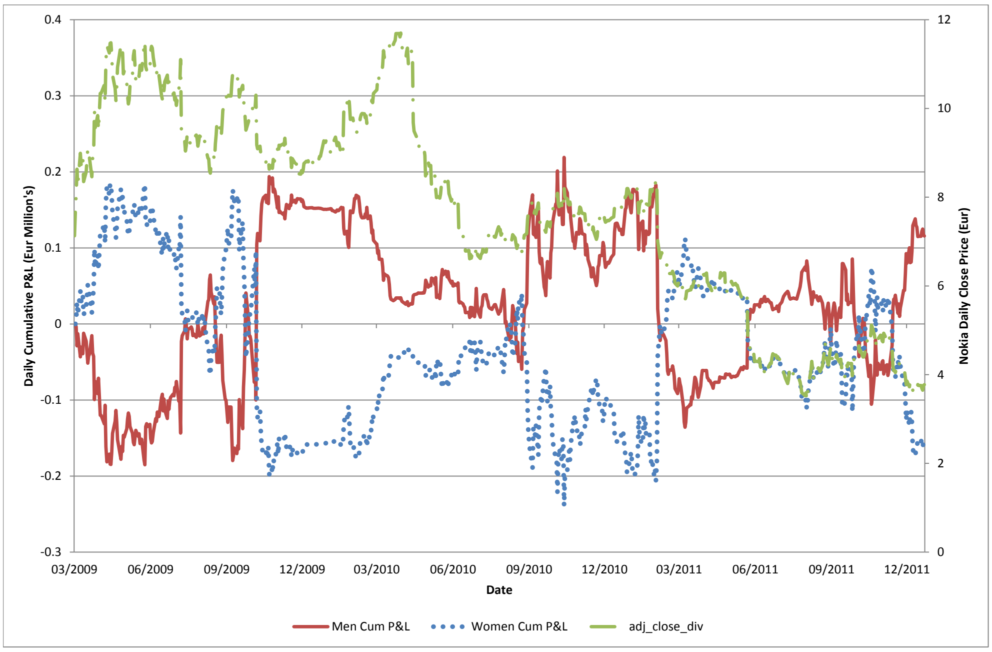


Figure 3.7 Cumulative daily Profits and Losses for Female and Male on Nokia and Nokia's Closing Price, March 9, 2009, to December 30, 2011

In the context of my analysis in Chapter 2, I further separately compare the *HPI* trading performance between each gender group and institutional investors, i.e., foreign nominees and domestic institutions, respectively, to understand whether gender effect plays significant roles when male and female investor in direct trades with institutional investors.[20] The results are presented in Table 3.4 Panel A and Panel B. The table confirms that females are far superior investors, whether trading directly against either males or against Foreign Nominees, or against domestic institutional investors. Overall, Finnish male investors are dominated by Finnish domestic institutions and Finnish female investors. Finnish female investors are ranked as the top superior traders among the entire Finnish investor category over the entire 17-year examined time period.

[20] I thank Ron Kaniel for suggesting to extend my analysis to compare the trading performance between male investors and domestic institutions and between female investors and domestic institutions.

3.5.6 Conventional investment performance proxy: Internal rate of return (IRR)

In consequence of the significant dollar profits made by female investors in trading with male investors, I apply a robustness check to perform the same analysis discussed in Lu, Swan, and Westerholm (2016), i.e., internal rate of return (IRR) calculations. Without imposing any horizon assumptions other than the start and end dates of the projects to evaluate the trading ability of female investors, male investors, non-female investors and non-male investors, respectively. I begin with computing each agent-type initial *HPI* trading portfolio value and marked to market on day 0 as its own initial investment outlay. Next, I take the daily value of stock purchases as additional investment outlay, with sales representing cash benefit over each one-day period from January 3, 1995 to December 31, 2011. On the final day, the value of the portfolio is marked to market as the cash realization.

Table 3.5 displays the IRR results of each matched pairs of trading parties for Nokia alone, 28 major stocks inclusive of Nokia and 27 stocks exclusive of Nokia over the entire seventeen years period, respectively. Column (1) shows female investors' trading with male investors' *HPI* investment portfolio in Nokia alone yields a unique 43.14 percent annualized continuous compounded internal rate of return, compared with a -43.14 percent international rate of return made by male investors over the seventeen years period. The counterfactual female investors "BuyOnly" IRR is massively lower at -13.04 percent p.a., showing that it is necessary to include the exact timing of asset sales, as wells as purchases, as the regular IRR method does. The "BuyOnly" IRR is but a crude extension of the conventional "buy and hold" *C-T* methodology, with my findings indicating that it severely distorts performance measurement. Column (2) and Column (3) extend the IRR calculations to the full sample of a portfolio of the 28 (27) designated stocks, with the entire portfolio treated in the same way as the IRR for a "single" stock. In the interests of space, I only report the entire sample period results. The IRR earned by female investors in trading with male investors in the 28 stocks yield a lower 21.44 percent p.a., which is about half the magnitude for Nokia alone. The rest of columns apply the same procedures of IRR calculations to other two pairs of trading parties, i.e., male investors with non-male investors and female investors with non-female investors. It is indisputable that both male investors and female investors in trading with their counterparty in Nokia alone yield a positive IRR with 43.76 percent p.a. and 46.28 percent p.a., respectively. These IRRs deliver the same conclusions as previous profits made in dollar analysis. In addition, female investor earned higher IRR than male investors' which is in accordance with results produced in Table 3.3 Panel A that female investors outperform male investors over the entire seventeen years period.

Table 3.5 Summary of Continuously Compounded Internal Rate of Return (IRR) and BuyOnly IRR for Various Periods using daily *HPI* Trading for Nokia for Trades between Female and Male

IRR presents the continuously compounded internal rate of return for Nokia, 28 (27) stocks with each group treated as a single investor in the entire portfolio of stocks each day. BuyOnlyIRR is computed using the same single investor methodology as for the conventional IRR except that sell trades are ignored until the portfolio is realized on the last day.

	Female direct trade from Male			Male direct trade from Non-Male			Female direct trade from Non-Female		
	Nokia	Inclusive of Nokia	Exclusive of Nokia	Nokia	Inclusive of Nokia	Exclusive of Nokia	Nokia	Inclusive of Nokia	Exclusive of Nokia
Number of Stocks	1	28	27	1	28	27	1	28	27
IRR	43.16%	21.44%	6.02%	43.76%	16.84%	7.66%	46.28%	24.70%	9.08%
BuyOnly IRR	-13.04%	1.14%	2.46%	-19.43%	-3.07%	0.58%	-17.17%	-1.06%	0.43%

3.6 Female Investors' Investment Strategy

The *HPI* portfolio methodology is elegant in aggregating a vast number of daily trades across all individual investors (i.e., female and male investors) and stocks into one return time series without imposing a portfolio turnover rate on each trading party group. Nevertheless, the interpretation of results would benefit from knowing the female investors' trading strategy. Could Finnish female investors' superior trading ability in stock market be due simply to chance or "luck" rather than to trading on the basis of information that is superior to that of their counterparties in this study?

3.6.1 Testing the model of informed trading following Lu, Swan and Westerholm (2016)

In this section I pose the question: does sufficient information exist in the daily price history to explain the collective trading success of female investors in the pairing for which they are successful?[21]

I follow the model of informed trading introduced by Lu, Swan, and Westerholm (2016). It has been used to analyze Finnish households' (as one investor group including male and female investors) exceedingly high returns in trading with either Finnish domestic or foreign institutional investors from 1995 through 2011. Since this model imposes no limitation in applying the method to different investor categories, I follow the same procedures in seeking to understand whether private informational variations exist between individual investors due to gender bias. The details are shown in Appendix B. I turn to the empirical estimation of investment equation (B.1.7) in Appendix B using Ordinary Least Squares (OLS), while estimating the Cochrane–Orcutt–Durbin–Waston values to check for autocorrelation. Interestingly, I am not able to deliver a statistically significant lambda, which represents the geometric informational decay rate for female investors. Thus, from the model of informed trading alone (Lu, Swan, and Westerholm, 2016), female investors do not display the ability to take advantage of their private signal of expected fundamental value to maximize their expected CARA exponential utility function of their wealth.

One of the limiting updating rules discussed in Lu, Swan and Westerholm (2016) is that, if $\lambda \rightarrow 0$, the signal moves according to the observed price and the random error

[21] I also perform weekly and monthly observations to estimate the same model as daily price history. There is no significant difference departing from daily observations' results.

term such that the trader gains no informational advantage and cannot be expected to systematically earn trading profits from exploiting any trend-following motivation in their male counterparties. In my estimated OLS regression[22], the daily price decay rate λ, for female investors trading with male investors, no matter in Nokia alone or the other 27 major Finnish stocks (exclusive of Nokia), it is not statistically significantly different from zero. In Lu, Swan, and Westerholm (2016), systematic buying and selling sequences generated by the trend-following propensity of foreign investors could be translated into the sizeable trading profits of household investors, but this is not the case here for male investors. Lu, Swan, and Westerholm (2016) have demonstrated a trading advantage for individual investors (i.e., female investors and male investors) over both domestic and foreign institutional investors. Collectively, then, female and male investors receive an informed signal of future price that results in their adopting a contrarian trading strategy against other classes of institutional investor in the market. However, I do not obtain a statistically significant lambda by applying the model to the trading parties within the individual gender groups. This lack of a significant lambda means that both groups seem to have rational expectations, and one cannot explain the superior performance of females by the receipt of this signal.

3.6.2 Testing the determinants of Female investors' trading behavior

If both female and male investors seem to have "rational expectations," then it would seem that Finnish female investors' superior performance cannot be explained by the stock's price history alone. I would like to explore the determinants of Finnish female investors' superior trading behavior. This has not yet been explored in the literature. The most relevant studies come from Kaniel et al. (2008) and Barber and Odean (2008) in evaluating individual investors as a whole group, including male and female investors. Kaniel et al. (2008) employed the weekly net dollar volume bought by individual investors in the NYSE audit trail data and found they tend to buy stocks following declines and sell stocks following price increases. Barber and Odean (2008) use retail brokerage data and conclude that individual investors are net buyers of "attention-grabbing" stocks[23] Based on these findings, I estimate the following stock fixed effect regression specification for

[22] I also estimate the Cochrane–Orcutt–Durbin–Watson values to check for autocorrelation.

[23] They identified "attention-grabbing stocks" based on three criteria (exclusively): (1) stocks have news; (2) stocks are experiencing high abnormal trading volume; (3) stocks have extreme one-day return.

female investors' *HPI* weekly net purchases in trading with male investors[24],

$$NetBuys_{i,t} = a_{i,0} + b_1 LagDif\,\mathrm{Pr}\,iceMA_{i,t,d} + Volatility_{i,t} + FemaleNumber_{i,t} + LagNetBuys_{i,t} + e_{i,t} \tag{3.1}$$

The stock-level fixed effects control for stock-level differences, such as stock size, and allow us to focus on the time series and female investors' view in the comparison of the current stock price and moving average of 2-week, 4-week, 8-week, 12-week, 26-week, and 52-week, respectively. I estimate equation (3.1) for female investors alone because the estimated coefficients of male investors will be exactly the same magnitude but with opposite signs in the *HPI* portfolio approach. For simplicity, I omit the subscripts. The dependent variable $NetBuy$ is the weekly net purchases traded in common by female investors' *HPI* trading portfolio with male investors over one week. Since both female and male investors face the same number of shares outstanding for the same stock on the same day, I do not consider scaling net buys on shares outstanding. $LagDifPriceMA$ is the lagged one-week value of the contemporaneous price minus the moving average over different week intervals, ranging from two weeks to one year. I compute the simple moving average by adding the closing price of the stock for a number of weeks and then dividing this total by the number of weeks. Short-term averages respond quickly to changes in the underlying price, while long-term averages are slow to react. I prefer to detect whether female investors act differently in short-term time intervals or longer-term periods. I apply this fairly simple and natural moving average methodology, which has been widely employed by both academia and practitioners in examining technical trading strategies. The only variable needed for moving average analysis is the stock price history, which can be easily constructed. $Volatility$ is the realized volatility defined by absolute weekly return on the current week[25] $FemaleNumber$ is the total numbers of female investors for each week. $LagNetBuys$ is the one-week lagged value of $NetBuys$, which I introduce to control for persistence in trading direction.

Panel A of Table 3.6 lists their definitions. Following my previous findings, through Figure 3.3 to 3.7, my hypothesis is that female investors will buy stocks if the contemporaneous price is less than the moving average but make a selling decision if the contemporaneous

[24] I also test equation (3.1) by adding the stock industry control variable. The results still hold.
[25] Swan (2017) provided the justification for using volatility as a risk measure.

price is over the moving average. I expect the coefficient b_1 to be statistically significant with a negative sign.

Table 3.6 Determinants of Female investors' *HPI* portfolio in trading with male investors

Panel A lists the variable definitions. Panel B lists the regression estimates and t-statistics in absolute value using standard errors clustered by date in parentheses. All regressions are in the presence of firm fixed effects and standard errors are clustered by trading week. The computations are based on the representative panel of weeks over the 1995 to 2015 period. This table estimates the following panel regression the female investors' weekly *HPI* net purchases in trading with male investors on difference between contemporaneous weekly close price and each moving average with Column (1) 2-week, Column (2) 4-week, Column (3) 8-week, Column (4) 12-week, Column (5) 26-week, Column (6) 52-week, Column (7) 104 -week, respectively. All regressions are with stock-level fixed effect. *, ** and *** denote statistical significant at 5%, 1% and 0.1% levels.

Panel A: Regression Variable List

Variable	Name	Definition
NetBuys	Female investors *HPI* net purchases	The number of shares bought minus the number of shares sold by female investor in *HPI* trading portfolio with male investors
Volatility	Volatility	The absolute weekly return on the current week
FemaleNumber	The number of female investors	The total number of female investors buy or sell shares on the current week
LagDifPriceMA	Lagged one period, the difference between contemporaneous price and moving averages	Lagged one week of the contemporaneous price minus moving averages over different week-interval.
LagNetBuys	Lagged female investors *HPI* net purchases	Lagged female investors *HPI* net purchases in trading with male investors

Panel B: Determinants of Female investors' *HPI* portfolio in trading with male investors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Net Buys	Net Buys	Net Buys	Net Buys	Net Buys	Net Buys	Net Buys
LagDifPriceMA2	-225.18						
	(1.31)						
LagDifPriceMA4		-262.08**					
		(2.38)					
LagDifPriceMA8			-219.35***				
			(3.05)				
LagDifPriceMA12				-210.41***			
				(3.76)			
LagDifPriceMA26					-152.30***		
					(4.02)		
LagDifPriceMA52						-109.93***	
						(3.54)	
LagDifPriceMA104							-88.81***
							(3.81)
Constant	234.88	243.39	253.66	263.5	273.34	274.16	286.38
	(1.23)	(1.27)	(1.32)	(1.36)	(1.41)	(1.41)	(1.47)
Volatility	788.08	607.46	445.09	304.67	182.38	323.05	522.55
	(0.24)	(0.18)	(0.13)	(0.09)	(0.05)	(0.1)	(0.16)
FemaleNumber	-0.58	-0.57	-0.56	-0.56	-0.57	-0.57	-0.56
	(1.22)	(1.19)	(1.18)	(1.18)	(1.21)	(1.22)	(1.2)
LagNetBuys	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***
	(4.89)	(4.87)	(4.85)	(4.85)	(4.85)	(4.86)	(4.89)
Observations	16,609	16,609	16,609	16,609	16,609	16,609	16,609
Number of Weeks	927	927	927	927	927	927	927
Firm Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.0207	0.021	0.0214	0.0217	0.022	0.022	0.0222

* $p < 0.10$, ** $p < 0.01$, *** $p < 0.001$

Panel B of Table 3.6 presents the regression estimates and the t-statistics based on standard errors clustered by date to control for cross-sectional correlation. Columns (1) to (5) provide estimates based on moving averages with different time intervals, from two weeks to one year. The lagged one week of the difference between contemporaneous price and moving averages are negatively statistically significant at a 1 percent level, except for the very short-term two-week moving average. That is, female investors have a tendency to sell stocks on days in which their prices are greater than the average of past prices over the previous one-month to one-year time interval, respectively. Similarly, they purchase these stocks if the current prices are less than the moving averages over time-interval from 4-week up to one-year. Hence, female investors' behavior suggests that they identify a stock's fundamental value by its past average stock price, but the fundamental value here is their "private fundamental value" rather than the more conventional definition. They believe that either under-priced or over-priced stocks will move back to their historical average due to mean reversion under the efficient market hypothesis. Either the short- or long-term moving average of past stock price provides a signal of fundamental value to female investors. The coefficients of $LagDifPriceMA$ are range from -225 to -89 from short-term to long-term moving average time window. That is, female investors prefer to estimate their own "fundamental value" based on the more recent stock price moving average.

Furthermore, if they were more risk-averse than male investors, they would not trade too much in anticipation of any existing mispricing opportunity in the market. While in general male investors may adopt a contrarian trading strategy for the same mispricing stock when trading with institutions, since females appear to be contrarian traders, their counterparty must, by definition, be positive-feedback in nature. For the control variables, except lagged net purchases (which is statistically significantly negatively correlated with current net buys), female investors' net buys are significantly affected by neither the current realized volatility nor the total numbers of female investors anticipated to be in the market. In all likelihood, these estimation problems stem from aggregating very short daily investment periods into weekly intervals in order to eliminate many non-trading and thus directionless trading days. The adjusted R-squared for each estimate regression is approximately 2.2 percent.[26]

3.6.3 Testing the risk preference of Female investors' trading behavior

Prior studies offer mixed results on gender bias in risk taking. A large experimental literature argues that females are intrinsically different from males. Jianakoplos and Bernasek (1998) report that single females show more risk aversion in investment decision-making than single males, resulting in a lower level of wealth. Barber and Odean (2001) claim that overconfident male investors prefer to hold riskier portfolios than do female investors. Croson and Gneezy (2004) show that women are intrinsically different from men and identify robust differences in risk preferences. When evaluating the gender difference on an actively managed *HPI* trading portfolio, i.e., female investors directly trade with male investors, one may also question whether female investors prefer to buy less risky stocks and sell more risky stocks. Hence, by the definition of the *HPI* portfolio approach, male investors who act as the counterparty are in favor of riskier stocks and reduce their *HPI* portfolio exposure in less risky stocks, this directly gives us a testable hypothesis that female investors prefer to hold lower beta stocks due to being less risk-seeking.

