# Do Individual Investors Have Asymmetric Information Based on Work Experience?*

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Forthcoming, *Journal of Finance*

**Abstract**

Using a novel dataset covering all individual investors' stock market transactions in Norway over 10 years, we analyze whether individual investors have a preference for professionally close stocks, and whether they make excess returns on such investments. After excluding own-company stock holdings, investors hold on average 11% of their portfolio in stocks within their two-digit industry of employment. Given the poor hedging properties of professionally close stocks, one would expect such investments to be associated with asymmetric information and abnormally high returns. In contrast, all our estimates of abnormal returns are *negative*, in many cases statistically significant. Overconfidence seems the most likely explanation for why individuals excessively trade in professionally close stocks.

JEL Classification: D83; G11; J24

Keywords: Asymmetric information, Behavioral finance, Familiarity, Household finance, Informed trading, Overconfidence.

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*This work is part of the project "Portfolio Choices of Norwegian Investors", funded by the Norwegian Research Council (Finansmarkedsfondet) under grant number 178944. We thank Verdipapirsentralen (The Norwegian Central Securities Depository) for providing the data. We thank Daniel Hoechle, Per Östberg, and seminar participants for their comments, Borsprosjektet at NHH and Øystein Hungerholt for their helpful assistance, and Bernt Arne Ødegaard for providing us with the risk factors for the Oslo Stock Exchange. Finally, we are especially thankful for the comments of an anonymous referee, an associate editor, and the editor, Campbell Harvey.

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*As time goes on, I get more and more convinced that the right method in investments is to put fairly large sums into enterprises which one thinks one knows something about and in management of which one thoroughly believes. It is a mistake to think that one limits one's risks by spreading too much between enterprises about which one knows little and has no special reason for special confidence. One's knowledge and experience is definitely limited and there are seldom more than two or three enterprises at any given time which I personally feel myself entitled to put full confidence.*

John Maynard Keynes

From a letter to a business associate, F. C. Scott, on August 15, 1934

# Introduction

A vast theoretical literature explores the implications of investors having asymmetric information, but less is known about the sources of this information. Grossman & Stiglitz (1976) suggest that individuals with a comparative advantage in collecting information can obtain asymmetric information and make abnormal returns. In this paper we hypothesize that professional proximity is a route in which individuals can have a comparative advantage in collecting information.

For example, in May 1998 the New York Times published a story about a potential breakthrough in cancer treatment. According to the story, the biotech company Entremed had the licensing rights to the breakthrough. Huberman & Regev (2001) report that after the story was published in the Times, Entremed experienced a large and sustained stock price appreciation. This appreciation occurred in spite of the invention being already well-known among experts through a scientific article published in Nature in November 1997. In the period prior to May 1998, there was therefore large potential gains from having the knowledge sufficient to interpret information about the promise of the Entremed discovery. As another example, between 2000 and 2005 there was considerable uncertainty about whether the oil reserves in the Barents Sea would be profitable to exploit or not. Reservoir size estimates based on four large trial wells were gradually released to the international press during 2001 and 2002. A geologist employed in the oil industry could be particularly well qualified to acquire and interpret information about the promise of a new oil field, and make a profit from trading on this knowledge.[1]

We hypothesize that professional proximity can either give a false feeling of competence or it can facilitate the acquisition of value-relevant information and lead to abnormally high return. Popular belief suggests that some individuals have asymmetric information and can gain from being undiversified (Merton, 1987). Over a 30-year period, Warren Buffet generated a strong investment performance using this approach (e.g., Martin & Puthenpurackal (2008)). In fact, a well-known investment advice from Buffet is to "Invest within your circle of competence. It's not how big the circle is that counts, it's how well you define the parameters" (Fortune, November 11, 1993). Also some hedge funds are relatively undiversified. For example, Atticus, a hedge fund managed by Timothy Barakett and Nathan Rotschild was the 13th largest hedge fund in Institutional Investor's

2008 Hedge Fund 100, and only invests in a dozen or so stocks.[2]

The academic literature is divided on whether individual investors can possess asymmetric information and make an abnormal return from stock-picking. Using data from a large U.S. discount brokerage house, Odean (1999) found that, on average, individual investors earn a negative abnormal return, and particularly so for those who trade frequently (Barber & Odean, 2000). Analyzing the same dataset, Ivkovic & Weisbenner (2005) argue that individual investors earn an abnormal return on stocks that are geographically close, but, as pointed out by Seasholes & Zhu (2009), Ivkovic & Weisbenner (2005) use an incorrect method to evaluate abnormal returns. Coval *et al.* (2005) document performance persistence for a small number of investors with high abnormal returns, while Barber *et al.* (2005) find a similar pattern using data from Taiwan. We contribute to the debate on whether individual investors possess value-relevant information by using an extraordinarily rich dataset from Norway to analyze whether professional expertise can be associated with abnormal returns.

The majority of professionally close individual investors cannot be expected to have asymmetric information, which raises the question of whether we will be able to detect abnormal returns across a large number of trades. However, since future returns of investments in professionally related stocks are likely to be correlated with future returns on human capital, uninformed individual investors should hedge by avoiding investments in professionally related stocks (e.g., Baxter & Jermann (1997), Cocco *et al.* (2005), Massa & Simonov (2006), Benzoni *et al.* (2007)). Thus investors should invest in professionally close investments only if they are informed, which means that there are good reasons to expect that the typical professional close investment should be associated with abnormally high returns.

Behavioral explanations have a different take on why investors would choose stocks that are professionally close. Heath & Tversky (1991) suggest that "holding judged probability constant - people prefer to bet in a context where they consider themselves knowledgeable or competent than in a context where they feel ignorant or uninformed" (p.7). In the overconfident investor model of Odean (1998), overconfident investors trade more because they more often disagree with market valuations. A natural hypothesis is that overconfident investors would focus their trading in stocks within the same industry, even if such stocks are poor hedges. If the excess holdings are based on overconfidence or a false feeling of competence, we would not expect such trades to give a positive excess returns.[3]

Our data is novel and covers the common stock transactions of all Norwegian individual investors at the Oslo Stock Exchange over a 10-year period. The dataset combines the full trade records of each individual with exceptionally detailed sociodemographic information at yearly level over a 20-year period. For example, the sociodemographic data contain a yearly panel of work history for each individual, including the industry and the ticker code of their employer. This enables us to identify trades in the stocks of current and previous employers. Since we have data on where the investors live, we can also control for the possibility that stocks close in a professional sense are also geographically close.

For each individual, we define expertise stocks to be stocks whose two-digit SIC code match the two-digit SIC code of the individual's employer. For example, for an individual that works in an oil company, stocks in the oil industry are defined as expertise stocks. We attempt to answer two questions. Do individual investors tend to overweigh professionally close stocks in their portfolio choice? Are investments in professionally close stocks associated with asymmetric information and abnormal returns, or is it evidence of poor hedging?

We find that individuals overweigh their holdings in expertise stocks. Before eliminating holdings in current and previous employer stock, the average holding of expertise stocks is 32% of the portfolio value. After eliminating own-company and previous employer stock, the average holding is 11%, and relative to the market portfolio the excess holding is 7%.

If holdings of expertise stocks were driven by value-relevant asymmetric information we would expect that those investments would generate abnormally high returns. On the other hand, if expertise investments have a behavioral explanation (such as overconfidence), expertise investments should not earn abnormal returns. We test whether expertise investments outperform using ten years of returns data.