Talpsepp (2013) examines risk preference according to gender difference by testing the stock beta in relation to Estonian male investors' trading behavior. I now follow their spirit to estimate stock risk using monthly beta from 1995 to 2011. My monthly Finnish stock estimated beta is based on Fama–Macbeth (1973) with a rolling five years monthly stock excess returns against Finnish market excess returns. I estimate the following two stock fixed effect regressions specification for female investors' *HPI* monthly net purchases in trading with male investors:

$$SellDummy_{i,t} = a_{i,0} + LagBeta_{i,t} + Beta_{i,t} + Volatility_{i,t} + FemaleNumber_{i,t} + e_{i,t} \quad (3.2)$$

$$BuyDummy_{i,t} = a_{i,0} + LagBeta_{i,t} + Beta_{i,t} + Volatility_{i,t} + FemaleNumber_{i,t} + e_{i,t} \quad (3.3)$$

[26]For the robustness check, I also estimate daily-horizon regression using moving average with 30-day, 60-day, 90-day, 120-day and 365-day, respectively. All estimations confirm the statistically significant contrarian behavior of female investors but with lower adjusted R-squared.

The stock-level fixed effects control for stock-level differences, such as stock size, and allow us to focus on the time series and female investors' view in the comparison of the current stock beta and lagged one month stock beta. I estimate equations (3.2) and (3.3) female investors alone because the estimated coefficients of male investors will be exactly the same magnitude but with opposite signs in the *HPI* portfolio approach. For simplicity, I omit the subscripts in the following disscussion. The dependent variable $SellDummy$ in equation (3.2) is 1 if monthly female net buys is positive and 0 otherwise. The *BuyDummy* in equation (3.3) equals 1 if monthly female net buys is negative and 0 otherwise. Since both female and male investors face the same number of shares outstanding for the same stock on the same day, hence I do not consider scaling net buys on shares outstanding. *LagBeta* is the lagged one month value of the monthly stock beta, which I introduce to control for persistence in trading direction. $Volatility$ is the realized volatility defined by absolute weekly return on the current week. $FemaleNumber$ is the total numbers of female investors for each week.

Table 3.7 reports the estimation results for equation (3.2) in column (1) and equation (3.3) in column (2). Finnish female investors' investment decisions do not significantly depends on the monthly stock beta variations. In other words, based on the beta estimation for stock risk analysis, both Finnish male and female investors show their investment decision making are not contributed by stock risk factor over the entire sample period, 1995 to 2011. This is in line with the experiment study undertaken by Harrison, Lau, and Rutstrom (2007) that documents no effect of sex on risk attitudes for individual investors in Denmark.

3.6.4 Householder informational advantage

Lu, Swan and Westerholm (2016) have confirmed that Finnish household trade on their basis of local information that is not necessarily "inside information", i.e., one possibility is so called "home informational superiority".[27] Is it possible that households who live close to Helsinki area are de facto insider traders as Nokia and other leading companies are headquarter there? The associated company employees could deliver price sensitive information to neighbouring households. However, this is not plausible as an explanation

[27]Coval and Moskowitz (2001) document evidence of local informational advantages while Hong, Kubik and Stein (2005) find that word of mouth is used to share information by mutual fund managers in close geographic proximity.

Table 3.7 Female risk taking behavior in direct trading with male investors

I estimate Fama-MacBeth (1973) regression to evaluate female investors' trading preference in relation with stock beta. The dependent variable is monthly *HPI* female net purchase with male investors. adjusted for serial correlation using the methodology described in Pontiff (1996). *** represents statistically significant at 0.001 probability level. ** represents statistically significant at 0.01 probability level.* represents statistically significant at 0.1 probability level.

Variables	Sell dummy	Buy dummy
	(1)	(2)
LagBeta	-0.017	0.023
	(0.342)	(0.463)
Beta	0.022	-0.024
	(0.467)	(0.515)
Volatility	-0.0941	0.03
	(0.955)	(0.381)
Numbers of Females	0	0
	(0.852)	(0.851)
Constant	0.404***	0.602***
	(6.223)	(9.501)
Observations	2,099	2,099
R-squared	0.03	0.033
Number of date	124	124
Firm FE	Yes	Yes
Adj. R-squared	0.018	0.021

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

for why female traders outperform male in the long-term since, being contrarian, females lose out to males trading on short-term and potentially inside information. Branikas, Hong and Xu (2016) claim the households' location choices contribute to their invested portfolio choices. However, in this study, Finnish households did not decide to be born in Finland and hence the scope for endogenous locational choice is not great. For the same Finnish households investors sample examined in Lu, Swan and Westerholm (2016), I now turn to investigate whether "local information" assists female investors outperform their male investor counterparts.

Since my database[28] is sufficiently rich to include a postcode identifier for every trader, I allocate male and female traders separately into two regions, those investors in the greater Helsinki area and those investors located elsewhere in Finland. Table 3.8 tests the hypothesis that female investors and male investors located close to Nokia headquarters possess better information on which to trade than do female and male investors elsewhere in the country. Panel A of Table 3.8 shows the cumulative profits for each trading group in millions of Euros, is split into four periods spanning the 17 years of the database based on the intervals specified by the lowest points in the Finnish Consumer Confidence Index (CCI) displayed in Figure 3.1 and Panel B presents the four periods analysis based on the stock price index. In Panel A, columns (1) and (2) show that Helsinki male investors profited by non-Helsinki male investors EUR 121.93 million and column (3) to column (4) indicate Helsinki female investors also outperform non-Helsinki female investors by EUR 52.72 million over the 17 years of my data in 28 large Finnish stocks inclusive of Nokia. Not surprisingly, the majority of the profits were made in Nokia alone.

In the remaining columns, I pit the two identified female investor groups and two identified male investors, i.e., Helsinki female (male) investors and the remainder, Helsinki female investors against Helsinki male investors and Non-Helsinki female investors against non-Helsinki male investors respectively, to test the hypothesis that Finnish female investors are collectively better informed than Finnish male investors even when not in receipt of insider information due to the close proximity of Nokia headquarters. Columns (5) and (6) present evidence the Helsinki female investors remain superior traders when pitted against their Helsinki male investors' rivals with a profit of 120.13 million and for the remaining female investors also profited by EUR 102.10 million with non-Helsinki male investors

[28]My database includes the local postcode addresses of the over one million Finnish trading accounts, including male investors, female investors and domestic institutional investors.

based on the 28 major Finnish stocks inclusive of Nokia. Nevertheless, non-Helsinki female investors has lost approximately EUR 0.53 million on non-Nokia stocks with its counterparty non-Helsinki male investors but gained EUR 6.97 million for Helsinki female investors in direct trading with Helsinki male investor on non-Nokia stocks in total. Hence, I conclude that Finnish female investors overall appear to have better access to information than do either Helsinki male investors or non-Helsinki male investors. Since a more informed investor group will on average buy low and sell high, they will appear to be contrarian when that might not be their strategy at all. For example, in Brennan and Cao's (1996, p.174) partially revealing rational expectations equilibrium informed traders will appear to be contrarian.

Table 3.8 Sub-periods cumulative Profits and Losses after transaction costs for direct trades between each trading pair in Large Finnish stocks (Nokia alone, 28 stocks, inclusive of and exclusive of Nokia, respectively)

I follow the turning points of CCI shown in Figure 1 to break down my entire sample period into three sub-periods, i.e., from trough to trough, January, 1995 to November, 2001; December, 2001 to December 2008; January, 2009 to December 2011. This alterative way in splitting seventeen year-period into three sub-periods is a robustness check that I use exogenous variable to estimate Finland economy movements. CCI has been proven that a powerful indicator to represent the whole economy. The table shows *HPI* portfolio daily cumulative profits and losses (EUR million) in four different pairs of trading groups, i.e., Column (1) through Column (4) present female and male investors who live near to Helsinki in the comparison of the rest Finnish female and male investors. Column (5) through Column (8) shows the trading performance between females in direct trading with males who live near to Helsinki, other females in direct trading with other males, respectively. *** represents 1% significant level. ** represents 5% significant level.

Panel A: This panel shows the *HPI* trading performance between Greater Helsinki female (male) investors with other female (male) investors, Greater Helsinki female investors with Greater Helsinki male investors, in each sub-period (Based on Finland Consumer Confidence Indicator)

Period (Trough to Trough)	Cumulative P&L (EUR M)							
Category	Greater Helsinki Males (1)	Other Males (2)	Greater Helsinki Fe-males (3)	Other Fe-males (4)	Greater Helsinki Fe-males (5)	Greater Helsinki Males (6)	Other Fe-males (7)	Other Males (8)
Nokia								
01/03/1995 - 11/30/2001	24.58***	-24.67***	4.79**	-4.83**	12.57***	-12.63***	27.19***	-27.24***
12/03/2001 - 12/31/2008	7.57	-7.63	7.62**	-7.64**	19.99***	-20.03***	6.32***	-6.35***
01/03/2009 - 12/30/2011	4.82	-4.86	-0.89	0.87	-2.42	2.39	1.27	-1.3
01/03/1995 - 12/30/2011	116.13***	-116.32***	42.72***	-42.80***	113.16***	-113.28***	102.63***	-102.74***
Ratio of trading profits to total trading value	53.38%	-53.47%	50.98%	-51.07%	90.40%	-90.49%	86.71%	-86.80%
Ratio of trading profits to total trading volume	6.10	-6.11	5.32	-5.33	10.02	-10.03	9.80	-9.81
Inclusive of Nokia (28 stocks)								
01/03/1995 - 11/30/2001	26.38***	-26.64***	4.13	-4.22	12.58**	-12.71**	28.82**	-28.96**
12/03/2001 - 12/31/2008	15.53	-16.06	13.39	-13.57	29.88**	-30.14**	10.1945	-10.41
01/03/2009 - 12/30/2011	8.03	-8.5	-0.18	0.05	-4.17	3.99	-0.8146	0.64
01/03/1995 - 12/30/2011	121.93***	-123.18***	52.72***	-53.13***	120.13***	-120.71***	102.10***	-102.63***
Ratio of trading profits to total trading value	9.54%	-9.64%	11.86%	-11.95%	19.04%	-19.13%	18.06%	-18.15%
Ratio of trading profits to total trading volume	0.97	-0.98	1.29	-1.3025	2.08	-2.09	2.43	-2.44
Exclusive of Nokia (27 stocks)								
01/03/1995 - 11/30/2001	1.79	-1.96	-0.66	0.61	0	-0.08	1.63	-1.72
12/03/2001 - 12/31/2008	7.96	-8.43	5.77	-5.93	9.88	-10.11	3.87	-4.06
01/03/2009 - 12/30/2011	3.21	-3.64	0.71	-0.82	-1.76	1.6	-2.08	1.94
01/03/1995 - 12/30/2011	5.8	-6.86	10	-10.33	6.97	-7.44	-0.53	0.11
Ratio of trading profits to total trading value	0.55%	-0.65%	2.77%	-2.86%	1.38%	-1.47%	-0.12%	0.02%
Ratio of trading profits to total trading volume	0.05	-0.06	1.25	-1.29	0.15	-0.16	-0.01	0.00

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: This panel shows the *HPI* trading performance between Greater Helsinki female (male) investors with other female (male) investors, Greater Helsinki female investors with Greater Helsinki male investors, in each sub-period (Based on historical index movement, the same as in the tables above)

Period (Trough to Trough)	Cumulative P&L (EUR M)							
Category	Greater Helsinki Males (1)	Other Males (2)	Greater Helsinki Females (3)	Other Females (4)	Greater Helsinki Females (5)	Greater Helsinki Males (6)	Other Females (7)	Other Males (8)
Nokia								
01/03/1995 - 07/03/2003	59.37***	-59.47***	17.27**	-17.31**	44.18***	-44.24***	56.41***	-56.46***
07/04/2003 - 03/06/2009	3.77	-3.83	7.55**	-7.56**	25.28***	-25.31***	7.88***	-7.90***
03/07/2009 - 12/30/2011	4.57	-4.61	-1.08	1.06	-3.14	3.11	1.34	-1.37
01/03/1995 - 12/30/2011	116.13***	-116.32***	42.72***	-42.80***	113.16***	-113.28***	102.63***	-102.74***
Ratio of trading profits to total trading value	53.38%	-53.47%	50.97%	-51.07%	90.39%	-90.49%	86.71%	-86.80%
Ratio of trading profits to total trading volume	6.10	-6.11	5.32	-5.33	10.02	-10.03	9.80	-9.81
Inclusive of Nokia (28 stocks)								
01/03/1995 - 07/03/2003	62.07***	-62.39***	17.56	-17.67	45.24***	-45.40***	58.79**	-58.95**
07/04/2003 - 03/06/2009	14.85	-15.34	15.77**	-15.93**	37.51***	-37.75***	10.91	-11.11
03/07/2009 - 12/30/2011	6.95	-7.39	-0.48	0.35	-4.67	4.5	-1.58	1.41
01/03/1995 - 12/30/2011	121.93***	-123.18***	52.72***	-53.13***	120.13***	-120.71***	102.10***	-102.63***
Ratio of trading profits to total trading value	9.54%	-9.64%	11.86%	-11.95%	19.04%	-19.13%	18.06%	-18.15%
Ratio of trading profits to total trading volume	0.97	-0.98	1.29	-1.30	2.08	-2.09	2.43	-2.44
Exclusive of Nokia (27 stocks)								
01/03/1995 - 07/03/2003	2.7	-2.92	0.29	-0.36	1.06	-1.16	2.38	-2.49
07/04/2003 - 03/06/2009	11.08	-11.51	8.22	-8.37	12.23	-12.44	3.03	-3.21
03/07/2009 - 12/30/2011	2.38	-2.78	0.6	-0.71	-1.54	1.39	-2.91	2.78
01/03/1995 - 12/30/2011	5.8	-6.86	10	-10.33	6.97	-7.44	-0.53	0.11
Ratio of trading profits to total trading value	0.55%	-0.65%	11.93%	-2.86%	1.38%	-1.47%	-0.12%	0.02%
Ratio of trading profits to total trading volume	0.05	-0.06	1.25	-1.29	0.15	-0.16	-0.017	0.00

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 3.8 I find that particularly females located in the greater Helsinki area seem to have a very sizeable trading superiority over males. This superiority raises the possibility that males who are insiders might use the account of their spouse to better hide potentially illegal insider trades. But this neglects the fact my approach is quite distinguished from Berhman, Koch and Westerholm (2014). What they document is child guardians make short-term insider trades while my framework examines female investors' long-term trading profitability. I obtain the family name identities of Finnish insiders and match them against my database of males and females. I treat both the male and female trading accounts at the address of an insider as insider accounts. Matched against non-insiders, these account holders are superior traders and thus insider spouse accounts could be responsible for some (potentially all) of the high profits of females trading with males. Hence in Table 3.9[29] I present the profits of non-insider female accounts when trading with males to show that females are still far superior. In Panel A, columns (1) and (2) show that non-insider female investors who live far away from Helsinki outperform non-insider male investors who live far away far away from Helsinki by EUR 101.05 million and Columns (3) and (4) non-insider Helsinki female investors profited by non-insider Helsinki male investors by EUR 119.54 million over the 12 years from 2000 through 2011 of my data in 28 large Finnish stocks inclusive of Nokia. The majority profits were generated from Nokia alone. In addition, non-insider Helsinki female investors present superior trading ability over other non-insider female investors by claiming more profits by approximate EUR 18 million in the comparison with the corresponding male counterparty. Hence potential insider trading does not seem to account for all of the high profitability of female traders but it does account for some. The absence of statistical significance is the results of the sample sizes. The key challenge here is the data sample dropped significantly relative to the original data sample due to each new filter introduced, according to my Monte Carlo simulations in particular when sample sizes become tiny.

[29]In Finland, insider trading laws has passed in 1989 and first enforced in 1993. (Bhattacharya and Daouk (2002), and Berkman and Westerholm (2014))."

Table 3.9 Sub-periods cumulative Profits and Losses after transaction costs for direct trades between non-insider accounts- each trading pair in Large Finnish stocks (Nokia alone, 28 stocks, inclusive of and exclusive of Nokia, respectively)

This table presents the results for the *HPI* portfolio performance in the pairs of the non-insider Finnish females' accounts and non-insider Finnish males' accounts over the period from 2000 to 2011. While the starting date of my insider corporate account information is from January, 2000, hence I adjust my sub-periods analysis starting from 3rd, January, 2000 instead of 3rd, January, 1995. In Panel A, I provide results following the CCI index turning points shown in Figure 1. Column (1) and Column (2) present non-insider female and non-insider male investors who live far away from Helsinki. Column (3) and Column (4) display the *HPI* trading performance in the comparison of non-insider females and non-males investors who live close to Helsinki. In Panel B, I apply the historical index movement to break down the period from 2000 to 2011 into four sub-periods for the same non-insider females and males' investors. Column (1) through Column (4) documents the *HPI* trading performance based on the location to Helsinki. *** represents 1% significant level. ** represents 5% significant level.

Panel A: The panel shows the *HPI* trading performance between Greater (less) Helsinki non-insider female investors with non-insider male investors, in each sub-period (Based on Finland Consumer Confidence Indicator.

Period (Trough to Trough)	Cumulative P&L (EUR M)			
	Not Insiders			
Category	Less Helsinki Females (1)	Less Helsinki Males (2)	Greater Helsinki Females (3)	Greater Helsinki Males (4)
Nokia				
01/03/1995 - 11/30/2001	26.93	-26.98	12.57	-12.63
12/03/2001 - 12/31/2008	6.18	-6.2	19.97	-20
01/03/2009 - 12/30/2011	1.27	-1.3	-2.41	2.38
01/03/1995 - 12/30/2011	101.7	-101.81	113.06	-113.17
Ratio of trading profits to total trading value	86.37%	-86.46%	90.65%	-90.74%
Ratio of trading profits to total trading volume	9.73	-9.74	10.03	-10.04
Inclusive of Nokia (28 stocks)				
01/03/1995 - 11/30/2001	28.57	-28.71	12.57	-12.71
12/03/2001 - 12/31/2008	9.81	-10.03	29.72	-29.99
01/03/2009 - 12/30/2011	-0.81	0.63	-4.39	4.19
01/03/1995 - 12/30/2011	101.05	-101.59	119.54	-120.13
Ratio of trading profits to total trading value	17.72%	-17.81%	18.84%	-18.93%
Ratio of trading profits to total trading volume	1.88	-1.89	2.03	-2.04
Exclusive of Nokia (27 stocks)				
01/03/1995 - 11/30/2001	1.65	-1.73	0	-0.08
12/03/2001 - 12/31/2008	3.63	-3.83	9.75	-9.98
01/03/2009 - 12/30/2011	-2.08	1.93	-1.98	1.81
01/03/1995 - 12/30/2011	-0.65	0.22	6.48	-6.96
Ratio of trading profits to total trading value	-0.14%	0.05%	1.27%	-1.36%
Ratio of trading profits to total trading volume	-0.02	0.01	0.14	-0.15

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: The panel presents the *HPI* trading performance between Greater (less) Helsinki non-insider female investors with non-insider male investors,, in each sub-period (Based on historical index movement, the same as in the tables above)

Period (Trough to Trough)	Cumulative Profits and Losses (EUR M)			
	Not Insiders			
Category	Less Helsinki Females (1)	Less Helsinki Males (2)	Greater Helsinki Females (3)	Greater Helsinki Males (4)
Nokia				
01/03/1995 - 07/03/2003	55.97	-56.03	44.16	-44.22
07/04/2003 - 03/06/2009	7.66	-7.68	25.13	-25.16
03/07/2009 - 12/30/2011	1.34	-1.37	-3.14	3.11
01/03/1995 - 12/30/2011	101.7	-101.81	113.06	-113.17
Ratio of trading profits to total trading value	86.37%	-86.46%	90.65%	-90.74%
Ratio of trading profits to total trading volume	9.73	-9.74	10.03	-10.04
Inclusive of Nokia (28 stocks)				
01/03/1995 - 07/03/2003	58.34	-58.5	45.25	-45.41
07/04/2003 - 03/06/2009	10.44	-10.64	37.1	-37.35
03/07/2009 - 12/30/2011	-1.57	1.4	-4.9	4.71
01/03/1995 - 12/30/2011	101.05	-101.59	119.54	-120.13
Ratio of trading profits to total trading value	17.72%	-17.81%	18.84%	-18.93%
Ratio of trading profits to total trading volume	1.88	-1.89	2.03	-2.04
Exclusive of Nokia (27 stocks)				
01/03/1995 - 07/03/2003	2.36	-2.47	1.09	-1.19
07/04/2003 - 03/06/2009	2.78	-2.96	11.98	-12.2
03/07/2009 - 12/30/2011	-2.91	2.77	-1.76	1.6
01/03/1995 - 12/30/2011	-0.65	0.22	6.48	-6.96
Ratio of trading profits to total trading value	-0.14%	0.05%	1.27%	-1.36%
Ratio of trading profits to total trading volume	-0.02	0.01	0.14	-0.15

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.6.5 Robustness Check

In this section, I pit my male investors and female investors' group into four independent subgroups by their age category. I assign every male or female investor who is over or equal to 50 to the 50+ "Aged" group and the remaining males or females are classified as the "Young" group. My interest is to examine whether the superiority of female traders over male could be due, at least in part, to a difference in female brain function relative to male or can simply be explained by the smaller proportion of active female traders and thus by self-selection from a population of identical ability, as was argued by Kumar (2010) for female analysts that he found dominated males.[30] Stanworth and Jones (2008) review the current evidence of clinical effects of testosterone treatment within an aging male population and document the effect of changes in testosterone levels with aging. They find on average the total testosterone levels fall 1.6 percent per year whilst free and bioavailable levels fall by 2 to 3 percent per year. In addition, twenty percent of males aged over 60 have total testosterone levels below the normal range and a sizeable 50 percent in those aged over 80. If testosterone is beneficial for male trader performance as evidenced by Coates and Herbert (2008), then young males should dominate aged males in trader performance and aged females should perform as well as young females since testosterone levels are low to begin with. Self-selection in the form of the departure of less successful male traders from the market could lead to aged males dominating young males, depending on the effect of the testosterone decline, and aged females dominating young females for the same reason.

Panel A of Table 3.10[31] reports the ratio of *HPI* trading profits to total traded value for all 28 stocks for direct trades between the two male, and between the two female, groups while Panel B reports the comparative trading performance of the different groups of male and female trader. It can be seen from Panel A that young males have a very slight advantage over aged males and that aged females have approximately a 2 percent profit per dollar traded advantage over young females. These findings are consistent with males suffering a decline in their testosterone level advantage as they age being offset by the withdrawal of less successful male traders to achieve a negligible net-effect, and the withdrawal of less successful female traders with ageing leading to quite a sizeable trading

[30]From Table 2.2 it can be seen that males traded with the residual by 5.1 times as much in value terms as did females.

[31]I also perform the same procedures based on the CCI sub-periods analysis but retain the similar results.

advantage for aged females. Panel B shows that both aged and young females sizeably dominate their male counterpart peers with aged females gaining in excess of a 20 percent profit per dollar traded advantage over young males and young females gaining only a 16 percent profit advantage over young males. Putting all these findings together, it would appear that female traders augment their considerable trading advantage over males by a process of withdrawal and self-selection as they age and this withdrawal of less-talented females is not matched by a similar improvement in males. The absence of statistical significance here is similar with the results shown in In Table 3.8. The key challenge here is the data sample dropped significantly relative to the original data sample due to each new filter introduced, according to my Monte Carlo simulations in particular when sample sizes become tiny.

These findings also suggest that variations in testosterone levels as males age does not play a very important part in explaining variations in their trading performance as they age and most likely does not account for the far superior trading performance of the women in my sample. Thus I am left with differences between male and female brains at birth and a role for self-selection by females according to trading ability, but not by males, as explanations for the relative trading superiority of females. If self-selection is the story, it is puzzling as to why female traders are consistently contrarian and, since there can be no discrimination against self-trading by female-headed households, why only females and not males seem to self-select. These findings would tend to indicate a difference in brain functioning between the genders.

Hence, I employ age as an exogenous variable to explain the relative performance of the different age and gender categories. However, if masculinity in the form of high testosterone levels also contributes to under-performance, I should see older males also performing better due to declining testosterone levels, as well as to self-selection. Thus the first hypothesis is that aged males should be less disadvantaged against aged females than young males are against young females while the null hypothesis of no role for “maleness” states that young females should dominate young males and aged females dominate aged males by approximately equal amounts.

Table 3.10 Cumulative Profits and Losses after Transaction Costs for Direct Trades between each Trading Pair of different age groups of males and females

The cumulative P&L is at the end of day of each period and the cumulative P&L of each period is independent which means that every starting point of the cumulative P&L is zero. Transaction cost per trade for households is EUR0.005. Total trading value is computed as the sum of daily total trading value in two from 1995 to 2011. For both female investors and male investors, the cut off age is 50 years. If they are over or equal to 50, then they are treated as aged females (males) and vice versa. Sub-periods analysis is based on the historical price index.

Panel A: Young Males versus Aged Males and Young Females versus Aged Females

	Period (Trough to Trough)	Cumulative P&L (EUR M)			
Category		Young Males (1)	Aged Males (2)	Young Females (3)	Aged Females (4)
Nokia	01/03/1995 - 07/03/2003	-7.77	7.68	-7.16	7.12
	07/04/2003 - 03/06/2009	-7.15	7.10	-0.97	0.96
	03/07/2009 - 12/30/2011	3.25	-3.30	1.29	-1.31
	01/03/1995 - 12/30/2011	-12.05	11.87	-10.76	10.69
Inclusive of Nokia (28 stocks	01/03/1995 - 07/03/2003	-2.29	2.02	-6.88	6.78
	07/04/2003 - 03/06/2009	17.04	-17.48	3.88	-4.03
	03/07/2009 - 12/30/2011	4.94	-5.30	1.66	-1.77
	01/03/1995 - 12/30/2011	4.37	-5.45	-8.67	8.31
Ratio of HPI trading profits to total trading value from 1995 to 2011		0.38%	-0.47%	-2.18%	2.10%
Exclusive of Nokia (27 stocks)	01/03/1995 - 07/03/2003	5.48	-5.66	0.29	-0.34
	07/04/2003 - 03/06/2009	24.19	-24.58	4.85	-4.99
	03/07/2009 - 12/30/2011	1.68	-2.00	0.37	-0.46
	01/03/1995 - 12/30/2011	16.42	-17.32	2.09	-2.38
Ratio of HPI trading profits to total trading value from 1995 to 2011		1.75%	-1.85%	0.65%	-0.73%

Panel B: Aged Males versus Young Females, Young Males versus Young Females, Aged Males versus Aged Females, and Young Males versus Aged Females

	Period (Trough to Trough)	Cumulative P&L (EUR M)							
Category		Aged Males (1)	Young Females (2)	Young Males (3)	Young Females (4)	Aged Males (5)	Aged Females (6)	Young Males (7)	Aged Females (8)
Nokia	01/03/1995 - 07/03/2003	-39.06	39.00	-47.96	47.90	-55.13	55.07	-77.12	77.05
	07/04/2003 - 03/06/2009	-11.42	11.40	-8.18	8.16	-21.07	21.04	-17.08	17.05
	03/07/2009 - 12/30/2011	-1.45	1.41	0.21	-0.24	0.14	-0.16	2.62	-2.65
	01/03/1995 - 12/30/2011	-85.41	85.30	-96.03	95.92	-115.13	115.02	-148.12	148.00
Inclusive of Nokia (28 stocks)	01/03/1995 - 07/03/2003	-42.81	42.65	-48.74	48.59	-58.95	58.79	-76.55	76.38
	07/04/2003 - 03/06/2009	-26.58	26.37	-12.97	12.77	-26.77	26.53	-17.08	16.83
	03/07/2009 - 12/30/2011	0.04	-0.21	2.21	-2.37	0.93	-1.09	6.22	-6.41
	01/03/1995 - 12/30/2011	-92.89	92.36	-95.74	95.23	-119.28	118.73	-145.05	144.45
Ratio of HPI trading profits to total trading value from 1995 to 2011		-16.22%	16.13%	-17.55%	17.46%	-18.21%	18.13%	-20.46%	20.38%
Exclusive of Nokia (27 stocks)	01/03/1995 - 07/03/2003	-3.75	3.65	-0.78	0.69	-3.82	3.71	0.57	-0.67
	07/04/2003 - 03/06/2009	-15.16	14.97	-4.79	4.61	-5.70	5.49	-0.01	-0.22
	03/07/2009 - 12/30/2011	1.49	-1.62	2.00	-2.13	0.79	-0.93	3.60	-3.76
	01/03/1995 - 12/30/2011	-7.48	7.06	0.29	-0.68	-4.15	3.70	3.06	-3.55
Ratio of HPI trading profits to total trading value from 1995 to 2011		-1.62%	1.53%	0.07%	-0.16%	-0.80%	0.71%	0.55%	-0.63%

3.7 Conclusion

In the present study I am the first to apply my *HPI* portfolio approach (Lu, Swan and Westerholm (2016)) to examine whether gender difference affect trading portfolio performance in stock markets. *HPI* methodology challenges the conventional *C-T* portfolio approach that had its origins in important contributions made by Jaffe (1974) and Mandelker (1974) over forty years. Furthermore, I adopt an extensive seventeen-year window of matched daily trade by male and female investors based on daily portfolio of all Finnish individual investors in Nokia and 27 other major Finnish stocks.

The conventional *C-T* portfolio unnecessarily assumes that all investors mechanically turn over their entire portfolio at a specified interval corresponding to an assumed horizon in a manner which is entirely inconsistent with actual trading data. Since informed but contrarian traders will never trade in such a mechanical and irrational manner, they are typically disadvantaged in any such comparison. By contrast, *HPI* methodology has the ability to correctly indicate the direction of the trading profit change and is able to recognize the endogenous nature of investment timing decisions made by the near million male and female investors in my data set.

I show that the direct trade portfolio of female with male investors in Nokia results in a gain to female investors of EUR 194.67 million over the seventeen years of my data set. This represents a striking internal rate of continuously compounded return of 43.16 percent p.a.. If the *C-T* "Buy and Hold" equivalent of the IRR, that I dub the "BuyOnly" IRR, is employed instead the return falls to minus 13.04 percent p.a., indicating severe methodological error. Furthermore, I examine the trading pairs of male in direct trading with non-male investors and female in direct trading with non-female investors. Both male and female investors in Nokia alone gained a larger reward of EUR 2,329 million and EUR 1,407 million, respectively, or an IRR of 43.76 percent p.a. and 46.28 percent p.a., in their trades with counter parties, 1995-2011. Females earn a sizeable 37.5 percent profit rate per dollar trade with the residual whereas males earn only 12.3 percent.

The trading advantage of female investors over both male investors and non-female investors is unlikely to be due purely chance. In order to elucidate informational issues I first follow the model of informed trading (Lu, Swan and Westerholm, 2016) to construct a simple Koyck distributed lag model describing the nature of the daily private signal received by female investors in direct trading with male investors. The estimation results have shown that female investors' Lambda is not significantly different from zero. In other words, recall the findings in Lu, Swan and Westerholm (2016), Finnish individual investors acting as informed traders outperform both domestic institutional investors and foreign institutional investors. With the same data set and identical time interval employed as in Lu, Swan and Westerholm (2016), it is difficult to find a statistically significant information advantage represented by Lambda for female investors over male investors within the same household investor group. Hence if both male and female investors have rational expectations, then female investors have a gain 43.16 percent IRR at the expense of male investors could be due to so called "home informational superiority" in gaining access to and processing local information that is typically not time-specific and thus does not represent insider-trading. With the data availability on postcode address, I am thus able to show female investors located geographically near Nokia headquarters dominate more distant female investors and also outperform both Helsinki and non-Helsinki male investors. The both Helsinki female investors and male investors over non-Helsinki female investors and male investors suggest that there remains an overall "home-bias" informational advantage which is most likely due to the better processing of data. For example, the female trader who discerns that it is "business as usual" in Nokia when Nokia's price is rising by 5,000 percent and falling by 98 percent will adopt a contrarian strategy. With respect to the risk taking attitudes of female investors, my regression estimation results suggest that there are no statistically significant risk preference biases relating to female and male investors' investment decisions.

According to the limits to arbitrage (Shleifer and Vishny (1997)) theory, male investors' may be overconfident and risk-taking relative to females but I find find no evidence of this in my analysis of male and female traders. However, I do find that as females age, less talented traders withdraw from market making aged females superior to young females, as well as to males of all ages. I see no comparable improvement in males as they age and declining testosterone levels with age seem to make little difference.

In order to understand the determinants of female investors' superior trading ability in matched trade portfolios with male investors, I choose a simple and natural methodology, i.e. simple moving average on past stock prices with weekly-interval. There is a vast literature using moving average to construct trading signals over past decades. Here my hypothesis is that female investors extract information from average stock price over different time-interval to identify mispricing opportunities in the market. I conclude that female investors prefer to buy underpriced stocks and sell overpriced stocks – compared with moving average prices. Furthermore, this short-term moving average estimation plays more important role than does long-term up to one year.

Could the superior trading ability of females relative to males be due simply to self-selection, perhaps arising from discrimination? After all, fewer females register as traders relative to males, and of the registered portfolio holders, females are less likely to trade their portfolios. The male trading volume with all other classes of investor other than female is five times that of female trading with all other classes apart from males. This self-selection hypothesis remains unconvincing. There would seem to be few barriers to females trading their own portfolios in the privacy of their own home and away from the pressures of work and especially in female-headed households. It is not as if one must seek a high-pressure job in a male-dominated, testosterone charged, environment in the workplace where there may be active discrimination. Since typically both males and females manage very small portfolios consisting of only a few stocks and successful contrarian strategies require a sizeable wait for the stock price to turn around, opportunities to make successful trades may be few and far between. Weaker female traders also seem to withdraw as they age, unlike similar males. Hence the limited trading activity. The parallels between female analysts who make bold and highly predictive stock recommendations, as in Kumar(2010), and females trading from home using their own funds and making bold contrarian trades that take a long time to pay-off, are strong. Both sets of findings may indicate innate female brain functioning that differs from that of males. These differences in brain functioning may also help to explain the puzzling low participation of women in self-trading.

In matched trade portfolio between female investors directly trade with male investors, their net purchases occur when the contemporaneous price falls and vice versa. They also moderately anticipate a mispricing opportunity, such as the Global Financial Crisis period, rather than undertaking too much trading activity (buying or selling) and thus bearing more risk. My findings are, in general, consistent with females making choices quite differently from males and utilizing different areas of the brain based on "theory of the mind" and pattern recognition that enables females to enjoy greater trading intuition.

Chapter 4

Trading Performance of Hedge Funds vs. Other Institutions

4.1 Introduction

The hedge fund industry has continued to grow at a phenomenal pace. The total assets under management of the hedge fund industry increased from $38 billion in 1990 to over $3.03 trillion in the first month of 2015.[1] According to a 2015 Deutsche Bank report, although two-thirds of hedge fund investors reported that returns lagged their expectations, hedge fund industry assets were still expected to increase and exceed $3.03 trillion by 2015.[2]

Do hedge fund investors have the required skills that would allow them to systematically earn superior net returns on their investments? This fundamental question has been attracting substantial attention from academics and industry practitioners. Many Wall Street analysts acknowledge that, on average, hedge fund managers have better trading skills and are more sophisticated than mutual fund managers. This means that hedge fund managers have a significant ability to exploit market inefficiencies to outperform their benchmarks, presumably by virtue of skill, knowledge, and insight. A number of studies provide evidence that hedge fund managers seem to possess superior trading skill.[3] By contrast, Griffin and Xu (2009) raise serious questions about the perceived skills of hedge fund managers, pointing out that they demonstrate little ability to precisely time sectors or pick stocks styles and that their trades may have contributed to market instability.

Principal–agent models (e.g., Ross (1973), Holmstrom (1982)) characterize the relationship between investors and fund managers. Fund managers should align their incentives with investors' objectives to reduce perk consumption and avoid incurring unnecessary risks that reduce investor returns. Hedge funds differ from mutual funds in several important ways. First, hedge funds are lightly regulated and offer limited transparency and disclosure. Second, the performance-based incentive fees charged by hedge funds will help align the interests of manager and investors. Finally, investors who invest in hedge funds must follow specific lock up periods and withdrawal notice rules to make redemptions. This procedure can limit their portfolio liquidity relative to that of mutual funds investors. Due to the differences between the structures of the hedge fund and mutual fund industries,

[1] https://www.evestment.com/resources/research-reports/2015-research-reports/global-hedge-fund-asset-flows-report—january-2015.