To test for abnormal returns, we follow the recommendations of Lyon *et al.* (1999) and use two different methods. Under the calendar-time portfolio approach, we analyze whether the returns to expertise stocks purchased (the expertise buy portfolio) are abnormally high under a given portfolio formation period. We use three different benchmarks: the expertise sell portfolio, the non-expertise buy portfolio, and the market portfolio. We test the null hypothesis of no difference in returns between the buy portfolio and these three benchmarks under a two-sided test. In other words, we also analyze whether expertise investments yield negative abnormal returns. We think a sufficient motivation for looking at this question is that prior work (e.g., Odean (1999)) have documented that individual investors do worse on their buys than sells, thus one might wonder if this is still true when investors trade stocks within their area of expertise.

Using the calendar-time portfolio approach, we do not find that expertise investments are associated with abnormal positive returns in the medium- or long-term. In fact, all our point estimates of abnormal returns are negative, and in some cases statistically significant. For example, for a 1-year portfolio formation period, the expertise buy portfolio has a negative and insignificant alpha at about five per cent yearly. The average raw returns of expertise sells outperform the raw returns of expertise buys by about four per cent annually. This difference is statistically significant. The average yearly raw returns of expertise stocks purchased are about three per cent lower than the average returns of non-expertise stocks bought, but statistically insignificant. These findings suggest a zero or negative abnormal return of expertise trades. The same conclusion holds after controlling for risk by a four-factor model (similar to Carhart (1997)). Professionally close trades do not seem to be well-informed.

To document whether expertise investments could be associated with value-relevant short-term pieces of information, we use a variant of the control-firm approach analyzed by e.g., Barber & Lyon (1997). This method compares actual short-term returns of expertise trades with the distribution of short-term returns for simulated non-expertise trades in stocks with similar market size and book-to-market characteristics.[4] The control-firm analysis strongly suggests that expertise investments underperform. For example, on a 1-month horizon, we find that expertise buys underperform the benchmark by 1.28%, which is statistically significant at the 1% level. Expertise buys also underperform in a statistically significant manner when compared with two other benchmarks; the returns of expertise sells, and the returns of non-expertise buys. We conclude that expertise buys generate an abnormally low return in the short run.

To focus on investors who are more likely to benefit from within-industry information flow, we analyze whether expertise investments yield an abnormal return if made by investors with at least 16 years of education (so that we include investors with an MSc or a Ph.D.). The results are similar to the main analysis - all our point estimates of abnormal returns of expertise investments are negative, and significantly so in the control-firm analysis. We also analyze the abnormal returns of expertise investments made by investors who are geographically close. The conclusions remain the same.

Coval & Moskowitz (1999) find that mutual funds tend to invest a disproportionate fraction of their portfolio in geographically close stocks. Zhu (2003) and Ivkovic & Weisbenner (2005) report a similar finding for individual investors. A concern is that the "expertise bias" documented in the present paper, i.e., individual investors overweighing their holdings of professionally close stocks, is a rediscovery of the local bias in investment choices found by Zhu (2003) and Ivkovic & Weisbenner (2005). This could be the case if expertise holdings are predominantly associated with holding geographically close stocks. Having data on the residential municipality of each investor allow us to disentangle expertise bias from local bias. We find that the relation between expertise bias and local bias is practically zero, which suggests that they are independent phenomena.

Overall, our findings provide clear evidence of a behavioral bias in the investment choices made by individuals. They invest in assets that are more risky and therefore require a higher return. In contrast, all our point estimates of abnormal returns are negative, and in many cases statistically significant. We believe this conclusion is important for two reasons. First, our results contribute to an ongoing debate on whether individual investors are able to acquire asymmetric information about future stock returns, and profit from it (Coval *et al.* (2005), Barber *et al.* (2009), Ivkovic *et al.* (2008) and Ivkovic & Weisbenner (2005)). The lack of any evidence of abnormal returns for a very plausible candidate - professionally close investments - suggests that individual investors are not able to profit from asymmetric information. Second, our results provide guidance to individual investors themselves. Since we do not find that individuals are compensated for the extra risk they take on expertise investments, advice to avoid professionally close investments, and offering of investment products tailored to hedge against variations in labor income, could provide an economic gain.

The paper is organized as follows. Section I presents the data and provides some summary statistics. Section II defines the basic measures of expertise and excess holdings, and analyzes the individual characteristics that determine excess holdings. Section III outlines the methodologies used to test for abnormal returns. Section IV analyzes whether expertise investments are associated with abnormal returns. Section V contains additional analysis, and Section VI concludes.

# I. Data and Summary Statistics

## A. Background

We start out with a brief description of the Norwegian economy and the Oslo Stock Exchange before describing the basis for the data collection. Several figures are drawn from Statistics Norway Yearbook 2000.

Norway is an industrialized country with a population of about 4.5 million. The Gross Domestic Product per capita, adjusted for purchasing power, was about $36,100 in 2000; this is almost identical to the U.S., $34,600, but higher than the average of the 27 European Union countries, $21,900. Norway has a large middle class and a lower inequality in disposable income than most other industrialized countries. At the end of 2000, about 9% of the individuals in Norway held direct holdings of common stocks at the Oslo Stock Exchange. The corresponding figure for Sweden was about 8% (Karlsson *et al.*, 2006). For households, about 22% held stocks directly in 2000, while the corresponding figure for the U.S. was about 21% (Survey of Consumer Finance, 2001). About 41% of Norwegian households held mutual funds in 2000. For the U.S. it was about 18% (SCF, 2001). The main reason for the large fraction of Norwegian households investing in mutual funds is that until 1999 such savings (up to about NOK 5,000 a year) benefited from a tax subsidy. Conditional on mutual fund ownership, the mean and median household holdings are NOK 104,715 and NOK 37,731, respectively.

Individuals also hold stocks indirectly via pension savings in private insurance companies. While many are on a defined benefit pension plan, with only a small exposure to equity risk, defined contribution plans became increasingly common towards the end of the dataperiod. About half of deposits in defined contribution plans are invested in equity. In addition to private pension plans, individuals receive guaranteed pension benefits from the government. Government pensions are funded partly by pay-as-you-go contributions and partly by oil revenue. For a person with an income level of about 450,000 Norwegian Kroner (NOK) before retirement (the mean income in our sample), roughly 30% of the pension benefits received each year will be paid from the insurance companies, and 70% from the government. The rate of exchange was 8.81 NOK/USD at the end of 2000.

By European standards, the Oslo Stock Exchange (OSE) is a medium-sized stock exchange. At the end of 2000, the market capitalization of the OSE was about 625 billion NOK, spread out over 214 companies. The OSE ranked 12th out of 21 European stock exchanges based on market capitalization and 11th based on the number of listed companies. In 2000, the turnover was 97%. The relative smallness of the OSE is in one sense an advantage since limited media and analyst attention makes the OSE a particularly suitable testbed for theories of asymmetric information.

The OSE is characterized by a large energy sector. Before the privatization and listing of the largest Norwegian oil company, Statoil, in 2001, the energy sector (GICS code 10) constituted about 25% of the market cap of the OSE, and afterwards about 40%. For the last ten years the average size of the energy sector in the MSCI World Index has been about 10%. SIC code 11, oil and gas extraction, is a narrower definition of oil and gas companies than GICS code 10. The average market capitalization for SIC code 11 across the years in our sample is 22%.