[2] https://www.linkedin.com/pulse/top-hedge-fund-industry-trends-2015-don-a-steinbrugge-cfa

[3] Studies that show on average hedge funds produce net-of-fee alphas around 3 percent to 5 percent, including Kosowski, Naik, and Teo (2007) and Agarwal, Daniel, and Naik (2009), and Ibbotson, Chen, and Zhu (2011).

hedge funds generally emphasize incentive contracts and ownership structure to mitigate principal–agent problems, whereas market forces and government regulation help mutual fund managers to alleviate their principal–agent issues with investors. These potential institutional differences have important implications for investors' allocation of money across different funds as well as the way money flows and how incentives or management fees determine future fund performance.

The question of whether hedge fund managers are informed and whether they can deliver superior performance is also at the core of the analysis of the hedge fund industry (Fung and Hsieh (1997), Ackermann, McEnally, and Ravenscraft (1999), Agarwal and Naik (2004), Getmansky, Lo, and Makarov (2004), Agarwal, Daniel, and Naik (2009, 2011), and Aragon and Nanda (2012)). With the increased involvement of hedge funds in the public equity market, many investors hold stocks owned and traded by hedge funds. These investors are either favorably or adversely affected by the higher or lower price efficiency of hedge funds trading. If hedge funds are informed on average, then the information in stocks prices guides hedge fund investment decisions. It is thus not surprising to find that changes in hedge fund flows are linked to stock price efficiency: more efficient stock prices improve investor welfare by facilitating hedging and risk sharing (Dow and Rahi, 2003) and also guide stocks in making better investment decisions.

In this study, I find strong empirical evidence that hedge fund managers outperform "other institutions"[4] when utilizing the collective daily trade portfolios of institutional investors in the U.S. equity market. By observing more than 10 percent of the institutional equity[5] trading volume of the market, I can determine who trades on a contrarian basis and which investors are on the other side of the contrarian trading strategy. My main findings are based on the *HPI* methodology (Lu, Swan and Westerholm (2016)), which precisely computes cumulative daily trading profits and losses regardless of the horizon and stock turnover rates of aggregated investor-types on the mutual trade portfolio by tying together the two investor-types. This methodology contrasts with the conventional *C-T* methodology, which is discussed extensively in the survey by Barber and Odean (2013).

[4] I classify plan sponsors as "other institutional investors" as well. However, the main group of "other institutional investors" comprises so-called "mutual funds" in the analysis.

[5] Russell (2016) has discussed the concern that ANcerno does not represent the population of all hedge funds with equity trading and indicated that, compared to 13F hedge funds, ANcerno hedge funds are significantly larger, which is consistent with Puckett and Yan (2011). This comparison eliminates any concerns about my results due to sample size.

I compare "apples to apples" over the relevant time periods without imposing investor horizons or implied stock turnover rates that have limited or no applicability to these collective investor-types. I therefore cope with the dilemma whereby two investor-type groups might have similar portfolio alphas based on factor models assuming a fixed investment horizon but that, in exceedingly volatile markets, may earn entirely different realized trading profits if one has better private market timing ability and information. Since market timing is endogenous rather than mechanical and exogenous and is also reliant on both the incentives and information base of the trader, any comparison of agent-type performance requires a performance measure that both recognizes and rewards stock-timing ability.

Moreover, rather than being dependent on some particular, and perhaps unrepresentative, "discount broker", my study contributes to the current debate on hedge funds using actual institutional trades to evaluate the trading performance. I solve the difficulty in conventional analysis whereby clients often have accounts with multiple brokers, making findings problematic.[6] Furthermore, I overcome the limitations of quarterly institutional holding data[7] by using a proprietary database of institutional trades provided by ANcerno Ltd.[8] The ANcerno data are uniquely suited for answering questions related to trading skill, since they identify the exact date and execution price of each transaction and allow us to distinguish the trades of each institution (and funds within these institutions) both in the cross-section and over time.

My analysis of data from ANcerno includes a time-window split into three sub-periods.[9] The first period spans January 4, 1999 to October 9, 2002, which is an extended high-tech bubble period[10] of a "bull" followed by a "bear" market. The second period, October 10, 2002 to March 9, 2009, is the boom prior to the financial crisis, including the subsequent collapse following the demise of Lehman Brothers. The third period, March 10, 2009 to

[6]Aiken, Clifford, and Ellis (2013) argue that most of the net-of-fee alphas generated by hedge funds stems from selection biases in the commercial database.

[7]Because institutional trading data are not publicly available, previous studies that examine trading performance have employed changes in quarterly institutional holdings based on 13F filings data to proxy for trading activity. However, changes in quarterly holdings do not capture intraquarter transactions. These studies commonly assume that all trades occur at the end of the quarter when, in fact, they could occur at any time within the quarter. This may limit the researchers' ability to identify superior trading ability if trades are motivated by short-lived private information, as profitable trading opportunities dissipate quickly (Kothari and Warner (2001), Puckett and Yan (2011)).

[8]Griffin and Xu (2009) find little evidence that hedge funds outperform by examining equity trades or holdings.

[9]I split my sub-periods followed the peaks and troughs of the S&P Index from 1999 to 2009 for each cycle.

[10]Due to data availability, I am not able to examine the whole 'bubble period' starting from 1997.

December 31, 2009, is the post-financial crisis recovery period. Finally, I evaluate the entire period from 1999 to 2009 inclusive.

I split the sample into several "bubble" (i.e., cyclical periods) to make valid comparisons between hedge funds and "other institutional investors". Since hedge funds are contrarian, hedge funds will invariably perform worse during any given up-swing or down-swing. Valid comparisons require an entire cycle in order to eliminate any effects caused by dominated short-term trend followers.

4.2 Literature Review

Hedge funds have rapidly expanded since 1997. The seminal literature on hedge funds was Fung and Hsieh (1997) and Ackermann et al. (1999). Since then, the literature on the hedge fund industry has expanded quickly. A large body of empirical research focuses on hedge fund performance and persistence in hedge fund performance.

There are two approaches to evaluating hedge fund performance. 1) Some studies, such as Ackermann et al. (1999), Brown et al. (1999), Liang (1999), Amin and Kat (2003b), Liang (2001, 2003), and Agarwal and Naik (2004), compare the performance of hedge funds with equity and other indices. Their findings are mixed. Brown et al. (1999) and Liang (1999) conclude that hedge funds are able to outperform these indices. However, Ackermann et al. (1999) and Agarwal and Naik (2004) are more cautious in their conclusions. The evidence that performance does not persist is widely regarded to imply that superior performance is attributable to luck rather than to differential ability across managers. If this implication is correct, as many researchers (e.g., Malkiel (1995), Ross, Westerfield, and Jaffe (2002)) maintain, it could also be interpreted as evidence of market efficiency. This would be troubling from an economic point of view: if all superior performance is due to luck, there should be no reason to reward hedge fund managers through higher fees. Together, these findings have led researchers to raise questions about the measurement of performance in the funds industry. Have I measured or compared fund performances using precise methods? Is the non-persistence performance result due in part to differences in the way fund performance has been evaluated? 2) Other studies compare the performance of hedge funds with that of mutual funds. In this context, Ackermann et al. (1999) use a large sample covering both U.S. and offshore funds with monthly frequency, finding that hedge funds persistently achieve performance superior to that of mutual funds and providing a potential explanation for the outperformance of hedge funds by linking one of the key hedge fund characteristics - incentive fees — to performance. McCrary (2002) states that hedge funds have higher returns, both in absolute terms and relative to the aggregate returns on stock and bonds. Due to diversification, hedge funds have a low correlation to stock and bond indices and therefore also carry lower risk than traditional assets (McCrary, 2002). All hedge funds are under active management; when a recession occurs, this confers the advantage of being able to react faster than mutual funds, which have a passive management strategy.

The most popular methodology for examining fund performance is the *C-T* approach, which analyses the risk-adjusted performance of fund managers using a two-step procedure. Since the seminal work of Jaffe (1974) and Mandelker (1974), it has been applied in many different areas of empirical finance, such as research on the performance of private investors (e.g., Barber and Odean (2000, 2001, 2002); Seasholes and Zhu (2005, 2007); Ivkovic, Sialm, and Weisbenner (2008); Kumar and Lee (2006), studies on the long-term performance of stocks (e.g., Brav and Gompers (1997); Fama (1998); Mitchell and Stafford (2000)), research on insider trading (e.g., Jaffe (1974); Jeng, Metrick, and Zeckhauser (2003)), and analyses of the performance of mutual and hedge funds (Kacperczyk, Sialm, and Zheng (2008); Fung, Hsieh, Naik, and Ramadorai (2008)). The survey by Barber and Odean (2013) provides an excellent summary of *C-T* and the related literature.

The noisy, partially revealing, rational expectations equilibrium models of Hellwig (1980) and Wang (1993) provide a platform for examining the effect of asymmetric information on both stock prices and trading behavior. These noisy rational models derive from a theory of equilibrium price information in which only some traders receive an informed signal and stock prices are not fully revealing of information.

4.3 Holding-Period-Invariant Trader Methodology

The *C-T* approach has been widely applied to many areas of finance including private investors' trading performance, long-run stock performance, insider trading, and the relative performance of mutual and hedge funds. Applying the *C-T* portfolio approach requires two steps to match groups of traders. (1) An aggregate portfolio of buy-trades for the group is constructed on a daily basis, and either the return or the excess return is then computed over a given horizon, such as one month or one year. (2) Similarly, a portfolio of sell-trades by the same group is constructed with the difference in return or excess return between the buy and sell portfolios over the same given horizon recorded. Trading prowess is greater the more positive the net difference in return is. The method is then reapplied from scratch for the next month or year, depending on the assumed horizon. These aggregate period-by-period portfolio return differences are then regressed on a set of market factors with the intercept interpreted as the performance alpha.

If the comparison is between two agent-types, then it would normally be assumed that each has the same exogenously given investment horizon, derived from an average turnover rate. An obvious weakness of this standard approach is that the holding period is far from constant and will partially reflect the very timing and trading skills that one wishes to model. Holding periods vary, in part, because traders are not pre-programmed mechanical robots, and better informed investors will display superior timing skills, giving rise to endogenous variation in the holding period.

Following the methodology firstly conducted in Lu, Swan and Westerholm (2016),[11] I proceed thusly. Since trading skill is most meaningfully revealed in comparison between two agent-types in the same market over identical periods, I mark both agents' portfolio value to market on the initial day with sufficient holdings to ensure non-negative holdings in the future. Initially, I include only net buys or sells between the two agent-types since this is the most relevant comparison. Trades made with third-parties without the two agents trading with one another may simply imply some commonality in belief (and trading direction) that is irrelevant to the initial comparison.

How best to choose the appropriate benchmark to assess both the economic and statistical significance of the trading ability of participants? Several studies have pointed out that biases are involved in the conventional approach to asset pricing, which is to introduce a market portfolio benchmark. They find that portfolios are never mean-variant efficient (Diacogiannis and Feldman, 2013). Grinblat and Titman (1993) propose an innovative method that computes the difference between the realized return on a particular portfolio and the expected return they would have achieved had the portfolio manager been uninformed.

[11] Details of this method are described in Chapter 2 Section 2.3

I utilize this insight (Grinblat and Titman (1993)) and carry out Monte Carlo simulations to examine my problem. As in Lu, Swan, and Westerholm (2016), for any given sequence of daily trades over any given interval between two types of institutions (here, "other institutions" and hedge fund families), I am able to observe one outcome corresponding to the realized wealth gain for one party and the corresponding loss to the other on the trade portfolio. However, one investor type may achieve a favorable outcome due to their good luck rather than superior trading skills, no matter how great the wealth gain to one party at the expense of the other. I thus perform Monte Carol simulations using 10 thousand trails and actual trades in every stock traded on every day and randomize the trade direction of the two types of investors to compute randomized wealth gains and corresponding losses, simulating informationless trading. By examining the proportion of times in which one investor category achieves either the same or better outcome purely by chance, I attach statistical probabilities to each actual outcome based on this random benchmark.

The main advantage of aggregating each of the entire trades of each agent-type within the *C-T* methodology is that it takes into account the cross-sectional correlation of stock returns that might otherwise bias the statistical significance of agent-type returns if a pooled cross-section time-series regression methodology were utilized (Seasholes and Zhu (2010)). As the net buyer and net seller portfolios constructed by employing *C-T* methodology with an imposed horizon are not aligned with the actual trading transaction data used to form the buyer and seller portfolios, this gives rise to measurement errors that may bias the findings toward one particular participant. However, the *HPI* methodology can be easily applied to construct net buyer and net seller portfolios by cumulating the actual realized daily profit/loss on a mark-to-market without imposing arbitrary or even contradictory holding periods and turnover rates on the aggregate trades of each agent-type.

The conventional wisdom in measuring trading performance in asset pricing is to suppose that the individual trade data display some type of average turnover rate. While these actual individual trades represent trades with each agent-type, as well as between agent type and at the level of the aggregate type, there may be no meaningful turnover rate of fixed duration. For example, over the 11-year period in the U.S. between January 1999 and 2009 (inclusive), hedge funds mainly sell the leading 205 stocks to "other institutions" when the stock price is rising and buy when it is falling, with these price movements likely due to the order imbalance of "other institutional investors". These price movements do not occur based on any mechanical pattern. Furthermore, my findings suggest that the hedge fund trading pattern is based on fundamental information as to whether stock is either under- or over-priced and is thus endogenous.

4.4 Data

4.4.1 Source of investor-level transactions

My data source is ANcerno Ltd,[12] a widely recognized consulting stock that works with institutional investors to monitor their execution costs, The ANcerno data contain detailed transaction information for all equity transactions executed by each client. ANcerno reports trade date, the stock trade with trade direction (buys or sells), the number of shares traded, the execution price, the price at the time the trade was placed, the commissions paid, and identity codes for the institution making the trade. ANcerno clients include money managers (such as Massachusetts Financial Services, Fidelity and Putnam Investments) and plan sponsors (such as CALPERS, the Commonwealth of Virginia, and United Airlines). I also collect returns, share price, and shares outstanding from the Center for Research in Securities Prices (CRSP).

ANcerno data use three identifier variables for each institution: an institution type identifier, a client identifier, and a manager identifier. The institution identifier indicates whether the clients are plan sponsors or money managers. The client identifier is a permanent numeric identifier without the names of clients and refers to the plan sponsors or money managers that subscribe to ANcerno. The permanent numeric manager code displays the management company executing the trades.[13] ANcerno provides a reference file corresponding to money management companies (e.g., manager 40 = Bear Stearns Asset Management). However, I am not able to identify funds that belong to the same money management company.

According to ANcerno's supplemental notes,[14] a management company can subscribe to ANcerno in two ways. 1) If the management company invests on behalf of a plan

[12] Previous studies that use ANcerno data include Anand et al. (2012), Anand et al. (2013), Green and Jame (2011), Green et al. (2013), Jegadeesh and Tang (2010), and Puckett and Yan (2011).

[13] ANcerno reports a manager code value of -1 or 0 to represent the unidentified money management stock (or the client). These observations are excluded from my sample.

[14] I offer special thanks to Russell Jame for providing this valuable information, and more importantly, helping me identify hedge fund management companies.

sponsor that subscribes to ANcerno, ANcerno will account the corresponding trades for the plan sponsor. 2) Alternatively, if the money management company directly reports their trades to ANcerno, ANcerno will include all of their trades on behalf of this money management company. I follow Russell (2016) in identifying hedge fund management companies. Details are provided in Appendix D.

Table 4.1 provides summary statistics for my basic ANcerno data over 11 years. The sample consists of 79 hedge fund management companies that manage money for 333 different ANcerno clients and 556 mutual fund management companies that manage money for 684 different ANcerno clients. There are 513 different client–manager pairs for hedge fund managers and 3,598 different client-manager pairs for mutual fund managers. Hereafter, following the fund definitions used in Russell (2016), I will generally define a fund based on a manager–client pair. Hence, I classify a fund management company's trades on behalf of two different clients as two separate funds, whereas it may or may not reflect the trading of the same fund's product. In my sample, 20 out of 79 hedge fund managers and 143 out of the 556 mutual fund managers directly hire ANcerno, respectively. Thus, my results are skewed toward hedge fund managers and mutual fund managers trading on behalf of plan sponsors. Due to the similarity in fund characteristics between mutual funds and plan sponsors, I treat mutual funds and plan sponsors as one trading group (i.e., "other institutions") as the counterparty of hedge fund managers in my *HPI* trading portfolio performance analysis.

Table 4.1 Panel B displays the number of funds that appear in the sample each year from 1999 to 2009. There are 228 hedge funds and 1,687 other institutional funds in 1999. The number of funds is relatively stable until around 2007, after which the sample steadily decreases.

Table 4.1 Hedge Fund Investor Summary Statistics, 1999-2009

Panel A: Aggregate sample size from 1999 to 2009

Client Category	Hedge fund Management Company	Mutual fund Management Company
Plan Sponsors	70	521
Money Management Companies	20	143
Total	79	556

Panel B: Time-Series of Yearly Statistics

	Hedge Funds			Other Institutions (Mutual funds & Plan Sponsors)		
Year	Managers	Clients	Manager_Client	Managers	Clients	Manager_Client
1999	55	144	228	410	346	1687
2000	53	135	202	388	335	1582
2001	51	148	205	374	345	1620
2002	52	144	196	376	336	1607
2003	49	144	203	354	317	1479
2004	50	141	195	340	320	1370
2005	52	132	171	306	282	1049
2006	52	130	162	274	270	873
2007	49	121	148	266	243	733
2008	43	96	117	236	199	534
2009	38	76	85	197	181	414
Total	79	333	513	556	684	3598

To describe entire cycles of boom and bust, I split up my entire data period into three sub-periods based on S&P 500 Index daily close price time-series: the high-tech boom and collapse period,[15] (01/04/1999-10/09/2002); the pre-GFC boom to the Lehman Brothers collapse (10/10/2002–03/09/2009); and the post-GFC period (03/10/2009–12/31/2009). I analyze the entire 11-year period for which data are available (01/04/1999–12/31/2009).

4.4.2 Data steps

From my data set, I compute the daily buys and sells undertaken by every hedge fund and "other institution" over the 11 years my daily data covers. On eliminating all daily trades between all hedge funds in my sample and between all “other institutions” in my sample, I am left with the daily net buys and sells of the two groups: "hedge funds" and “other institutions”. While many trades between these two groups can be matched at the level of individual trades, this is not possible for all trades. I solve for the unique allocation of trades that equates daily buys and sells between each of the two groups. For example, on the same trading day for the same stock C, the first scenario is: if the net buys[16] of agent-type *A* (i.e., hedge funds) in stock C is three shares and the net buys of agent-type *B* (i.e., “other institutions”) is minus ten shares, then in the *HPI* trading portfolio framework, the *HPI* net buys of agent-type *A* is recorded as three shares with corresponding minus three shares recorded as the *HPI* net buys for agent-type *B* and vice versa. As discussed in Section 4.3, I include only net buys or sells (i.e., the three shares traded by agent-type *A* and agent-type *B* in stock C) between the two agent-types since this is the most relevant comparison. Trades made with third-parties, i.e., the remaining seven shares sold by agent-type *B* with other investor groups in the market may simply imply some commonality in belief (and trading direction) that is irrelevant to the initial comparison.

According to Puckett and Yan (2011), ANcerno’s institutional clients account for approximately 10 percent of all institutional trading volume. ANcerno’s institutional trading data covers a representative set of institutional investors and has been used by

[15] The high-tech boom and collapse period starts at the beginning of 1997. However, my earliest data starts from January 4, 1999.

[16] The net buys is defined as the aggregated daily buys minus the aggregated daily sells.

many studies to investigate institutional trading behavior.[17] Researchers may be concerned that the ANcerno data do not include non-equity trading, such as 13F holdings, However, Russell (2016) identified over 90 percent of the funds in the ANcerno sample as long/short or equity market neutral funds, indicating that the primary investment approach of most institutional investors is equity trading. Furthermore, Russell (2016) claims that the ANcerno data sample displays a number of advantages over commercial databases and 13F quarterly holdings.[18]

Table 4.2 summarizes my sample of *HPI* portfolio daily trades (1999–2009) and the overall traded value in U.S. dollars of my two investor groups: hedge fund managers and "other institutions".

Table 4.2 Summary Statistics of daily *HPI* Portfolio Trades and Trading Value in USD by Hedge Funds direct trade with Other Institutions from 1999 to 2009.

		Value
HPI trades	Mean	15,897.63***
	Median	0
	Maximum	3,165,0594
	Standard Deviation	109,205.16
	t-value	102.84
	Number observations	498,873
HPI traded value	Mean	412,843.57***
	Median	0
	Maximum	764,362,053
	Standard Deviation	2,736,407.7
	t-value	106.56
	Number observations	498,873

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I select 205 leading stocks traded in the U.S. equity market based on three criteria. The first is being ranked among the top 1000 of stocks comprising "other institutions"' trade and trade value from 1999 to 2009. The second is being a leading stock from among the sample of approximately 12000 surviving stocks, sorted by average traded value per day during the sample period. Finally, I further restrict my sample by only considering stocks

[17] See, for example, Chemmanur et al.(2009), Goldstein et al.(2011), Anand, Irvine, Puckett, and Venkataraman (2012, 2013), Ben-Rephael and Israelsen (2014), Brown, Wei and Wermers (2013) and Russell (2016).

[18] Russell (2016) clearly introduces two benefits of ANcerno data relative to commercial databases and quarterly holdings related to my analysis. (1) ANcerno sample contains all equity trades, inclusive of short-sales, confidential fillings, and intra-quarter round-trip trades. (2) ANcerno data do not suffer from many of the biases resulting from commercial databases (Fung and Hsieh, 2009).

with more than 250 trading days (appropriately one year) between hedge funds and "other institutions" in the *HPI* trading portfolio. I then combine these three ranking filters with a limit of 205 stocks. My method implies a "look ahead" bias in the choice of the 205 stocks. This counts against my findings, in that my stock sample is chosen on the basis that "other institutions" chose to trade these relatively large stocks due to a self-selection process in which this investor class selects stocks through which they expect to outperform.

4.5 Results

I focus on the 205 leading stocks and present aggregated trading profits and losses of each agent type and their counterparties in Tables 4.3.

Table 4.3 Cumulative Profits and Losses after Transaction Costs for Direct Trades between Other Institutions and Hedge Funds in ANcerno Stocks

From	To	Other Institutions Cum. P&L (USD M)	Hedge Funds Cum. P&L (USD M)
01/04/1999	10/09/2002	567.57*	-587.93*
10/10/2002	03/09/2009	-4,014.53*	3,968.65*
03/10/2009	12/31/2009	48.01*	-49.04*
01/04/1999	12/31/2009	-3,095.66*	3,028.26*
Ratio of *HPI* trading profits to total trading value from 1999 to 2009		-1.50%	1.47%

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Once the net trade flows in each stock between hedge funds and "other institutions" have been analyzed, the *HPI* methodology introduced in Chapter 2 Section 2.3 is applied to trades between hedge funds and "other institutions".

Table 4.3 shows the results when trading commissions are considered.[19] I do not adjust the institutional transaction costs for the bid–ask spread or market impact, as these metrics are difficult to measure reliably across a large sample of transactions and over a long time period. In addition, as my two groups are institutional investors, similar transaction cost rules should apply to both because they both trade through U.S. stock exchanges. In today's highly liquid automated market, transaction costs are a relatively small factor that is unlikely to explain the results.

Figure 4.1 to 4.3 graph the aggregated cumulated daily profit and loss for hedge funds and "other institutions" in the 205 leading stocks over each subperiod, respectively. Figure 4.4 shows the aggregated daily net purchases of 205 stocks by hedge funds and "other institutions" over my entire sample period while Figure 4.5 presents the cumulative profit and loss for hedge funds and "other institutions" over the entire period. It can be seen that "other institutions"' cumulative daily profits almost perfectly track the S&P 500 daily price over the entire period, because "other institutions" almost follow the trend in S&P 500 prices over the period, consistent with the noisy rational expectations literature (e.g., Brennan and Cao (1996)), in which foreign investors are relatively uninformed.

4.5.1 Period 1: January 4, 1999 to October 9, 2002

Hedge fund managers did not commence significant trading with "other institutions" until halfway through the period in March 2000, when the S&P 500 Index had almost reached its peak. Hedge fund managers continued to purchase until July 2011 before commencing modest sells. Over this period, Figure 4.1 shows that hedge fund managers lost significantly with respect to their trades in the leading 205 stocks with "other institutions" until November 2000 but more than made up for these losses during most of the first two years, to continue rising to its peak of USD 2,033.5 million gain for hedge fund managers in June 2011. However, hedge funds lost significantly with respect to their trades in the leading 205 stocks with "other institutions" over the last year, to finish at a USD 587.93

[19] The ANcerno data set reports commissions per trade per day per client. I compute end-of-the-day institutional investors' commissions by simply summing up their daily trades' commissions.

million loss and a corresponding profit for "other institutions" of 567.57 million, as shown in Table 4.3, where profits and losses is measured net of trading commissions[20] provided from ANcerno.

Figure 4.1 Cumulative daily Profits and Losses for Other Institutions and Hedge Funds on ANcerno Stocks of Average Market Capitalization, January 4, 1999 to October 9, 2002

4.5.2 Period 2: October 10, 2002 to March 9, 2003

In the post high-tech boom period prior to the GFC collapse, hedge fund managers made modest purchases and sold stocks until January 2004, after which they continued to sell until March 2009. Their cumulative trades are almost precisely the mirror image of S&P 500 Index price movements until February 2008, while, of course, "other institutions"' cumulative trades almost exactly match S&P 500 Index price movements in the opposite direction. Thus, hedge fund managers buy a leading 205 stock when it is a recent loser (i.e., its price is falling), and they hold on to their existing inventory, and they sell leading 205

[20] If one trading party paid daily total commissions for an *HPI* trading portfolio for a stock and its counterparty paid commissions more than those, then the counterparty's total paid commissions would be subtracted from the dollar returns of both parties' daily *HPI* trading portfolios. The *HPI* trading commission is adjusted according to the daily *HPI* dollar transactions with respect to each trading party reported in ANcerno.

stock when it is a recent winner (i.e., when its price is rising). Hedge fund managers appear to be successful traders or speculators. Figure 4.2 shows that hedge fund managers made significant accumulated profits as they heavily sold leading 205 stocks until their reached their peak but more than recouped these losses once the full force of the GFC collapse was evident. In fact, Table 4.3 shows that hedge fund managers significantly profited by USD 3,968.65 million net of transaction costs at the expense of “other institutions” by the end of the GFC bubble period.

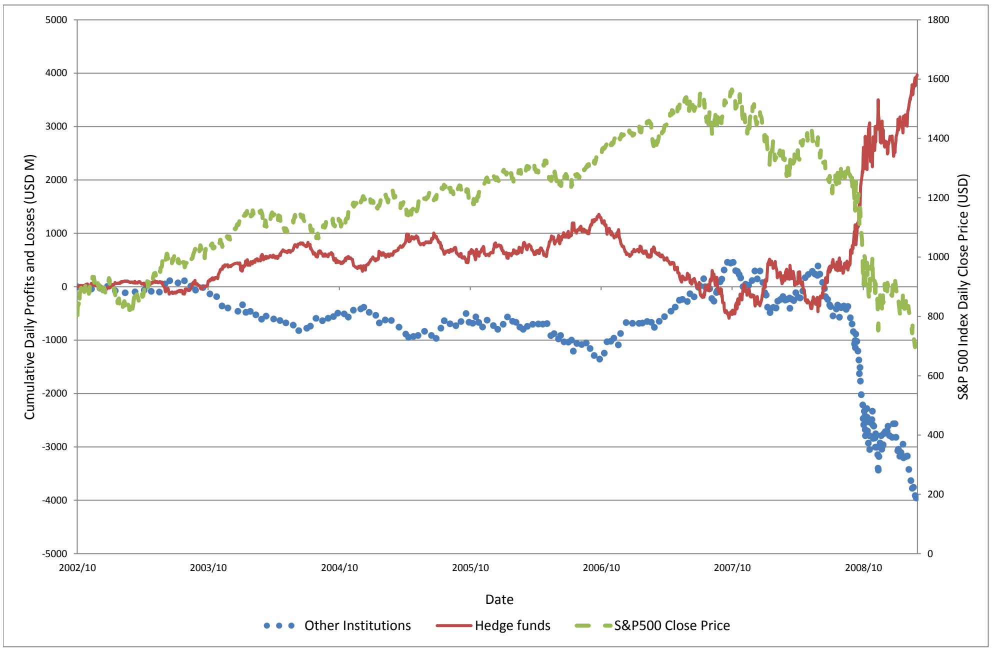


Figure 4.2 Cumulative daily Profits and Losses for Other Institutions and Hedge Funds on ANcerno Stocks of Average Market Capitalization, October 9, 2002 to March 9, 2009

4.5.3 Period 3: March 10, 2009 to December 31, 2009

Hedge fund managers continued to sell to “other institutions” over this entire period while the S&P 500 Index continued to increase in price. Figure 4.3 and Table 4.3 show that, within this data period, this acquisition strategy is yet to pay off with a significant accumulated loss of 49.04 million but events past the cut-off date suggest that this has nonetheless proved to be a winning strategy.

Figure 4.3 Cumulative daily Profits and Losses for Other Institutions and Hedge Funds on ANcerno Stocks of Average Market Capitalization, March 10, 2009 to December 31, 2009

4.5.4 Entire Period: January 4, 1999 to December 31, 2009

Figure 4.4 shows that hedge fund managers have been net sellers of leading 205 stocks from “other institutions” when the S&P 500 index was increasing in price and vice versa until December 2008. However, hedge fund managers seem to have undertaken a trend-following strategy over much of the latest period. Figure 4.5 and Table 4.3 shows that, after trading commissions, hedge fund managers made significant trading gains at the expense of “other institutions” that totaling USD 3,028.26 million for “other institutions”, the 908 million differences being due to differential trading commissions. Hence, trading commissions, while not a deciding factor, affecting the profits of hedge fund managers more than for “other institutions”.

Figure 4.4 Daily cumulative net purchases for Other Institutions and Hedge Funds, January 4, 1999, to December 31, 2009

Figure 4.5 Cumulative daily Profits and Losses for Other Institutions and Hedge Funds on ANcerno Stocks of Average Market Capitalization, January 4, 1999, to December 31, 2009

4.5.5 Conventional investment performance proxy: Internal rate of return (IRR)

As a robustness check, I perform internal rate of return (IRR) calculations without imposing any horizon assumptions other than the start and end dates of the projects to evaluate hedge fund managers' and "other institutions"' trading ability. IRR takes an NPV "investment view" of expected financial results. This essentially means that the magnitudes and timing of cash flow returns are compared to cash flow costs. IRR analysis begins with a cash flow stream, the series of net cash flow figures required for the investment with a positive realization of the portfolio at the end. I compute the *HPI* portfolio's initial values of each agent-type, as described above, and marked to market on day 0 as its own initial investment outlay. I then take the daily value of stock purchases as additional investment outlay, with sales representing a cash benefit over each one-day period from January 4, 1999 to December 31, 2009. On the final day, the value of the portfolio is marked to market as the cash realization, following the same procedures for IRR calculations used in Lu, Swan and Westerholm (2016). Details are shown in Chapter 2 Section 2.5. Table 4.4 shows the IRR results for the full sample of a weighted average portfolio by the mean trading volume of the 175 designated stocks[21] over the entire 11-year period. The hedge funds' *HPI* investment portfolio yields a unique 8.36 percent annualized continuous compounded internal rate of return, compared with a negative 8.36 percent internal rate of return made by "other institutions" over the entire sample period. The counterfactual hedge funds "BuyOnly" IRR is lower, at -9.71 percent p.a., indicating that it is necessary to include the exact timing of asset sales, as well as purchases, as the regular IRR method does. The "BuyOnly" IRR is but a crude extension of the conventional "buy and hold" *C-T* methodology, with my findings indicating that it severely distorts performance measurement. To save space, only the entire sample period's results are shown.

The equal weighed average IRR earned by hedge fund managers in trading with "other institutions" for the full sample of the 175 stocks over the entire 11-year period is statistically significant with 9 percent p.a.. The final row in Table 4.3 above shows that this

[21] There are 30 stocks without valid IRR results from SAS IRR functional computation. I exclude these 30 stocks from the IRR sample analysis in Table 4.4.

Table 4.4 Summary of Continuously Compounded Internal Rate of Return (IRR) of daily Hedge Funds *HPI* Trading for ANcerno stocks from 1999 to 2009, respectively.

Category			Value
Weighted Average by Trading Volume	Mean	IRR_HPI	8.36%
		IRR_BuyOnly	-9.71 %
	Number observations	IRR_HPI	175
		IRR_BuyOnly	175
Equal Weighted	Mean	IRR_HPI	9 %***
		IRR_BuyOnly	-8 %***
	t-value	IRR_HPI	2.88
		IRR_BuyOnly	-3.47
	Number observations	IRR_HPI	175
		IRR_BuyOnly	175

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

return corresponds to a trading profit rate on trades of 0.21 percent. Thus, relatively small trading profit rates translate into quite high IRR, given the magnitude of trading.

4.6 Hedge Fund Managers' Investment Strategy

4.6.1 Model of informed trading following Lu, Swan and Westerholm (2016)

The high dollar return earned by hedge funds trading with "other institutions" over the 11-year period suggests that they trade on the basis of information. Could the trading success of hedge fund managers have occurred because they were able to extract information from the daily price history? Clearly, this would be impossible in a fully efficient market in which both hedge funds and their counterparties have rational expectations.

Following the model of informed trading demonstrated in Lu, Swan, and Westerholm (2016), I assume that hedge fund managers in their paired relationships with "other institutions" receive a private and noisy signal of the stock's fundamental (i.e., "true") value at time t, denoted p_t^T, and that this estimate is not observable by the hedge funds' counterparties. If this valuation is identical to the current observed stock price, p_t, then the relatively informed party does not trade, $s_t = 0$, as in my framework, it is informational advantage rather than, say, risk sharing, is the major trading motivation. This observed price is set in global markets and is taken as exogenously given by hedge fund traders.

Alternatively, if $p_t^T > p_t$ then $s_t > 0$ and a purchase is made with the counterparty making an identical sale. Then again, if $p_t^T < p_t$ a sale is made, $s_t < 0$, with the counterparty making an identical purchase.

How does the relatively informed hedge fund manager receive this noisy signal as the expected true price? A highly plausible and simple assumption is that informed hedge fund traders learn iteratively by observing a private signal of the geometric informational decay rate or probability, $0 < \lambda \leq 1$, on the informed trader's current valuation signal, p_{t-1}^T, i.e., λp_{t-1}^T, while assigning the residual or remaining information, $1 - \lambda$, to the current observed price, i.e., $(1 - \lambda)\, p_t$. I go on to show that, given my 11 years of daily matched pairs of trades between the various counterparties and the entire price histories (which are public), econometricians can recover the private signals received by the most informed of each matched trading pair type. It would not have been possible for "other institutions" to extract such signal information, even had they the incentive to do so, as the paired daily stock investment sign and magnitude data are not publicly available. Details on implementing this method are provided in Appendix B.

4.6.2 Testing the model of informed trading

I use Ordinary Lease Squares (OLS) to perform the empirical estimation and check autocorrelation using the Cochrane Orcutt Durbin Watson values. Table 4.5 columns (1) to column (4) show the summary descriptive statistics for the hedge funds' *HPI* trading portfolio with "other institutions" in the 205 leading stocks from January 1999 to December 2009. Of these buys and sells, on average, a positive and significant 11.92 percent are in the direction opposite to the contemporaneous price movement, and 11.54 percent are in the same direction; on 76.54 percent of days, there was no direct trade between hedge funds and "other institutions". Unsurprisingly, the informed trading group, hedge funds, did not have a majority of contrarian trades when viewed narrowly with a one-day horizon.

Table 4.6 displays two sets of regression results and implied parameter values found by estimating equation (B.1.7) using the daily data in column (1) and weekly data in column (2) for hedge fund managers' trade volume in 205 leading stocks for January 1999 to December, 2009,[22] with "other institutions" as the dependent variable. All parameter

[22]Each sub-period result offers the same conclusion as that offered for the entire period—that, on average, hedge funds do not show significant contrarian trading behavior on a daily interval.