At the end of the sample period, the government owned about 30% of the OSE. The government ownership is concentrated in four large companies - Statoil (energy), Hydro (energy), Telenor (telecommunications), and Den norske Bank (banking).[5] Foreign ownership of OSE is around 30%, which reflects that Norway is a small, open economy with few restrictions on foreign ownership. Odegaard (2009) provides additional descriptives on OSE. The question of whether OSE is representative will be discussed at the end of Section I.C.

## B. Data

The data are proprietary and have been collected from three sources. First, a record of all common stock trades made at the OSE by Norwegian residents from January 1994 to December 2005 was collected from Verdipapirsentralen (the Norwegian Central Securities Depository).[6] For each transaction made by an individual, the data contain the (anonymized) ID of the individual, the date of transaction, the ticker of the security and the number of shares bought or sold. Second, from the OSE we obtained daily ticker prices and other company information such as market capitalization and company ID number. Where needed, we supplemented with data from Borsprosjektet at the Norwegian School of Economics and Business Administration. Third, from the government statistical agency, Statistics Norway, we obtained register data on the sociodemographic characteristics of the investors per December 31 from 1986 to 2006. For each individual, this data include income and wealth variables, age, gender, education, residence code at municipal level, distance between municipalities, and employer variables such as the five-digit SIC code and the unique employer ID number. Since the data are collected from government registries, their reliability are high.[7]

Own-company stock holdings are subject to employer matching and tax breaks, and including these holdings would blur the interpretation of the estimates of excess weights and returns. We exploit several features of the data to identify and exclude such holdings. First, linking the company ID of a stock and the company ID of an individual enables us to identify own-company stock holdings for 1996-2005. Second, having data on the work history from 1986 onwards for each individual in the dataset enables us to exclude holdings in previous employer stocks when constructing measures of excess holdings and excess returns in own-industry stocks. Third, for the years 1996-2000 and 2004, Statistics Norway provided the company ID of directly and indirectly owned subsidiaries, broken down on each listed company. The definition of a subsidiary is that the mother owns more than 50%. We use the data on subsidiary ownership to impute a hierarchy of indirectly owned companies for the full period 1996-2005. We analyze the holdings and stock market returns for Norwegian individual investors in the 10-year period 1996-2005. Our results are the same if we confine our attention to 1996-2000 and 2004. We exclude individuals employed in Financial Services (SIC codes 65, 66, and 67) as a simple way to eliminate professional investors from the sample.

## C. Summary Statistics

[TABLE I ABOUT HERE].

Panel A in Table I reports summary statistics at the end of 2000 for stock owning individuals that are employed in an industry with at least one listed industry. Counting individuals whose portfolio value exceeds NOK 5000 (USD 600) our main sample consists of 93,865 individual investors at the end of 2000. The average investor is 44 years old, has 12.4 years of education, and 18.4 years of work experience. The average wage income is NOK 441,423, with an average gross wealth of about NOK 1.4 million. The average investor holds a portfolio worth NOK 183,096 in direct stock investments. He holds 2.2 stocks, and performs 6.4 trades yearly. The average yearly portfolio turnover is 111.3%. 44% of the investors owns more than one stock. Across all years there are 169,929 unique individuals and 636,594 individual-years. The yearly aggregate number and value of trades for the individuals in our main sample are reported in Appendix A.

Panel B in Table I reports descriptive statistics for all Norwegian individual investors, including those that do not work in an industry with a listed company. The average age is somewhat higher than that in Panel A (since retirees are included in Panel B), and the average wealth somewhat lower (presumably because individuals employed in the public sector are included in Panel B). Norwegian individual investors are on average somewhat less wealthy and hold a smaller portfolio than in Barber & Odean (2000), or compared to summary statistics from the Survey of Consumer Finance, see for example Heaton & Lucas (2000). The summary statistics are similar to the representative investor sample from Sweden used by Massa & Simonov (2006) and Calvet *et al.* (2007). For example the mean value of the stock portfolio for all investors was $\$9,971$ at the end of 2002, while Calvet *et al.* (2007) find that the mean household portfolio value was $\$9,261$ in Sweden in 2002.

The question of whether the data are representative can be split into two; whether the OSE is representative and whether the individual investors in our sample are representative. First, with the exception of the large government ownership, we believe that OSE is representative of a large number of small and middle-sized stock exchanges in industrialized countries. Although the government owns almost a third of the OSE, the government accounts for much less of the yearly stock transactions. Second, based on the comparison of individual investor characteristics from Sweden and the U.S., we believe that the individual investors in our dataset are representative of individual investors in a large number of industrialized countries.

# II. Do Individuals Overweigh Their Holdings of Expertise Stocks?

## A. Measure of Expertise

To operationalize the notion of professional closeness, we link individuals' stock holdings to their industry of employment. For each individual employed in the private sector, our dataset contains the five-digit SIC code of the employer at year-end. For each company listed on the OSE, we have the primary five-digit and up to two supplementary SIC codes at year-end from 1996 to 2005. We define an expertise holding to be a holding of a stock where the worker SIC code matches one of the SIC codes of the stock (all our results are robust to only including the primary SIC code). For example, for an individual who works in an oil company per December 31, 1999, and holds shares in a company in the oil and gas industry (SIC code 11) per December 31, 1999, we treat this as an expertise holding. We report results for both the two-digit and the five-digit SIC code mapping.

## B. Measures of Excess Weights

We define two alternative measures of excess portfolio weight in expertise stocks. The first measure, $w_i^{act}$, is the fraction of the portfolio value that an individual holds in expertise stocks. If we wish to capture deviations from a portfolio that shies away from professionally close stocks, $w_i^{act}$ is the appropriate measure of excess weight. To encompass differences in market capitalization across industries, we define an alternative measure of excess weight, $w_i^{corr}$. Defining $w_i^{mkt}$ as the fraction of market capitalization within that investor's industry,

$$w_i^{corr} = w_i^{act} - w_i^{mkt}. \tag{1}$$

If we wish to measure deviations from the market portfolio in the direction of professionally close stocks $w_i^{corr}$ is the appropriate measure.

## C. Evidence of Excess Weights

[TABLE II ABOUT HERE]

For each year, we match the employer ID per December 31 with reported portfolio holdings per December 31. In Table II, we report equal-weighted averages across investors for 1996-2005. Under both measures of excess weight in expertise stocks, $w_i^{act}$ and $w_i^{corr}$, the average excess weight is positive. The results are not sensitive to using value-weighted averages.

Panel A reports the estimates on excess weights without excluding own-company stock. Panel B reports the estimates for excess weights after excluding holdings in the current and previous employers. We exclude holdings in previous employers going back 10 years. The table shows results for both a two-digit and a five-digit SIC code mapping. There is not much difference between the two. The sample is smaller for the five-digit mapping since fewer individuals have the possibility to invest in stocks from their five-digit industry. As there are only minimal differences in the results between the two-digit and the five-digit mapping, we only present results for the two-digit mapping in the rest of the paper.

We can compute $w_i^{mkt}$ in Equation (1) from the market value of the equity owned by individual investors, as in Ivkovic & Weisbenner (2005). This measure is labeled $w_i^{mkt,1}$. We can also compute $w_i^{mkt}$ in Equation (1) from the market capitalization of the company, defined as $w_i^{mkt,2}$. As shown in Table II, the estimated averages of $w_i^{mkt,1}$ and $w_i^{mkt,2}$, denoted by $w^{mkt,1}$ and $w^{mkt,2}$, are almost identical. The same holds for the estimated averages $w^{corr,1}$ and $w^{corr,2}$. For the rest of the paper, we only report results for $w_i^{mkt,1}$ and

$w_i^{corr,1}$, and denote them by $w_i^{mkt}$ and $w_i^{corr}$, respectively.