Table 4.5 *HPI* Daily Trading Strategy Summary for aggregated 205 leading stocks, January 1999 - December 2009

Statistics	Contrarian		Positive Feedback	
	Purchase following a negative return (1)	Selling following a positive return (2)	Purchase following a positive return (3)	Selling following a negative return (4)
Mean	6.03 %***	5.89 %***	5.43 %***	6.11 %***
Median	5.67 %	5.33 %	5.07 %	5.70 %
Standard Deviation	0.0238	0.0283	0.023	0.0212
Minimum	2.10 %	1.50 %	1.55 %	2.25 %
Maximum	12.20 %	16.54 %	12.28 %	11.78 %
t-value	29.82	36.3	33.85	41.34
Number of Stocks	205	205	205	205
Sum of Means	11.92 %		11.54 %	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

values are statistically significant at the 1 percent level, and the Durban Watson values indicate no evidence of serial correlation. In column (1), the implied intercept, α_0, is small, statistically significant, and positive at 0.25, while the overall discount parameter, α, is very close to 1, at 0.995. The daily price decay rate, λ, for hedge fund managers trading with "other institutions" is not only highly statistically significant and higher than its no-information value of 0 at 0.1786, or 17.86 percent per day, but also lower than the rational expectations efficient markets hypothesis predicted value of 1, as noted above. The investment sensitivity parameter β is also very statistically significant and large in magnitude at 13,532.

In all likelihood, the estimation problem stems from the very short daily investment period, giving rise to many non-trading and thus directionless trading days. Column (2) presents the weekly rather than daily trading interval, resulting in an improved model fit and a similar estimated value for the information decay rate, Lambda. This is probably because the longer daily investment period does not contribute more for information. In other words, the informational home bias is not as great.

For the parameter values estimated in Table 4.7, I simulate the projected private signal of expected fundamental value for my trading pair, hedge fund managers and "other institutions", in order to compute the percentage differences between the projected 'true' and actual prices. The findings provided in Table 4.7 shows the summary statistics for the

Table 4.6 Model Explaining the Weekly Hedge Funds Purchases from Other Institutions, January 1999 - December, 2009.

This table presents results from daily and weekly regressions on ANcerno stocks. Standard errors employ the Newey-West (1987) correction for autocorrelation in the time series of the averaged regression coefficients. Average coefficients and Newey-West (1987) standard errors with lags equal to 4, i.e., approximate one month horizon are presented.

Variable: Stock Purchases		
	Hedge Funds with Other Institutions	
	Daily	Weekly
	(1)	(2)
Intercept	-2,779***	13,570***
(t-value)	(2.85)	(2.78)
Closing price	-2,600.16***	-4,248.63***
(t-value)	(3.26)	(3.01)
Lag closing price	2,416.97***	-3,401.52***
(t-value)	(3.19)	(2.89)
Lag net hedge funds purchase	0.17861***	0.17904***
(t-value)	(27.47)	(20.92)
Number observations	544,644	114,849
R Square	0.0445	0.0563
Implied values		
Lambda measure of market efficiency	0.17861	0.17904
Intercept	-0.25002	0.87003
Alpha coefficient	0.98352	0.94568
Beta investment sensitivity	13,532	18,998

Absolute t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.7 Summary of Trading Model Simulation Utilizing the Percentage of the Difference between Weekly Informed Investor Expected Fundamental Value and Actual Price deflated by Actual Price for ANcerno stock of each quintile, respectively.

Descriptive Statistics - Weekly	
	Hedge Funds directly trades with Other Institutions
Mean	-3.00 %***
Median	-1 %
Skewness	1.16
Standard Deviation	0.22
t-value	34.54

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

set of investigated U.S. stocks, with a mean of the projected 'true' prices is statistically significantly lower than the actual averaged price by about 3 percent for the trading pair, hedge fund managers, and "other institutions".

Based on an efficient markets rational expectation benchmark, the informed trader's decay rate of information in the stock price would be 100 percent, not the estimated 17.9 percent per week that I find. Thus, the profitable trader groups I analyze act as if they receive a private signal based on information extracted from past stock prices in order to formulate their investment strategy, which I demonstrate to be "contrarian" in nature, with the purchase of "losers" and the sale of "winners."

4.7 Conclusion

I follow the *HPI* portfolio approach in Lu, Swan, and Westerholm (2016) and apply it to the granularity of transaction data to better understand institutional investors' equity trading skill. This is in contrast to the conventional *C-T* portfolio methodology that had its origins in important contributions made by Jaffe (1974) and Mandelker (1974) approximately 40 years ago. I also adopt an extensive 11-year window of matched daily trades organized by investor trading pair comprising hedge fund managers and "other institutions". Many studies strongly advocate the *C-T* portfolio approach, as it examines cross-sectional correlations of stock returns rather than assuming that individual investors' decisions are independent. Hence, it can aggregate individual trades to the level of a single investor-type. However, this method unnecessarily assumes that all investors mechanically turn over their entire portfolio at a specified interval corresponding to an assumed horizon.

By contrast, the *HPI* methodology is free of this error and bias, enabling it to recognize the endogenous nature of investment timing decisions made by hedge funds and their counterparties in my data set.

I find that the direct trade portfolio of hedge funds with “other institutions” in 205 major stocks in the ANcerno data sample results in a gain to hedge fund managers of USD 3,028.26 million over the 11 years of my data set. This represents an average internal rate of continuously compounded return of 8.36 percent p.a.. weighted by trading volume. If the *C-T* “Buy and Hold” equivalent of the IRR, which I dub the “BuyOnly” IRR is used instead, the return falls to minus 9.71 percent p.a., indicating severe methodological error. The trading advantage of hedge fund managers over “other institutions” is unlikely to be due purely to luck. It appears dependent on principal–agent incentive issues, with the concomitant better risk–reward incentives possessed by hedge funds and an ability to better exploit “inside” information.

To understand these informational and incentives issues, I construct a simple Koyck distributed lag model describing the nature of the daily private signal received by the informed group in each trading pair. This private signal sets the daily and weekly differential between the fundamental value derived from the private signal and the observed price. Assuming that informed investors maximize their expected CARA utility of wealth, I estimate weekly informational decay rates of 17.9 percent for hedge fund trades in the 205 leading stocks with “other institutions”. The noisy, partially revealing rational expectations model of Brennan and Cao (1996) is nested by my specification. However, my estimated informational decay rates are much lower than the “rational expectations efficient market” conjecture of 100 percent. Hence, I can safely empirically reject the rational expectations model based on my method and data.

My findings indicate that informed traders (i.e., hedge fund managers), who trade on fundamentals—unlike “other institutions”, who appear to be largely trend followers—receive a private signal that can be extracted from past informed trades and price movements that inform their current investment decisions. Net purchases occur when the contemporaneous price falls and vice versa, indicating that informed traders are contrarian, while the noisy rational expectations literature helps explain why “other institutions”, lacking private information and suffering agency issues, appear to be trend followers and relatively informed traders appear to be contrarian.

Chapter 5

Conclusion

This dissertation studies delegated investment managers and retail investors' trading behavior in the Finnish and U.S. equity markets. In particular, this dissertation first introduces a new *HPI* portfolio approach and deliberately conducts an "apples-to-apples" comparison using matched trades over relevant periods without imposing mandated investor horizons in the pairs of trading groups to evaluate trading performance, as in previous research, to ascertain whether behavior bias, informed trading, and home bias exist in the different investor categories.

First, in Chapter 2, I investigate retail investors, domestic institutional investors, and foreign investor nominees by employing a well-established database from Euroclear Finland Ltd that includes all transactions in the share depository for all 1.061 million investor accounts with holdings in 232 unique common stocks listed on the Nasdaq OMX Helsinki Exchange, which includes Nokia and 32 other major Finnish stocks. By assessing the weakness of the *C-T* traditional portfolio approach used in research on the performance of investors, my new *HPI* methodology captures precisely the timing ability of each trading party to foresee future price movements without imposing arbitrary portfolio turnover assumptions about endogenous trader horizons on either group. In this framework, I find that Finnish households gain a profit of EUR 4,923 million in the *HPI* portfolio with foreign institutional investors as their exclusive counterparties from 1995 to 2011. I also show that households located near the headquarter of the corresponding company display far superior trading ability compared to foreign investors and domestic institutional investors.

In Chapter 3, I further investigate whether gender significantly affects the Finnish equity market using feasibility data support sourced from Euroclear Finland. My aim was to understand whether differences exist in male and female investors' trading behavior using my proposed *HPI* portfolio approach to overcome the problem that two investor groups might have similar portfolio alphas based on factor models, assuming a fixed investment horizon, but in exceedingly volatile markets. By allowing the two endogenous factors of market timing ability and information bias in the *HPI* framework, I show that the direct trade portfolio of female and male Finnish investors in 28 major Finish stocks results in a gain to female investors of EUR 194.67 million over the seventeen years of my data set. Furthermore, I show that female Finnish investors prefer to buy underpriced stocks and sell overpriced stocks relative to both fast and slow moving average prices.

Finally, I shift my focus to compare the trading performance within hedge fund money managers and "other institutional investors" as an investment manager category in Chapter 4. Rather than depending on some unrepresentative broker data, I source my data set from a widely recognized consulting firm that works with institutional investors to monitor their execution costs. More importantly, I apply my new *HPI* portfolio approach to use matched trades over the same period for a paired trading group without assuming a fixed investment horizon. My empirical results strongly demonstrate that hedge fund managers gain USD 3,028.26 million from 1999 to 2009 in direct trade with "other institutional investors". This represents an average internal rate of continuously compounded return of 8.36 percent p.a. weighted by trading volume. I also show that hedge fund managers appeared as informed traders by receiving a private signal, which I extract from past informed trades and price movements. They prefer to trade on fundamentals rather than following trends.

With the limited aims in this dissertation, I focus only on trades between counterparties such as households with institutional investors, female investors with male investors, and hedge fund managers with "other institutional investors". This study does not address the performance of their overall stock portfolios. Furthermore, I was not able to access data for every investor's derivatives accounts and income information, although I do have data for Finnish households' ages, geographic locations, gender, and each individual's daily trades and daily equity portfolio covering 17 years. The data also identified family names and I could identify spouses, including the spouses of designated insider traders. Thus, I do not claim to offer a comprehensive treatment of the overall performance of each investor type, but rather emphasize the differences in both knowledge and timing ability that are reflected in matched counterparty trades over extended periods.

Future studies in this research area could concentrate on the role of households' trading behavior in the overall financial market rather than emphasizing institutional money managers. In practice, both private information and agency considerations do affect investment performance. A future study may be able to document the determinants of households' superior trading ability and their risk-taking behavior. Future studies could also apply the *HPI* portfolio approach to a similar type of trading performance comparison for pairs of agent groups since market timing is endogenous rather than mechanical and exogenous, and relies on both the trader's incentives and information base.

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A Additional Robustness Analysis - Chapter 1

Portfolio holdings vs. Shares outstanding

Could my finding that, in the long-term households outperform foreign delegated money managers, be due to errors in the data? One necessary consistency check is to ensure that neither households nor foreign nominees hold negative balances. Since short-selling requires borrowed script and is inherently expensive it would be surprising if any one investor class had negative holdings. I undertake a comparison between daily shares outstanding computed from Compustat Global and portfolio holdings in each agent-class, respectively. An inspection of the comparison in Figure A.1.1 shows that the sum of each class of portfolio holdings relative to shares outstanding is less than 100 percent throughout the entire period.

Non-negative portfolio holdings of each agent

Furthermore, for each trading party's portfolio holdings over the entire seventeen years, I need to verify that neither of these party's portfolio holdings become negative on any trading day. I adjust for share splits and issues transfers. I also track other issues of shares based on changes in the number of shares outstanding (dividend re-investment, executive option exercises and bonus issues). Figure A.1.2 clearly displays both households and foreign nominees' portfolio positions stay positive throughout entire period. My verification ensures that the raw data smyce is sufficiently rigorous to investigate trading performance in each agent by employing my *HPI* method and to ensure that my findings are not a consequence of faulty or inconsistent data.

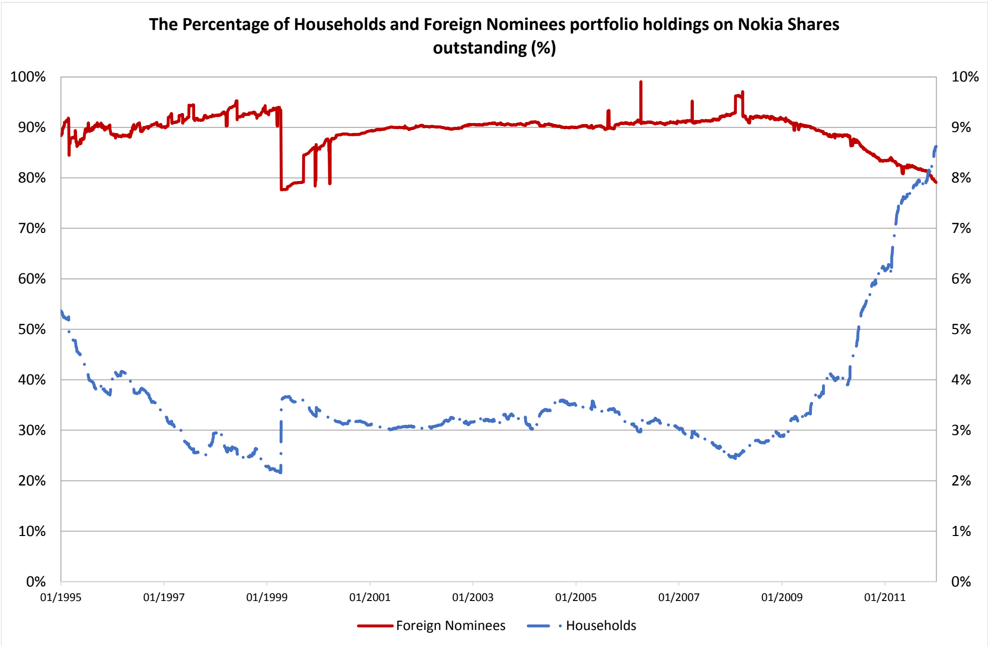

Figure A.1.1 The ratios of portfolio holdings in Nokia's shares outstanding for Households and Foreign nominees over the entire period

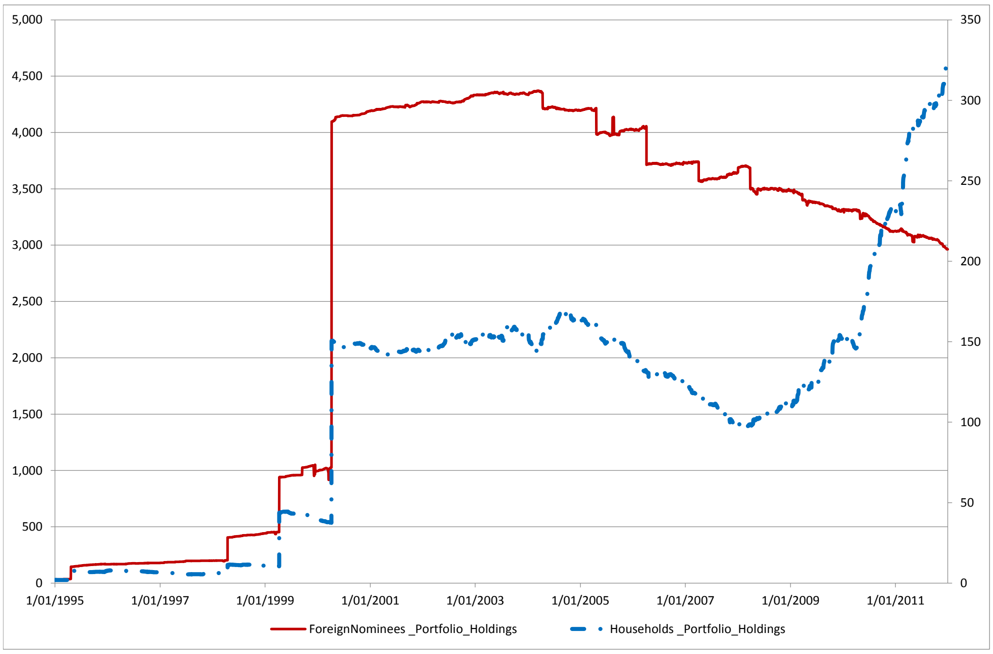

Figure A.1.2 Portfolio holdings of Households and Foreign Nominees for Nokia

Summary of 32 Selected Sample Stocks - Chapter 1

Table A.1.1 Summary of Selected 32 leading Sample Stocks - Chapter 1

Panel A reports descriptive statistics for the 32 Sample Stocks selected based on the three criteria

ISIN	Company Name	Number of days traded	Mean daily volume (M)	Mean daily value (EUR M)	Mean daily market capitalisation (EUR M)	Daily turnover	Mean Foreign Nominees market share %
FI0009000681	NOKIA CORP	4,277	205	3,618	64,817	5.58%	96%
FI0009005961	STORA ENSO OYJ	3,918	35	316	5,494	5.76%	94%
FI0009005987	UPM-KYMMENE CORP	3,932	23	369	7,206	5.13%	94%
FI0009007132	FORTUM OYJ	3,271	20	357	11,899	3.00%	91%
FI0009003305	SAMPO PLC	3,634	19	299	6,527	4.59%	94%
FI0009013296	NESTE OIL OYJ	1,692	14	256	4,500	5.68%	92%
FI0009000665	METSA BOARD CORP	4,271	9	33	860	3.85%	89%
FI0009007835	METSO OYJ	3,155	8	196	2,884	6.80%	92%
FI0009013403	KONE CORP	1,677	8	242	5,579	4.33%	93%
FI0009007884	ELISA CORP	3,010	7	112	2,331	4.82%	91%
FI0009002422	OUTOKUMPU OY	4,271	7	110	2,092	5.25%	91%
FI0009014575	OUTOTEC OYJ	1,317	5	152	1,279	11.91%	92%
FI0009000277	TIETO CORP	4,239	5	95	1,481	6.39%	90%
FI0009005318	NOKIAN TYRES OYJ	3,931	4	89	1,300	6.85%	80%
FI0009006829	SPONDA OYJ	3,350	4	18	612	2.99%	87%
FI0009003552	RAUTARUUKKI OYJ	4,273	4	66	1,629	4.03%	83%
FI0009014377	ORION CORP	1,399	4	53	1,336	3.93%	92%
FI0009014351	ORIOLA-KD CORP	1,388	3	10	289	3.43%	83%
FI0009012843	KEMIRA GROWHOW O	860	3	21	439	4.90%	81%
FI0009003727	WARTSILA OYJ ABP	4,270	3	79	1,702	4.67%	87%
FI0009013429	CARGOTEC OYJ	1,664	3	66	1,492	4.42%	91%
FI0009004824	KEMIRA OY	4,203	2	24	1,176	2.01%	84%
FI0009005870	KONECRANES PLC	3,938	2	53	792	6.74%	91%
FI0009000202	KESKO OYJ	4,272	2	48	1,242	3.90%	83%
FI0009000285	AMER SPORTS CORP	4,267	2	28	748	3.71%	88%
FI0009000459	HUHTAMAKI OYJ	4,268	2	22	905	2.48%	85%
FI0009013114	ALMA MEDIA OYJ	1,618	2	16	562	2.76%	78%
FI0009002158	UPONOR OYJ	4,209	1	21	836	2.55%	75%
FI4000008719	TIKKURILA OYJ	448	1	17	678	2.44%	81%
FI0009006696	POYRY PLC	3,177	1	7	447	1.58%	74%
FI0009010854	LASSILA & TIKANO	2,527	0	7	531	1.30%	75%
FI0009009567	VACON OYJ	2,722	0	5	320	1.52%	78%