Panel A in Table II summarizes the averages across 1996-2005 for all investors working in an industry with at least one company listed on the OSE. To denote averages, we skip subscripts. For example, the estimated average of $w_i^{act}$, denoted by $w^{act}$, equals 31.6%. After correcting for the market capitalization of the expertise industry, we find that the excess weight is 27.6%. For individuals working in a public company (or a daughter company) the excess weight is 62.7%. In Panel B, we report the summary statistics after excluding all holdings in own-company and previous employer stock for investors that are employed in a listed company or in one of its daughter companies. Depending on whether we measure excess holdings by $w_i^{act}$ or by $w_i^{corr}$, the overall average excess weight ranges from 7% to 11%. For individuals employed by private firms, the average excess weight ranges from 7% to 9%, and for individuals employed by listed firms it ranges from 9% to 18%. The measure $w_i^{corr}$ ranges from $-22.9\%$ to nearly 100% across individuals. The low extreme is typical of the individuals that only invest in other industries than their own. The high extreme is typical of investors working in sectors with few listed companies, yet their entire portfolio is concentrated in the industry where they are employed. In Appendix B, we list all two-digit industries with corresponding $w_i^{corr}$ and $w_i^{mkt}$. The table shows that industry outliers do not drive our finding of an excess holding in expertise stocks.

Excess weight in expertise stocks could be driven by investors holding only one stock. To investigate this possibility, we have replicated Table II for investors holding more than one stock. Appendix C shows that the excess weights are only slightly smaller for this group of investors.

## D. Excess Weight and Trading Activity

To investigate the trading activity of professionally close investors, we define two measures of trading activity in expertise stocks. The first measure of trading activity is the fraction of all trades that individual $i$ makes in expertise stocks, denoted by $tr_i$. The second measure of trading activity, denoted by $et_i$, is the fraction of expertise trades subtracted the fraction of expertise stocks in the portfolio, i.e., $et_i$=$tr_i$-$w_i^{act}$. While $tr_i$ measures the intensity in which individual $i$ trades in expertise stocks relative to other stocks, $et_i$ measures individual $i$'s trading intensity in expertise stocks relative to his holdings of expertise stocks.

[TABLE III ABOUT HERE]

Panel A in Table III summarizes trading activity across 1996-2005. On average, $tr$ = 32.7% while $w^{act}$ = 31.6%. The estimated difference, 1.1%, is not statistically significant different from zero. In Panel B, we report the two trading measures after excluding all holdings in own-company and previous employer stocks for investors who work in a listed company (or a daughter company). The estimated average of $tr_i$ equals 11.7%, while the estimated average of $et_i$ equals 0.8%, which is not significantly different from zero. The excess trading is a little larger for individuals employed in public firms than for those employed in private firms, 3.0% versus 0.4%, the difference not being significant. We conclude that individuals have a high trading intensity in expertise stocks relative to other stocks, while they do not have a high trading intensity in expertise stocks relative to their holding of such stocks.

## E. Excess Weight and Individual Characteristics

Table IV reports the results of fitting pooled cross-sectional regressions of excess weight, as measured by $w_i^{corr}$, on sociodemographic and portfolio characterstics of the individual. The results using $w_i^{act}$ as dependent variable rather than $w_i^{corr}$ are very similar and not reported.

[TABLE IV ABOUT HERE]

In Regression (2) we explore the relation between individual characteristics and an excess holding in expertise stocks. The results are quite intuitive. The positive coefficients on industry experience and income indicate that higher industry specific knowledge and human capital result in a higher excess holding. For an individual with 50% more industry specific experience, the excess weight increases by $1.1\%(= 0.5 \cdot 0.021)$. The excess weight is smaller for more wealthy individuals, and higher for individuals employed in listed companies. We also find that women exhibit a larger excess weight by about 1.6% than men. General work experience and the length of education are less important. In Regression (3), we add portfolio characteristics to the explanatory variables. As expected, having more individual stocks in the portfolio leads to a smaller excess weight. Controlling for portfolio diversification, we find that the higher number of stocks in the industry, the more biased is the investors. We performed several robustness tests of the regressions in Table IV. The regressions were run without year and industry dummies. The signs and levels of the variables are equal, but $R^2$ decreases. Since the dependent variable is truncated between the lowest value (minus the largest sector) and the highest values, we also performed Tobit regressions. These regressions exhibit the same pattern and levels of significance as the reported linear regressions. In Appendix D we present the correlation matrix for the variables.

## F. Local Bias

One concern is that the excess holding in expertise stocks is a rediscovery of the local bias of individual investors documented by Zhu (2003) and Ivkovic & Weisbenner (2005). This could be the case, for example, if the excess holding in expertise stocks is predominantly associated with holding geographically close stocks.

Since we have data on where the investors live, we can estimate the extent of local bias in individuals' holdings. We define a stock as local if the company is headquartered within 100 kilometers of the individual. For each individual, we calculate the fraction of his portfolio invested in local stocks. We also calculate the fraction of the market within the same radius. The difference between these two measures represents our measure of local bias.

The average local bias is 13.0%. The correlation between excess holding in expertise stocks (as measured by $w_i^{corr}$) and local bias is close to zero, $-0.014$, and not statistically significant. After controlling for industry-specific experience, we see from Regression (4) in Table IV that the relation between local bias and expertise is still practically speaking zero. This suggests, interestingly, that excess holding in expertise stocks and excess holding in local stocks are independent phenomena.

# III. Abnormal Returns: Methodology

If holdings of expertise stocks were driven by value-relevant asymmetric information we would expect that those investments would generate abnormal returns. On the other hand, if expertise investments stem from individuals being overconfident about their industry knowledge, expertise investments would likely not earn positive abnormal returns.

There are three methodological issues when testing whether expertise trades are associated with an abnormal return. The first is that when calculating a test statistic, we need to compare the returns of expertise trades against an appropriate benchmark. The second is that cross-sectional dependence in portfolio returns across individuals, due to the number of individuals far exceeding the number of securities, makes distributional properties of test statistics difficult to evaluate. Test statistics that assume independence will produce excessive $t$-statistics, and are thus not employable. The third issue is whether the test statistics have sufficient power to detect abnormal returns, if present. There is no universal solution that deals with all these issues. We use suggested methods from the recent literature (see e.g., Kothari & Warner (2007) for a survey of recent methodological developments).

We analyze whether the returns of expertise buys exceeds that of three different benchmark returns: (i) the market returns, (ii) the returns to expertise stocks sold, as in Odean (1999), and (iii) the returns to non-expertise stocks. To accommodate differences in risk across these benchmarks, we use the four-factor model of Carhart (1997). In order to construct valid test statistics, we follow the recommendations of Lyon *et al.* (1999) and employ two different approaches; the calendar-time portfolio approach and a control-firm approach.

## A. Calendar-Time Portfolio Approach

The calendar-time portfolio approach eliminates the problem of cross-sectional dependence by bundling trades into an aggregate portfolio. For each calendar month $t$, we calculate the excess return on a portfolio with one position in each stock for each expertise buy (sale) during the portfolio formation period in that stock. The average holding period for both expertise and non-expertise stocks are about 300 days for those that sell within five years. We therefore consider portfolio formation periods of 4, 12, and 24 months prior to calendar month $t$. For example, under a 12 month portfolio formation period a particular expertise trade will be included in the expertise buy portfolio for the 12 consecutive months. A stock may have been purchased (sold) several times during the portfolio formation period. If so, each purchase generates a separate position in the expertise buy (sell) portfolio. Each position is weighed equally. In the same manner, we form and calculate returns for portfolios consisting of non-expertise buys and sells.

A critique of all methods that test for long-run abnormal returns, including the calendar-time portfolio approach, is the lack of power (e.g., Kothari & Warner (2007), Nekrasov *et al.* (2009)). One reason for the limited power of the calendar-time portfolio approach, in its standard implementation, is that different time periods are weighed equally even if they contain a different number of observations (see Loughran & Ritter (2000)). This aspect is particularly relevant in the current context, as the number of expertise trades vary considerably with time (see Appendix A). To increase power, we use a weighting scheme closely related to the suggestion by Fama (1998), and weigh each trade equally.

## B. Control-Firm Approach

The calendar-time portfolio approach updates positions monthly and may not capture investors earning an abnormal return on short-term pieces of information. In order to analyze this possibility, we use a variant of the control-firm approach analyzed by Barber & Lyon (1997). We test for abnormal returns by comparing the short-run buy-and-hold returns of expertise trades with a simulated distribution of short-term returns for fictitious trades in similar stocks. The returns are computed using prices at the end of the trading day.

We construct the distribution of returns for the fictitious trades in the following way. For each year, we start out by ranking all companies according to their market value at the end of the previous year. Within each size quartile, we split the companies into quartiles according to their market-to-book value evaluated at the end of the previous year. For each expertise trade, we randomly draw (with replacement) a security from the same size/market-to-book category, and evaluate the returns of the replacement security. Since expertise trades might reflect asymmetric information about industry prospects (rather than asymmetric information about specific stocks within the industry), we exclude securities from the same 2-digit industry when drawing a replacement security. Calculating the average returns across the fictitious trades in the randomly chosen replacement securities yields one observation from the empirical distribution. This procedure is repeated 1000 times.

To test the null hypothesis that the mean abnormal return is equal to zero, we use the 1,000 simulated return observations to approximate the empirical distribution of mean abnormal returns. This test is recommended in Lyon *et al.* (1999), listed as Alternative C on page 175. Under the assumption that the return distribution of the actual trades and the replacement trades are the same, we can test for abnormal returns in the following way.[8] The null hypothesis is that the returns of actual trades equals the mean return of the empirical distribution of returns. Under a two-sided test with $\alpha$ confidence level, the null hypothesis is rejected if the actual returns are lower than $(\frac{\alpha}{2})$ or exceed the $(\frac{1-\alpha}{2})$ percentile of the simulated return distribution. This approach answers the following question: how much would investors gain or lose if, instead of purchasing an expertise stock, they had randomly chosen a non-expertise stock with similar size and book-to-market characteristics?

## IV. Does Expertise Give Abnormal Returns?

The period covered in the returns analysis is January 1, 1996, to December 31, 2005. For each year, we define expertise trades via the employment status of the individual. For example, for an individual employed in the oil industry at the end of 1999, we define purchases of shares in oil companies in 2000 as expertise investments. Purchases of shares in companies outside the oil industry are defined as non-expertise investments. We use the workplace and list of subsidiaries per December 31, 1996, to identify expertise and own-company trades both in 1996 and in 1997. Our results are robust to dropping 1996. We report the results based on weighing each position equally. All our results are robust to using value-weighted positions.

The null hypothesis is that there is no abnormal return to expertise investments. We retain the null hypothesis if neither the calendar time nor the control firm analysis gives a significantly positive abnormal returns. The null hypothesis is rejected if one or both method yields abnormal returns, since this would suggest abnormal returns in either the short or long run. The case where the abnormal returns to expertise trades are positive but non-significant would warrant additional analysis. Throughout, we perform a two-sided test of the null hypothesis. In other words, we also analyze whether expertise investments yield *negative* abnormal returns. Prior work (e.g., Odean (1999)) have documented that individual investors do worse on their buys than sells, thus one might wonder if this is still true when investors trade stocks within their area of expertise.

## A. Calendar-Time Portfolio Analysis

[TABLE V ABOUT HERE]

In Panel A in Table V we report the mean excess return for the four calendar-time portfolios - Expertise Buys, $R_{b,e,t}$, Expertise Sells, $R_{s,e,t}$, Non-Expertise Buys, $R_{b,ne,t}$, and Non-Expertise Sells, $R_{s,ne,t}$ - and the excess return of the OSE. In this panel each time period is equally weighted.

In Panel B in Table V we first report the average monthly calender-time return of the Expertise Buys portfolio, $R_{b,e,t}$. In this panel, and for the rest of the analysis, each time period is weighed by the number of trades.

We test the null hypothesis that the mean value of $R_{b,e,t}$ is zero. To obtain our second performance measure, we regress the monthly return of the buy portfolio against the loading on specific types of risk. The time-series regression equation is:

$$R_{b,e,t} = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \varepsilon_t \tag{2}$$

where $RMRF$ is the excess return on the value-weighted aggregate market, and $SMB$, $HML$, and $MOM$ are returns on value-weighted, zero-investment, factor-mimicking portfolios for size, book-to-market equity, and momentum. The size and book-to-market factors are constructed following Fama & French (1993), and the momentum factor follows the approach of Carhart (1997). The factors for the Oslo Stock Exchange are calculated by Odegaard (2009). The intercept term ($\alpha$) provides our second performance measure. We test the null hypothesis that the mean value of $\alpha$ is zero. We use Newey-West standard errors. These standard errors account for time-series dependence of the portfolio returns.

The results provide no evidence that expertise buys are associated with abnormal long-run returns. All our point estimates of abnormal returns are negative, and in some cases statistically significant. For example, in Panel B we find that with a 1-year formation period, the expertise buy portfolio has a negative alpha at 44 basis points monthly or about five per cent yearly. The alpha is also negative for a 4-month and a 2-year formation period. Panel C provides the difference in returns between the expertise buy and the expertise sell portfolio, $(R_{b,e,t} - R_{s,e,t})$. With a 1-year formation period, the expertise buy portfolio gives 33 basis points monthly or about four per cent yearly, lower raw returns than the expertise sell portfolio. The difference between buy and sell is significantly *negative*. In risk-adjusted returns the difference is 14 basis points monthly in favor of the sell portfolio, which is statistically insignificant.

In Panel D we compare expertise buys and non-expertise buys, $(R_{b,e,t} - R_{b,ne,t})$. The raw and risk-adjusted expertise buy returns are statistically insignificant lower than the non-expertise buy returns. Finally, in Panel E, we find that an expertise long-short portfolio does not outperform a non-expertise long-short portfolio, $(R_{b,e,t} - R_{s,e,t}) - (R_{b,ne,t} - R_{s,ne,t})$. For a 1-year formation period the risk-adjusted difference is minus one per cent yearly, which is statistically insignificant. Overall, there is nothing that suggests that investors employed in an industry with a listed company can utilize their industry knowledge to earn an abnormal long-run return. All our point estimates of expertise buy abnormal returns are negative and in a few cases statistically significant.