Panel B reports descriptive statistics for the remaining 68 stocks out of the top 100 stocks selected based on three selection criteria

ISIN	Company Name	Number of days traded	Mean daily volume (M)	Mean daily value (EUR M)	Mean daily market capitalisation (EUR M)	Daily turnover	Mean Foreign Nominees market share %
FI0009000251	Stockmann Oyj Abp Class B	4,262	0	11	566	1.88%	70%
FI0009003644	Finnlines Oyj	4,196	0	7	484	1.52%	73%
FI0009002943	Raisio Oyj Class V	4,179	2	11	423	2.55%	71%
FI0009000236	Stockmann Oyj Abp Class A	4,126	0	1	529	0.24%	53%
FI0009003222	Pohjola Bank Plc Class A	4,119	3	26	986	2.65%	63%
FI0009900401	Olvi Oyj Class A	3,991	0	1	100	0.87%	33%
FI0009000400	Fiskars Oyj Abp	3,982	0	2	541	0.42%	45%
FI0009800643	YIT Oyj	3,937	3	54	1,127	4.81%	70%
FI0009900682	Vaisala Oyj Class A	3,896	0	4	321	1.13%	64%
FI0009005953	Stora Enso Oyj Class A	3,848	1	7	1,768	0.41%	69%
FI0009001127	Alandsbanken Abp Class B	3,841	0	0	98	0.21%	18%
FI0009900898	Talentum Oyj	3,692	0	2	127	1.61%	51%
FI0009900336	Lemminkainen Corporation	3,689	0	2	341	0.72%	47%
FI0009006738	Elcoteq SE	3,412	1	7	192	3.69%	70%
FI0009006381	PKC Group Oyj	3,412	0	2	136	1.44%	46%
FI0009000640	Metsa Board Corporation Class A	3,370	0	0	192	0.16%	29%
FI0009007264	Bittium Corporation	3,337	2	5	308	1.66%	44%
FI0009002471	Citycon Oyj	3,250	5	14	407	3.36%	70%
FI0009007694	Sanoma Oyj	3,185	2	33	2,167	1.53%	70%
FI0009005078	Ponsse Oyj	3,121	0	1	204	0.49%	35%

Panel B *Continued.*

ISIN	Company Name	Number of days traded	Mean daily volume (M)	Mean daily value (EUR M)	Mean daily market capitalisation (EUR M)	Daily turnover	Mean Foreign Nominees market share %
FI0009000939	Tamfelt Pref	3,112	0	1	127	0.53%	18%
FI0009007728	Teleste Oyj	3,061	0	3	141	1.80%	53%
FI0009800395	Raisio Oyj Class K	3,056	0	0	151	0.32%	22%
FI0009801310	F-Secure Oyj	2,998	2	6	375	1.66%	68%
FI0009007918	Aldata Solution Oyj	2,996	1	4	121	3.08%	57%
FI0009801302	Stonesoft Oyj	2,995	0	2	128	1.51%	32%
FI0009008072	Aspo Plc	2,946	0	1	136	0.53%	32%
FI0009003719	Wartsila Oyj Cl A	2,939	0	2	467	0.45%	53%
FI0009008221	Comptel Oyj	2,926	1	5	302	1.75%	60%
FI0009000145	Pohjola Group Oyj	2,868	1	30	956	3.12%	89%
FI0009008924	Sievi Capital Oyj	2,815	0	1	167	0.39%	34%
FI0009008403	Basware Oyj	2,811	0	1	117	0.75%	39%
FI0009006548	Atria Oyj Class A	2,793	0	2	165	1.16%	42%
FI0009007355	Rapala VMC Oyj	2,773	0	2	200	1.17%	67%
FI0009900476	Cramo Oyj	2,737	1	14	286	4.95%	62%
FI0009006308	HKScan Oyj Class A	2,732	0	4	249	1.58%	58%
FI0009009377	CapMan Oyj Class B	2,678	1	2	144	1.18%	59%
FI0009006886	Technopolis Oyj	2,664	1	4	161	2.33%	59%

Panel B *Continued.*

ISIN	Company Name	Number of days traded	Mean daily volume (M)	Mean daily value (EUR M)	Mean daily market capitalisation (EUR M)	Daily turnover	Mean Foreign Nominees market share %
FI0009000939	Tamfelt Pref	3,112	0	1	127	0.53%	18%
FI0009007728	Teleste Oyj	3,061	0	3	141	1.80%	53%
FI0009800395	Raisio Oyj Class K	3,056	0	0	151	0.32%	22%
FI0009801310	F-Secure Oyj	2,998	2	6	375	1.66%	68%
FI0009007918	Aldata Solution Oyj	2,996	1	4	121	3.08%	57%
FI0009801302	Stonesoft Oyj	2,995	0	2	128	1.51%	32%
FI0009008072	Aspo Plc	2,946	0	1	136	0.53%	32%
FI0009003719	Wartsila Oyj Cl A	2,939	0	2	467	0.45%	53%
FI0009008221	Comptel Oyj	2,926	1	5	302	1.75%	60%
FI0009000145	Pohjola Group Oyj	2,868	1	30	956	3.12%	89%
FI0009008924	Sievi Capital Oyj	2,815	0	1	167	0.39%	34%
FI0009008403	Basware Oyj	2,811	0	1	117	0.75%	39%
FI0009006548	Atria Oyj Class A	2,793	0	2	165	1.16%	42%
FI0009007355	Rapala VMC Oyj	2,773	0	2	200	1.17%	67%
FI0009900476	Cramo Oyj	2,737	1	14	286	4.95%	62%
FI0009006308	HKScan Oyj Class A	2,732	0	4	249	1.58%	58%
FI0009009377	CapMan Oyj Class B	2,678	1	2	144	1.18%	59%
FI0009006886	Technopolis Oyj	2,664	1	4	161	2.33%	59%
FI0009007900	Kesko Oyj Class A	2,641	0	1	792	0.15%	34%
FI0009000566	Kone Corp Ser'B'Eur3	2,621	1	27	1,221	2.22%	#N/A
FI0009010219	Glaston Oyj	2,600	0	1	225	0.40%	39%
FI0009008833	Teleste Oyj Class A	2,546	0	2	132	1.89%	44%
FI0009800205	Ilkka-Yhtymae Oyj	2,489	0	0	99	0.50%	23%

Panel B *Continued.*

ISIN	Company Name	Number of days traded	Mean daily volume (M)	Mean daily value (EUR M)	Mean daily market capitalisation (EUR M)	Daily turnover	Mean Foreign Nominees market share %
FI0009007066	Ramirent Oyj	2,439	2	21	663	3.09%	72%
FI0009000103	Alandsbanken Abp Class A	2,419	0	0	116	0.14%	17%
FI0009005250	Viking Line Abp	2,361	0	1	307	0.22%	25%
FI0009007819	Perlos Oyj	2,192	1	14	565	2.48%	79%
FI0009000855	Tamro Oyj	2,190	1	3	410	0.83%	64%
FI0009000509	Instrumentarium Oyj	2,174	1	17	592	2.95%	66%
FI0009000426	Fiskars K	2,115	0	1	232	0.26%	15%
FI0009000749	PARTEK OYJ AB ORD	1,937	0	4	560	0.64%	45%
FI0009900013	Chips B	1,878	0	1	138	0.57%	24%
FI0009900070	Hartwall Oyj	1,870	1	21	793	2.70%	78%
FI0009800098	Afarak Group Oyj Class A	1,832	10	18	345	5.15%	60%
FI0009007025	Alma Media Series 2	1,673	0	6	267	2.06%	58%
FI0009000137	POHJOLA-YHTYMÄ VAKUUTUS OYJ A	1,580	0	5	590	0.88%	65%
FI0009801245	Wm-Data Novo Oyj Npv	1,507	1	4	165	2.29%	40%
FI0009010391	Ahlstrom Oyj	1,462	0	7	701	0.98%	69%
FI0009014369	Orion Oyj Class A	1,392	0	3	761	0.35%	64%
FI0009014344	Oriola Corp Class A	1,375	0	1	150	0.51%	60%
FI0009000053	Merita Oyj	1,310	14	61	2,833	2.15%	87%
FI0009013924	Salcomp PLC	1,282	0	1	101	0.83%	40%
FI0009008569	Saunalahti Group Npv	1,262	2	5	150	3.05%	37%
FI0009007686	Sanoma Wsoy Oyj Npv Ser'A'	1,240	0	1	367	0.26%	12%
FI0009000483	INSTRUMENTARIUM OYJ A	1,233	0	3	472	0.56%	55%
FI0009007553	Eimo	1,154	1	4	148	2.71%	52%
FI0009015309	SRV Yhtiot Oyj	1,147	1	4	209	1.83%	55%

B Householder Investment Strategy

A model of informed trading

The exceedingly high returns earned by households trading with either domestic or foreign institutional investors over the 17-year period, or for that matter, domestic institutions with foreign, suggests that they trade on the basis of information. In this section I pose the question: does sufficient information exist in the daily price history to explain the collective trading success of both households and domestic institutions in the pairings for which they are successful? I find that such information is contained in stock price movements and my model is able to successfully recover this informative signal in regression analysis. I believe that this is the first time that this has been done.

Individual households in their paired relationships with either domestic or foreign institutions and, similarly, individual domestic institutions paired with foreign, receive a private and noisy signal of the stock's fundamental, i.e., 'True', value at time t, denoted p_t^T, with this estimate not observable by either the household's counterparties, domestic or foreign, nor the local institution's counterparty, foreign institutions. This household or local institutional advantage could be due to local knowledge possessed by both households and local institutions and the household's particular advantage which is the absence of agency issues and thus better motivation. If this valuation is identical to the current observed stock price, p_t, in the absence of asymmetric information then the relatively informed party does not trade, $s_t = 0$, as in my framework informational advantage rather than, say, risk sharing, is the major trading motivation. This observed price is set in global markets and is taken as exogenously given by individual Finnish households and domestic institutional traders. Alternatively, if $p_t^T > p_t$ then $s_t > 0$ and a purchase is made with the counterparty making an identical sale. Then again, if $p_t^T < p_t$ a sale is made, $s_t < 0$, with the counterparty making an identical purchase.

How does the relatively informed domestic trader receive this noisy signal about the expected true price? A highly plausible and, for that matter, simple assumption is that individual informed traders learn iteratively by observing a private signal of the geometric informational decay rate or probability, $0 < \lambda \leq 1$, on the informed trader's current valuation signal, p_{t-1}^T, i.e., λp_{t-1}^T, while assigning the residual or remaining information, $1-\lambda$, to the current observed price, i.e., $(1-\lambda)\, p_t$. I go on to show that given my 17 years of daily matched pairs of trades between the various counterparties and the entire price histories which themselves are public, it is possible for us as econometricians to recover the private signals received by the most informed of each matched trading pair type. It would not have been possible for the biggest counterparty losers, namely foreign delegated money managers, to extract such signal information as the paired daily stock investment sign and magnitude data is not publicly available, even had they the incentive to do so.

To implement this method, suppose the imperfect signal of the 'true' valuation depends on current and past prices according to an intercept term, α_0, a multiplicative constant discount term, $1 \geq \alpha > 0$, and decays each period at the constant geometric rate $0 < \lambda \leq 1$, as given by Koyck's (1954) distributed lag signal equation:

$$p_t^T = \alpha_0 + \alpha(1-\lambda)\Big(p_t + \lambda p_{t-1} + \lambda^2 p_{t-2} + \cdots\Big) + \tilde{\varepsilon}_t, \tag{B.1.1}$$

where $\tilde{\varepsilon}_t$ is normally and independently distributed with mean 0 and varianceσ_ε^2. Expressing the lagged value of the same signal by:

$$p_{t-1}^T = \alpha_0 + \alpha(1-\lambda)\Big(p_{t-1} + \lambda p_{t-2} + \lambda^2 p_{t-3} + \cdots\Big) + \varepsilon_{t-1}, \tag{B.1.2}$$

evaluating $p_t^T - \lambda p_{t-1}^T$, and rearranging, yields the private valuation:

$$p_t^T = (1-\lambda)(\alpha_0 + \alpha p_t) + \lambda p_{t-1}^T + \tilde{\varepsilon}_t - \lambda \tilde{\varepsilon}_{t-1}. \tag{B.1.3}$$

If the α value is approximately 1 and the intercept α_0 approximately zero, as turns out to be the case, then this Koyck updating expression for the private fundamental value achieves my objective of placing a geometric weight of $(1-\lambda)$ on contemporaneous stock price and λ on the lagged fundamental value.

There are two limiting updating rules. First, if $\lambda \to 0$, the signal moves according to the observed current price and the random error term, as in an efficient market with rational expectations, such that the trader gains no informational advantage from observing the magnitude and direction of past trades and past prices and cannot be expected to systematically earn trading profits from such information. Second, if $\lambda \to 1$, updating is random with the best estimate of tomorrow's private valuation being today's private valuation, with no weight placed on the current price. Hence there is no random walk in prices.

The informed investor takes advantage of his private signal of expected fundamental value, p_t^T, to choose his risky stock investment of s_t at date t to maximize his expected CARA exponential utility function of his wealth gain from trading:

$$\begin{aligned} s_t &= \arg\max_{s_t} \; E\left[-\exp\left(-\frac{w_t}{r}\right)\right], \\ &= \arg\max_{s_t} \left[x_{t-1} + s_t\left(p_t^T - p_t\right) - \frac{1}{2}\frac{\sigma^2}{r}(s_t)^2\right], \\ &= \frac{r}{\sigma^2}\left(p_t^T - p_t\right) \equiv \beta\left(p_t^T - p_t\right), \end{aligned} \tag{B.1.4}$$

where exp denotes the exponential value, $E[w_t] = x_{t-1} + s_t\left(p_t^T - p_t\right)$ is the informed investor's expected wealth gain from trading, x_{t-1} represents his existing cash reserve, r represents his risk tolerance, i.e., inverse of his CARA constant absolute risk aversion coefficient, σ^2 the variance of the normally distributed risky asset return, and the slope of the investment demand function with constant slope is $\beta \equiv \frac{r}{\sigma^2} > 0$. Since my CARA/Normal setup resembles that of Kyle's (1989) linear model, it is not surprising that my derived asset investment demand function is also linear.

Given that the investor receives an informative signal, it is possible to retrieve this signal from the previous period's investment decision. Lagging the investment function given by equation (B.1.4) by one period and solving for the unknown value of the lagged private valuation yields a term that depends on both the previous investment and stock price:

$$p_{t-1}^T = \frac{s_{t-1}}{\beta} + p_{t-1}. \tag{B.1.5}$$

Substituting equation (B.1.5) back into the private signal updating expression, equation (B.1.3), yields an expression for the contemporaneous private signal:

$$p_t^T = (1-\lambda)\alpha_0 + \alpha(1-\lambda)p_t + \lambda\left(\frac{s_{t-1}}{\beta} + p_{t-1}\right) + \tilde{\varepsilon}_t - \lambda\tilde{\varepsilon}_{t-1}. \tag{B.1.6}$$

Writing the informed investor's expected profit per share as $\pi_t \equiv p_t^T - p_t$, and solving for the investment demand schedule, equation (B.1.4) expressed in terms of observables, yields:

$$s_t = \beta\{(1-\lambda)\alpha_0 - [1-\alpha(1-\lambda)]p_t + \lambda p_{t-1}\} + \lambda s_{t-1} + \varepsilon_t - \lambda\varepsilon_{t-1}, \tag{B.1.7}$$

an expression for the optimal trade size and direction for the informed investor as a function of observable values consisting of the contemporaneous and lagged stock prices and the exogenously given trade size and direction in the previous period represented by s_{t-1}.

The magnitude of this informed trade motivated by the private signal is not perfectly observable by other market participants, as in Kyle (1985). Thus the trade magnitude s_t in period t evolves according to the simple equation that depends on the price change in the current period and choice of investment made in the previous period. It represents an estimable regression equation if the magnitudes of these informed trades with counterparties are observable to the econometrician.

Conditional on the previous period's investment choice, this investment regression equation predicts that the informed group will relatively disinvest in the event of a positive return, i.e.,$s_t - \lambda s_{t-1} < 0$, if $[1-\alpha(1-\lambda)]p_t - \lambda p_{t-1} > 0$, as the estimated respective price coefficients for p_t and p_{t-1}, $[1-\alpha(1-\lambda)]$ and λ, are both positive. That is, the informed group must be contraries, as is also the case with partially revealing rational expectations (e.g., Brennan and Cao (1996)).