## B. Control-Firm Analysis

To analyze whether industry expertise is associated with abnormal short-run returns, we first calculate the buy-and-hold returns of expertise trade $i$ on an $x$ trading days horizon as

$$r_{i,x} = (P_{i,d+x} - P_{i,d})/P_{i,d}, \tag{3}$$

where $P_{i,d}$ is the security price at the end of day of purchase, and $P_{i,d+x}$ is the security price after $x$ trading days. The mean return on $x$ trading days horizon, denoted by $m_x$, is computed as the average $r_{i,x}$ across all trades $i$. To test whether $m_x$ reflects excess returns we compare $m_x$ to the distribution of fictitious trades, using the bootstrapping procedure described in Section III.B, and report the average excess returns with p-values using a two-sided test.

[TABLE VI ABOUT HERE]

Panel A in Table VI depicts the mean excess returns for expertise buys versus the mean excess returns for fictitious non-expertise buys. On all horizons, expertise buys underperform relative to the fictitious buys. For example, fictitious buys outperform expertise buys by about 128 basis points on a 1-month horizon (21 trading days). The negative abnormal returns are statistically significant at the 1% level.

Panel B considers the difference between expertise buys and expertise sell return. The difference is again significantly negative at the 1% level on all horizons. For example, on a 1-month horizon, the difference is 60 basis points. We also compare expertise buys and non-expertise buys in Panel C and the expertise long-short portfolio and non-expertise long-short portfolio in Panel D. Overall, Table VI strongly suggests that expertise buys have short-run returns that are abnormally negative.

We note from Table VI that the fictitious expertise buy returns seem puzzlingly high on the very short horizons. Let us take the 1-week horizon as an example. From Panel A we see that fictitious buys yield 44 basis points, which is 41 basis points higher than the expertise buy returns. Part of the large difference is simply that expertise buy returns are low; the difference between fictitious expertise buy returns and actual non-expertise buy returns is a more modest 14 basis points.

It is still interesting to analyze what causes the relatively high fictitious buy returns. We first checked whether the high fictitious returns could be due to a timing effect. Using weights determined by the number of expertise buys (sells) on each date, we calculated the returns of the Oslo Børs Benchmark Index (OSEBX) if the expertise buys (sells) had been made $t$ weeks after the actual date, where $t$ ranges from 1 to 15 (4 months). For expertise buys the results were as follows. While the 1st week returns of the index equals 30 basis points, the average index returns over week 2-16 equals 26 basis points. 4 out of 15 observations of future index returns were higher than 30 basis points. An analysis of expertise sells gave the same conclusion. Based on this, we conclude that the high fictitious returns unlikely result from a general market timing effect. We then checked whether the high fictitious returns could be due to small stocks (which expertise buys disproportionally are made in) having a relatively high returns in our sample. We calculated the 1-week index returns over our sample period, by giving each stock and each date equal weights. The returns equal 30 basis points. This figure is still around 15 basis points below the returns of the fictitious buys. The difference of 15 basis points is due to a relatively high returns of small stocks on dates where expertise trades were made intensively, i.e., a timing effect specific to small stocks. To illustrate this point, when, within each year, we skip the days with more than median expertise buy activity from the returns calculations, the fictitious expertise buy 1st week returns drop to 32 basis points. Although small stocks experience relatively high returns following dates with high expertise buy activity (a similar finding is reported by Gervais *et al.* (2001) and Barber *et al.* (2009) using US data), the individual investors are not able to pick the small stocks that drive up the market through their expertise investments. We conclude that there is no evidence suggesting that individual investors can make a profit from their industry expertise. In fact we find that individual investors get abnormally low short-term returns from trading on such expertise.

In the calendar-time portfolio approach analysis, the estimated 4-month return using a 4-month build-up period equals -44 basis points, while the average 4-month returns in the control-firm analysis equals 59 basis points. This difference of 103 basis points, which corresponds to about three per cent yearly returns, seems puzzling. The explanation is quite straightforward. In the control-firm analysis we use the return from the end of the actual trade date, while we in the calendar-time portfolio analysis build up a portfolio over a period and use the returns of the following month. The sample period the two methods cover is therefore not exactly the same; compared to the calendar-time portfolio approach using a four month build-up period, the control-firm analysis has four extra months with returns data in the start of the sample period and three extra months at the end. The reason why the returns of the control-firm analysis are higher than the returns in the calendar-time portfolio analysis is that the stock market experienced an appreciation both at start and at the end of the period covered by the dataset. The average equal-weighted monthly return of OSE was 322 basis points during the seven months January-April 1996 and February-April 2006.[9]

# V. Further Analysis

Although expertise investments overall perform poorly, it is conceivable that subgroups of individuals can obtain a positive abnormal returns through such investments. In Section V.A. we analyze whether highly educated investors can obtain positive abnormal returns. In Section V.B., we focus on investors that live close to the headquarters of a listed company, similar to in Ivkovic & Weisbenner (2005). We then, in Section V.C., consider alternative behavioral interpretations of our findings.

We report the results from the calendar-time portfolio approach using a 12 month portfolio formation period. We have run the same regressions for different formation periods, with the same conclusions.

On a methodological note, the traditional calendar-time portfolio approach allows only a single binary investor characteristic (e.g., gender) to be incorporated in the analysis. We apply a method recently developed by Hoechle *et al.* (2009) to embed the calendar-time portfolio approach in a multivariate regression framework that enables us to include several and continuous investor characteristics (e.g., gender and income level).[10]

[TABLE VII ABOUT HERE]

For example, In Regression (2) in Table VII we find that the risk-adjusted return of expertise buys do not outperform the risk-adjusted return of expertise sells even if we control for the number of stocks in the investors' portfolio. In Regression (3), we only investigate trades performed by investors owning more than five stocks. We find that the risk-adjusted return of expertise buy portfolio significantly underperforms the risk-adjusted return of expertise sell portfolio. Generally we find that $t$-values increase if we include more variables in the regression. We find significantly negative abnormal returns of expertise buys in several specifications.

## A. Expertise and Education Level

We have defined professional proximity through the current workplace of an investor. Formal competence obtained through education could also play a role in producing excess returns. Most interestingly, work experience and education could be complements in the production of value-relevant information. To investigate this possibility, we analyze whether expertise investments are associated with abnormal returns for individuals with more than 16 years of education (so that we include individuals with an MSc or a Ph.D.).

Our conclusions are very similar to previous ones in the main analysis. In Regression (4) in Table VII, we find that the difference between the the risk-adjusted expertise buy and the risk-adjusted expertise sell portfolio is insignificant minus 16 basis points monthly. Appendix E reports the results of the control-firm analysis. The expertise buy returns significantly underperform the expertise sell returns.

We also tested whether more experience within an industry can be associated with an abnormal returns. To this end, we included industry experience as a control variable in the calendar time analysis, where industry experience is defined as the fraction of the last

7 years in which an individual was employed in the industry. The results are reported in Regression (9), where industry experience turns out positive but non-significant. The difference expertise buy and sell is still negative.

## B. Local Investments

It could be the case that the combination of professional and geographical proximity can give value-relevant information and abnormal returns. As in Section II.E., we define an investment to be local if the company has its headquarter within 100 kilometers of the individual's residence.

Our conclusions are very similar to those in the main analysis - all our point estimates of abnormal expertise buy returns are negative, and significantly so in the control-firm analysis. Regression (5) in Table VII shows that local expertise buys make insignificantly lower risk-adjusted returns than local expertise sells. The local expertise buys yield 19 basis points monthly or about two per cent yearly, lower risk-adjusted return than local expertise sells. Appendix F reports the results of the control-firm analysis. The expertise buy returns are significantly less than the expertise sell returns. The results do not suggest that geographical and professional proximity are complements in providing value-relevant information.

## C. Which Behavioral Bias is Driving our Results?

We have shown that in spite of their poor hedging properties, individuals extensively trade and hold professionally close stocks. They invest in assets that are more risky and - according to standard theory - should therefore obtain a higher return. Instead we find that professionally close investments yield a negative abnormal returns, which is statistically significant in the majority of specifications. It is difficult to reconcile this result with rational behavior. In this section we discuss two alternative behavioral explanations for our results; overconfidence and familiarity.

Investors being overconfident means that they overestimate the precision of their information about future returns of financial securities. In Odean (1998) such miscalibration leads to heterogeneity in investor opinion, which in turn causes them to trade.[11] It seems reasonable that the accuracy of information about industry prospects might be overrated by professionally-related investors, which leads them to trade excessively. Hence excess trading in expertise stocks is consistent with investor overconfidence.

Alternatively, individuals might prefer professionally close stocks because they are more familiar with, or simply aware of, these stocks from e.g., interaction at the workplace. For example, Huberman (2001) shows that shareholders of a Regional Bell Operating Company tend to live in the area which it serves, and Lee *et al.* (2008) show that a high fraction of employees in Taiwan voluntarily holds stocks in their own company. The familiarity hypothesis is also consistent with individuals choosing stocks that are in the same industry.

Our findings are consistent with both familiarity and overconfidence being the behavioral driver behind our results, and our study was not designed to distinguish these. One finding that seems more consistent with overconfidence is that investors make a negative short-run abnormal returns on expertise investments. We are not aware of why this should be a prediction from familiarity-based theory. Although we do not know of formal models of overconfidence that contain this feature, it does not seem unreasonable that professional investors would be able to exploit miscalibration of individual investors' beliefs in order to make a profit at their detriment.

## VI. Conclusion

A large literature considers how asymmetric information affects the pricing of financial assets, but little is known about the sources of asymmetric information. Individuals spend much of their time building and maintaining their professional career, and thus they gain a considerable amount of industry-specific experience. Therefore, we conjectured that professional proximity is a route in which individuals can have a comparative advantage in acquiring value-relevant information and obtain abnormal stock market returns. Professionally close investments is a particularly fitting environment to detect abnormal returns, following conventional portfolio theory, since investors should invest in professionally close investments only if they are informed.

To test whether industry expertise is associated with asymmetric information, we use an exceptionally detailed dataset from Norway which combines individual level sociodemographic data over a 20-year period and common stock transactions data over a 10-year period. Although professionally close stocks are more risky, we find no evidence that professional proximity is associated with abnormally high investment returns. On the longer horizons, all point estimates of abnormal returns are negative, and in some cases statistically significant. In the short run, all point estimates of abnormal returns are negative and statistically significant. These findings provide clear evidence of a behavioral bias in individuals' investment choices. Overconfidence seems to be the most likely explanation for why individuals trade in professionally close stocks.

Our results contribute to an ongoing debate on whether individual investors are able to acquire asymmetric information about future stock returns, and profit from it. The lack of any evidence of abnormal returns for a very plausible candidate suggests that individual investors are not able to profit from asymmetric information. This result might seem at odds with recent findings by Coval *et al.* (2005), Barber *et al.* (2009), Ivkovic *et al.* (2008) and Ivkovic & Weisbenner (2005). Arguably, our results only differ at a superficial level: only Barber *et al.* (2009) found that a group of individual investors consistently beat the market (when transaction costs are accounted for), and then only for a small number of investors.

Another take-home of our results is to provide guidance to individual investors themselves. Conventional portfolio theory recommends investors to shy away from professionally close stocks unless they have superior information, since such stocks carry extra risk. We find that investors have a preference for professionally close stocks even if such holdings generate negative abnormal returns. It seems plausible to us that individual investors themselves are not aware of their poor investment choices. Advice to avoid professionally close investments and investment products tailored to hedge against variations in labor income could provide an economic gain.

Third, while several studies have shown how the media (or the stock market itself) could attract the attention of investors (e.g., Barber & Odean (2008)), our work emphasizes the importance of communication in the workplace as a vehicle for attracting attention. Future work could look more into how the workplace interacts with other channels of communication in affecting investor choices.

Finally, while a zero abnormal return from expertise investments is what we would expect from investor overconfidence, it is puzzling that expertise investments make a negative abnormal return, particularly in the short run. To our knowledge no existing theory of overconfidence, such as Daniel *et al.* (1998), Gervais & Odean (2001), can explain this finding. Future theoretical work could gain from investigating this question.

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# Notes

[1]In the context of mutual fund managers, Cohen *et al.* (2008) document that such managers make an abnormal return on investments in companies they are connected to through their professional and social network. Kacperczyk *et al.* (2005) show that mutual funds that are concentrated in specific industries perform better than widely diversified mutual funds and attribute that difference to the skilled mutual fund managers' tendency to select their asset holdings from a limited number of industries, presumably because their expertise is linked to those industries.

[2]An interesting innovation in the mutual fund industry, the Marketocracy Masters 100 (MOFQX) gets its stock picks from the 100 best amateur investors that manage simulated stock portfolios. Investors are asked to buy and sell stocks in a virtual portfolio. The investors with the highest returns have many of their stock selections included in the MOFQX. Since its inception in 2001, the MOFQX has exceeded the $S\&P$ 500 by almost 1.5% in yearly raw returns.

[3]Familiarity would be an alternative behavioral explanation for the excess holding of professionally close stocks. Familiarity is discussed in Section V.C.

[4]A number of recent work on event-study methodology analyzes this method and closely related ones, see e.g., Lyon *et al.* (1999), Kothari & Warner (2007), and Nekrasov *et al.* (2009). For a similar application to the study of individual investors, see Odean (1999).

[5]The historical background for the large government ownership is partly that Statoil and Telenor were fully government owned prior to their IPOs in 2001 and 2000, and partly that the largest Norwegian banks, including Den norske Bank, were temporarily nationalized following the banking crisis in the early 1990s.

[6]Verdipapirsentralen (the Norwegian Central Securities Depository) is a centralized register where all common stock trades at the OSE are recorded. To preserve anonymity, the trade records of the 20 most active investors are not contained in the data.

[7]Every year throughout their lives, Norwegian households are subject to both a capital income tax and a wealth tax. In contrast, the U.S. tax system requires wealth reporting only in connection with estate tax,

which is only imposed on the very rich at the time of death (Campbell, 2006). Because of the existence of the wealth tax, Statistics Norway collects yearly data on wealth and income at the individual level from a variety of sources, including the Norwegian Tax Agency, welfare agencies, and the private sector. Financial institutions supply information to the tax agency on their customers' deposits, interest paid or received, and dividends. Employers similarly supply statements of wages paid to their employees.

[8]Excluding securities in the same industry from being replacement securities could make the distributional assumption problematic. The statistical analysis of Nekrasov *et al.* (2009) using U.S. securities data suggests that this is not a great concern, as the incremental value of matching on industry in addition to size and book-to-market in their data is marginal.

[9]We have also run the calendar-time portfolio analysis using a 1 month build-up period. For this time horizon the different periods covered by the two methods is a smaller issue, as the control-firm analysis has just one extra month in the start of the sample. The estimated 1-month returns using a 1-month build-up period in the calendar-time portfolio approach (not reported) equals 30 basis points, while the average 1-month returns in the control-firm analysis equals 43 basis points.