In the limiting case in which the informed signal and contemporaneous price are the same then prices follow a random walk. If the discount factor, $\alpha = 1$ then the informed trader does not trade as no valuable information is received. Moreover, in the limiting case in which the private valuation p_t^T follows a random walk, the informational decay rate, $\lambda = 1$, transaction price contains no information, and the change in the investment outlay is given by:

$$\Delta s_t \equiv s_t - s_{t-1} = -\beta(p_t - p_{t-1}) \equiv -\beta\Delta p_t, \tag{B.1.8}$$

as the only new information and trade motivation is reflected in the price update. Once again, the investment policy is contrarian in nature with a negative relationship between the change in investment and the change in prices. More importantly, it is identical to Brennan and Cao's (1996, p.174, equation 15) partially revealing rational expectations equilibrium. It thus enables us to interpret the coefficient β as the product of the investor's risk tolerance r (inverse CARA coefficient) as investors are assumed to have constant absolute risk aversion (CARA) preferences and, the difference in the value of the private informational signal between in the informed and uninformed participant. Hence, in the limiting case, the interpretation of mys and the Brennan and Cao (1996) model are the same. Since I find evidence that the λ coefficient is significantly greater than zero but less than 1, this nested rational expectations model is empirically rejected by the data, as is the uninformative random walk in transaction prices when $\lambda = 0$.

Testing the model of informed trading

I now turn to the empirical estimation of investment equation (B.1.7) using Ordinary Least Squares (OLS), while estimating the Cochrane Orcutt Durbin Watson values to check for autocorrelation. Table B.1.1 column (1) summaries the 4,292 daily household trades in Nokia with foreign institutional investors over the period, January 1995 to December 2011. Of these buys and sells, 47.09 percent are in the opposite direction to the contemporaneous price movement, 15.89 percent are in the same direction and on 37 percent of days there was no trade. Similarly, column (2) summarizes daily household trades in 33 major Finnish stocks including Nokia, with foreign institutional investors and column (3) the same except excluding Nokia. Similarly, columns (4) to (6) summarize household trades with domestic institutional investors. Unsurprisingly, the only informed trading group not to have a majority of contrarian trades when viewed narrowly with a one-day horizon is domestic institutional investors when they trade with foreign nominees.

Table B.1.1 *HPI* Daily Trading Strategy Summary in each Trading Group, respectively, January 1995 - December 2011

This table summarizes the daily Household trading strategy with Domestic Financial Institutions, daily Households trading strategy with Domestic Financial Institutions, and daily Domestic Financial Institutions with Foreign Nominees from 1995 to 2011, in Nokia, with 33 stocks and 32 stocks, respectively. Trading actions are shown relative to the number of stock-days in the sample.

Trading Action	Household with Foreign Nominees			Household with Domestic Institutions			Domestic Institutions with Foreign Nominees		
	Nokia	33 stocks inclusive of Nokia	32 stocks exclusive of Nokia	Nokia	33 stocks inclusive of Nokia	32 stocks exclusive of Nokia	Nokia	33 stocks inclusive of Nokia	32 stocks exclusive of Nokia
	(1) % (out of 4,292)	(2) % (out of 99,947)	(3) % (out of 95,656)	(4) % (out of 4,292)	(5) % (out of 99,947)	(6) % (out of 95,656)	(7) % (out of 4,292)	(8) % (out of 99,947)	(9) % (out of 95,656)
Contrarian Strategy									
Purchase following a negative return	26.61%	19.97%	19.67%	13.14%	11.42%	11.34%	10.14%	14.42%	14.07%
Selling following a positive return	20.48%	18.80%	18.73%	13.58%	10.70%	10.57%	13.23%	13.74%	13.58%
Sum	47.09%	38.77%	38.41%	26.72%	22.11%	21.91%	23.37%	28.16%	27.65%
Positive Feedback Strategy									
Purchase following a positive return	7.06%	10.05%	10.18%	5.59%	6.17%	6.20%	22.13%	11.36%	11.42%
Selling following a negative return	8.83%	10.28%	10.34%	5.99%	6.25%	6.26%	17.26%	10.90%	10.79%
Sum	15.89%	20.33%	20.52%	11.58%	12.42%	12.46%	39.40%	22.26%	22.21%
Hold position - No action									
Sum	37.02%	40.90%	41.07%	61.70%	65.47%	65.63%	37.23%	49.58%	50.14%

Table 5 Panel A, displays three sets of regression results and implied parameter values found by estimating equation (B.1.7) using the daily household trade volume in Nokia over the period, January 1995 to December, 2011, with foreign nominees as the dependent variable in column (1), households with domestic institutions in column (3), and domestic institutions with foreign nominees in column (5). All parameter values are statistically significant at the 1 percent level and the Durbin Watson values indicate no evidence of serial correlation. In column (1) the implied intercept, α_0, is both small, statistically significant, and positive at 0.0670 and the overall discount parameter, α, is very close to 1 at 0.9950. The daily price decay rate, λ, for households trading with foreign nominees is not only highly statistically significant and high in comparison with its no-information value of 0 at 0.2364 or 23.64 percent per day but also low compared with the rational expectations efficient markets hypothesis predicted value of 1, as noted above. The investment sensitivity parameter β is also highly statistically significant and large in magnitude at 613,541. For the matched trading pairs summarized in columns (3) and (5) the estimated Lambda information decay rate is lower at 7.57 and 16.68 percent respectively, indicating a greater departure from the partially revealing rational expectations equilibrium. Moreover, the explanatory power of these two models is lower.

In all likelihood, these estimation problems stem from the very short daily investment period, giving rise to many non-trading and thus directionless trading days. Columns (2), (4) and (6), present the a weekly rather than daily trading interval, resulting in far better model fits and naturally, a sizably larger estimated values for the information decay rate, Lambda, especially in the column (6) trades between domestic and foreign institutions. The information decay rate on a weekly basis rises to approximately 40 percent and R-Squared is also much higher at 21 percent.

The weekly-horizon regression results for all 33 major Finnish stocks are presented in columns (1), columns (3) and column (5) of Table 5 Panel B and excluding Nokia, in columns (2), (4) and (6), but the results are not quite as good as for Nokia alone. For example, the estimated Lambda value for domestic institutions trading with foreign nominees is only about half the magnitude of Nokia alone and the explanatory power is far lower. This is probably because I do not see the vastly dominant role of foreign nominees in these smaller stocks together with the same sizeable swings in valuation as with Nokia. In other words, the informational home bias is not as great.

Table B.1.2 Householder Investment Strategy

Panel A: Model Explaining the Daily and Weekly Household Nokia Stock Purchases by Households from Foreign Nominees, Households from Domestic Institutional Investors, and Domestic Institutional from Foreign Investors, respectively, January 1995-December, 2011.

	Households with Foreign Nominees		Households with Domestic Institutions		Domestic Institutions with Foreign Nominees	
	Daily	Weekly	Daily	Weekly	Daily	Weekly
Variable: Stock Purchases	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	42,670***	185,288***	2,364	7,891	-332	-9,669
(t-value)	(4.18)	(2.91)	(0.76)	(0.47)	(0.03)	(0.15)
Closing price	-147,392***	-247,774***	-20,357***	-32,103***	-66,369***	-116,753***
(t-value)	(16.51)	(9.11)	(7.47)	(4.47)	(6.76)	(4.24)
(DW)	(2.0598)	(2.1221)	(2.0169)	(2.0874)	(2.0666)	(2.0909)
Lag closing price	145,041***	237,750***	20,243***	31,760***	63,231***	106,607***
(t-value)	(16.25)	(8.75)	(7.43)	(4.42)	(6.44)	(3.9)
(DW)	(1.8467)	(1.6782)	(1.8601)	(1.6862)	(1.6823)	(1.8366)
Lag net household purchase	0.2364***	0.2846***	0.0757***	0.2449***	0.1668***	0.4028***
(t-value)	(16.43)	(8.75)	(5.00)	(7.59)	(11.14)	(13.20)
(DW)	(1.8473)	(1.7854)	(1.8649)	(1.9624)	(1.7885)	(1.8849)
Number observations	4,292	888	4,292	888	4,292	888
R Square	0.1203	0.1748	0.0187	0.0829	0.0461	0.2057
Implied values						
Lambda measure of market efficiency	0.2364	0.2846	0.0757	0.2449	0.1668	0.4028
Intercept	0.0670	0.2222	0.0088	0.0608	-0.0008	-0.0365
Alpha coefficient	0.995	0.9831	0.9995	0.9964	0.9900	0.9358
Beta investment sensitivity	613,541	835,382	267,410	129,685	379,082	264,665

Absolute *t* statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Model Explaining the Weekly Household 33 and 32 Stock (Excluding Nokia) Purchases from Foreign Investors and Domestic Financial Institutional investors, Domestic Financial Institutional Nokia Stock Purchases from Foreign Investors, respectively, January 1995-December, 2011.

	Households with Foreign Nominees		Households with Domestic Institutions		Domestic Institutions with Foreign Nominees	
	33 stocks	32 stocks	33 stocks	32 stocks	33 stocks	32 stocks
Variable: Stock Purchases	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	46,602***	42,128***	9,706***	9,765***	30,987***	32,299***
(t-value)	(4.01)	(3.79)	(3.47)	(3.39)	(3.41)	(3.39)
Closing price	-105,644***	-101,059***	-19,249***	-18,834***	-49,275***	-47,097***
(t-value)	(5.63)	(5.92)	(6.23)	(6.56)	(6.04)	(5.73)
Lag closing price	101,115***	96,708***	18,478***	18,049***	44,904***	42,912***
(t-value)	(5.68)	(5.99)	(6.31)	(6.66)	(5.74)	(5.44)
Lag net household purchase	0.2789***	0.2787***	0.2063***	0.2051***	0.2014***	0.195***
(t-value)	(9.9)	(9.56)	(12.44)	(12.12)	(9.18)	(9.02)
Number observations	20,796	19,908	20,796	19,908	20,796	19,908
Average R Square	0.2036	0.2045	0.0959	0.0962	0.0741	0.0574
Implied values						
Lambda Market Efficiency	0.2789	0.2787	0.2063	0.2051	0.2014	0.195
Intercept	0.1285	0.1214	0.1084	0.1110	0.174	0.1823
Alpha coefficient	0.9826	0.9826	0.9878	0.9888	0.9755	0.9764
Beta investment sensitivity	362,540	346,965	89,545	88,000	222,959	220,063

Absolute *t* statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For the parameter values estimated in Table 5 I simulate the projected private signal of expected fundamental value, p_t^T, for each of my trading pairs, households and foreign nominees, households and domestic institutions, and domestic institutions and foreign nominees, in order to compute the percentage differences between the projected 'true' and actual prices. The findings provided in Table B.1.3, column (1) to column (3) show that the projected 'true' price of Nokia is substantially lower than the actual price by about six percent for the trading pair, domestic institutions and foreign nominees and about 4 percent higher for households and foreign nominees. However, columns (4) to columns (9) of Table B.1.3 indicate that the differences are mostly slight for the set of investigated Finnish stocks with the highest discrepancy of about 3 percent for the trading pair, households and domestic institutions.

Table B.1.3 Summary of Trading Model Simulation Utilizing the Percentage of the Difference between Weekly Informed Investor Expected Fundamental Value and Actual Price deflated by Actual Price for Nokia, All 33 stocks and 32 stocks, respectively.

Descriptive Statistics - Weekly

	Nokia			33 stocks			32 stocks		
	Household with Foreign Nominees	Household with Domestic Institutions	Domestic Institutions with Foreign Nominees	Household with Foreign Nominees	Household with Domestic Institutions	Domestic Institutions with Foreign Nominees	Household with Foreign Nominees	Household with Domestic Institutions	Domestic Institutions with Foreign Nominees
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean	4.38%	-0.39%	-6.26%	-0.45%	3.12%	0.32%	-0.66%	3.20%	0.68%
Standard Error	0.22%	0.06%	0.10%	0.07%	0.19%	0.04%	0.07%	0.19%	0.04%
Median	2.26%	-0.48%	-6.43%	0.78%	0.35%	0.03%	0.74%	0.34%	0.11%
Standard Deviation	6.57%	1.84%	3.08%	9.87%	29.20%	5.49%	9.95%	29.74%	5.28%
Skewness	1.684	-1.965	-1.580	-3.102	15.198	5.761	-3.161	14.920	6.830
Confidence Level (95.0%)	0.00433	0.00121	0.00203	0.00134	0.00367	0.00075	0.00138	0.00381	0.00073

Based on an efficient markets rational expectations benchmark, the informed trader's decay rate of information in the stock price would be 100 percent, not the estimated 20 to 40 percent per week that I find. Thus the profitable trader groups I analyze act as if they receive a private signal based on extracted information from the contemporary and previous period's stock price and the previous period's order-flow (trade direction and magnitude) in order to formulate their investment strategy which I demonstrate to be 'contrarian' in nature with the purchase of 'losers' and the sale of 'winners'. Thus I have demonstrated that autocorrelation in both actual prices and order-flow contains sufficient information on which to base a successful trading strategy. This is especially so for households located close to Nokia headquarters as they seem to receive the best signal of future shareholder value.

C Additional Robustness Analysis - Chapter 2

Summary of 28 Selected Sample Stocks - Chapter 2

Table C.1.1 Summary of 28 Selected Sample Stocks - Chapter 2

ISIN	Company Name	Mean Volume	Mean Value (EURO)	Mean share out-standing	Mean turnover rate	Mean market capital-ization	Mean Men Share
FI0009013296	NESTE OIL OYJ	1,289,223	22,132,332	256,403,686	0	4,020,037,875	89.40%
FI0009014575	OUTOTEC OYJ	460,319	13,348,013	43,849,818	0	1,359,240,457	89.16%
FI0009013429	CARGOTEC OYJ	246,709	6,512,188	54,697,280	0	1,465,286,800	87.67%
FI0009005961	STORA ENSO OYJ	4,758,081	36,644,065	612,949,118	0	4,698,950,016	86.58%
FI0009002422	OUTOKUMPU OY	2,074,503	23,927,025	333,741,715	0	2,705,784,105	86.57%
FI0009007132	FORTUM OYJ	2,466,920	49,930,620	887,556,530	0	17,804,113,922	86.27%
FI0009003305	SAMPO PLC	2,089,425	38,009,067	564,804,908	0	10,514,412,236	85.97%
FI0009007835	METSO OYJ	1,104,503	31,176,959	145,500,991	0	4,255,837,732	85.70%
FI0009007884	ELISA CORP	832,895	13,789,200	166,331,462	0	2,682,423,612	85.45%
FI0009000681	NOKIA CORP	30,056,016	352,527,651	3,851,781,129	0	44,535,020,668	85.20%
FI0009000665	METSA BOARD CORP	1,661,534	4,390,216	291,826,062	0	749,217,384	85.17%
FI0009003552	RAUTARUUKKI OYJ	780,927	15,545,602	140,055,775	0	2,700,174,160	85.12%
FI0009005870	KONECRANES PLC	477,856	10,409,925	60,274,976	0	1,332,696,923	84.85%
FI0009007066	RAMIRENT OYJ	248,076	2,590,314	93,743,173	0	909,162,740	84.74%
FI0009014377	ORION CORP	346,545	5,308,255	90,615,622	0	1,383,790,688	84.30%
FI0009005318	NOKIAN TYRES OYJ	909,119	19,050,977	125,919,141	0	2,802,348,374	83.70%
FI0009800643	YIT CORP	722,791	11,208,209	124,855,561	0	2,000,628,845	83.64%
FI0009000277	TIETO CORP	617,052	10,594,628	73,002,822	0	1,135,993,832	83.54%
FI0009004824	KEMIRA OY	418,128	4,809,597	138,714,628	0	1,528,469,852	83.15%
FI0009005987	UPM-KYMMENE CORP	3,268,632	40,551,702	522,068,598	0	6,352,455,198	82.78%
FI0009003222	POHJOLA BANK PLC	568,040	5,586,034	209,326,104	0	2,035,088,417	82.54%
FI0009002158	UPONOR OYJ	218,560	3,415,267	73,246,967	0	1,048,811,116	81.42%
FI0009007694	SANOMA CORP	339,396	4,978,985	161,297,536	0	2,385,122,054	80.77%
FI0009000285	AMER SPORTS CORP	338,888	4,259,139	95,391,607	0	1,023,411,289	80.18%
FI0009003727	WARTSILA OYJ ABP	544,324	17,482,803	116,406,594	0	3,653,204,142	79.85%
FI0009000459	HUHTAMAKI OYJ	326,315	3,145,042	105,605,055	0	1,038,009,789	79.71%
FI0009013403	KONE CORP	518,043	17,286,929	187,275,360	0	6,595,849,331	79.31%
FI0009000202	KESKO OYJ	331,852	9,710,509	66,344,202	0	1,892,409,245	78.15%

D Identifications of Hedge fund management companies

Identifying Hedge Fund Management Companies

According to Russell (2016) methodology, use the Form ADV to identify 534 hedge fund managers out of 653 managers within in ANcerno sample. Following Brunnermeier and Nagel (2004) and Griffin and Xu (2009), a manager could be classified as a hedge fund if more than half of its investors are categorized as high net worth individuals or pooled investment vehicles in item 5.D. In addition, the manager needs charge a performance-based fee (item 5.E). However, this approach incorrectly includes some funds with no hedge fund operations. Then go to visit each company's website and eliminate any firms that do not report any hedge funds on their website. This filter eliminates private equity firms (e.g., New Harbor Capital), real estate firms (e.g., ERE Rosen), and investment advisors who have high net worth investors but do not offer hedge fund products (e.g., Denver Investment Advisors). The large banks (e.g., Bank of America) are exclude as well. After these filters, the sample includes 55 hedge fund management companies. An additional concern is that Form ADV fails to capture many hedge funds. Thus need examine the Form ADV of Institutional Investor's Top 100 Hedge Funds and find that the Form ADV approach correctly classifies 78 of the 100 hedge funds.11 Of the 22 remaining funds, the majority list pensions and profit sharing plans as part of their investor base (see, e.g., Bridgewater Associates). To capture additional hedge funds that do not meet the Form ADV criteria, further step needed to investigate a list of roughly 1000 13F-filing hedge funds provided by Morningstar. According to Morningstar, the list is self-reported by the money management company, and typically reflects whether the management company is predominantly a hedge fund manager. 27 management companies appeared on the

Morningstar list of hedge funds, but failed to meet the Form ADV hedge fund criteria. Of the 27 hedge funds, 24 charged performance-based fees and had over 50% of their investors as high net worth individuals, pooled investment vehicles, or pensions and profit sharing plans. For the other three funds, Form ADV was unavailable, but inspection of the company's website indicated significant hedge fund operations. Based on this information, all 27 companies are identified as hedge funds. The final sample thus consists of 82 hedge fund management companies.