[10]The generalized calendar-time portfolio method of Hoechle *et al.* (2009) is achieved by pooled linear regression model with Driscoll & Kraay (1998) standard errors and extended with additional investor specific variables (see Equation (5) in Hoechle *et al.* (2009)). This model is similar to the structure of Ferson & Schadt (1996)'s conditional performance measurement model. In Regression (1) in Table VII we reproduce the risk-adjusted result from the traditional calendar-time portfolio method (see Table V, Panel C, 1 year formation period).

[11]This accords with Heath & Tversky (1991), who state that people are more willing to bet on their own judgments when they feel skillful or knowledgeable. Using survey data, Graham *et al.* (2009) find that investors who self-report being more competent about investment products tend to trade more frequently than investors who feel less competent.

# Tables

Table I: **Summary Statistics**

The table presents summary statistics for individuals holding stocks in Norway at the end of 2000. General work experience is the difference between age and age at end of education. Income is gross income less capital gains. Trades are number of trades performed in 2000. Turnover is the average of yearly sales and purchase turnover in 2000 (see definition in Barber & Odean (2000), footnote 8). Panel A presents summary statistics for individuals with employer belonging to a SIC-code with at least one company listed at OSE. We exclude individuals from Financial Services (SIC codes 65, 66, and 67). Panel B shows statistics for all individuals holding stocks. The value of the stock portfolio has to exceed NOK 5000 (≈ USD 600) at the end of 2000. The rate of exchange was 8.81 NOK/USD at the end of 2000.

**Panel A: Employed in industry with at least one listed company**

| | Mean | Std. Dev. | Median | 5% | 95% | N |
|---|---|---|---|---|---|---|
| Age | 44.0 | 11.4 | 44 | 26 | 62 | 93,865 |
| Length of education | 12.4 | 3.3 | 12 | 8 | 17 | 93,865 |
| General work experience | 18.4 | 9.9 | 19 | 3 | 30 | 91,917 |
| Income | 441,423 | 493,497 | 378,556 | 149,031 | 860,358 | 93,824 |
| Gross wealth | 1,416,491 | 17,404,070 | 528,893 | 81,320 | 3,538,673 | 93,824 |
| Value stock portfolio | 183,096 | 3,412,378 | 27,900 | 6,500 | 470,833 | 93,865 |
| Diversification (Number of stocks) | 2.2 | 2.5 | 1 | 1 | 6 | 93,865 |
| Number of trades | 6.4 | 26.6 | 1 | 0 | 28 | 93,865 |
| Yearly turnover (%) | 111.3 | 163.1 | 54.8 | 0 | 459 | 93,865 |

**Panel B: All investors**

| | Mean | Std. Dev. | Median | 5% | 95% | N |
|---|---|---|---|---|---|---|
| Age | 47.9 | 13.9 | 49 | 25 | 70 | 292,734 |
| Length of education | 12.2 | 3.3 | 12 | 7 | 17 | 292,734 |
| General work experience | 20.0 | 10.1 | 22 | 3 | 30 | 286,843 |
| Income | 357,218 | 456,244 | 304,774 | 59575 | 765,136 | 292,540 |
| Gross wealth | 1,166,740 | 14,125,580 | 482,926 | 43,197 | 2,993,014 | 292,540 |
| Value stock portfolio | 137,227 | 6,373,535 | 15,300 | 192 | 3,700,080 | 292,734 |
| Diversification (Number of stocks) | 2.0 | 2.4 | 1 | 1 | 6 | 292,734 |
| Number of trades | 4.3 | 23.1 | 0 | 0 | 17 | 292,734 |
| Yearly turnover (%) | 76.3 | 142.7 | 0 | 0 | 372 | 292,734 |

## Table II: **Excess Weight**

The table reports summary statistics for different measures of excess weight in expertise stocks at year-end for the period 1996-2005. A stock is defined as an expertise stock for an individual if it has the same SIC code as the employer of that individual at year-end. Panels A and B include three different measures of expertise bias. $w^{act}$ is defined as the average weight in expertise stocks across investors. $w^{corr,1}$ is equal to $w^{act}$ subtracted the average market weight of the industry, calculated as individual holdings in that industry relative to total individual holdings across all industries. $w^{corr,2}$ is equal to $w^{act}$ subtracted the average market weight of the industry, calculated as market capitalization of that industry relative to the market capitalization of the OSE. We describe results based on a five-digit mapping of SIC codes in addition to a two-digit mapping. The sample consists of individual-years where the individual has at least NOK 5000 in stock holdings and works in an industry with at least one listed company. We split the individuals into two groups; individuals that work in a private (non-listed) company and individuals that work in a public (listed) company. Individuals in subsidiaries of public companies are included in that group. Panel A includes holdings of previous and current company stocks, while in Panel B current and previous (10 years) employer and subsidiaries stocks are excluded.

| | | **Two-digit SIC** | | | | | **Five-digit SIC** |
|---|---|---|---|---|---|---|---|
| | Benchmark | Mean | Std. Dev. | Median | 5% | 95% | Mean |
| Panel A | | | **Not corrected for own-company stock** | | | | |
| | | | | **All** | | | |
| $w^{act}$ | | 0.316 | 0.444 | 0 | 0 | 1 | 0.428 |
| $w^{corr,1}$ | $w^{mkt,1}$ | 0.276 | 0.428 | -0.008 | -0.064 | 0.978 | 0.393 |
| $w^{corr,2}$ | $w^{mkt,2}$ | 0.268 | 0.414 | -0.022 | -0.057 | 0.987 | 0.386 |
| Number of unique ind. | = 211,314 | | Observations N = 894,511 | | | | N = 626,976 |
| | | | | **Private** | | | |
| $w^{act}$ | | 0.127 | 0.310 | 0 | 0 | 1 | 0.100 |
| $w^{corr,1}$ | $w^{mkt,1}$ | 0.096 | 0.302 | -0.016 | -0.069 | 0.951 | 0.083 |
| $w^{corr,2}$ | $w^{mkt,2}$ | 0.101 | 0.297 | -0.005 | -0.071 | 0.943 | 0.084 |
| Number of unique ind. | = 163,298 | | Observations N = 592,128 | | | | N = 291,830 |
| | | | | **Public** | | | |
| $w^{act}$ | | 0.687 | 0.433 | 1 | 0 | 1 | 0.713 |
| $w^{corr,1}$ | $w^{mkt,1}$ | 0.627 | 0.421 | 0.856 | -0.046 | 0.989 | 0.662 |
| $w^{corr,2}$ | $w^{mkt,2}$ | 0.597 | 0.413 | 0.804 | -0.038 | 0.996 | 0.650 |
| Number of unique ind. | = 81,293 | | Observations N = 302,383 | | | | N = 335,146 |
| Panel B | | | **Corrected for previous and current employer stock** | | | | |
| | | | | **All** | | | |
| $w^{act}$ | | 0.109 | 0.287 | 0 | 0 | 1 | 0.092 |
| $w^{corr,1}$ | $w^{mkt,1}$ | 0.074 | 0.278 | -0.015 | -0.089 | 0.917 | 0.064 |
| $w^{corr,2}$ | $w^{mkt,2}$ | 0.073 | 0.277 | -0.006 | -0.134 | 0.921 | 0.061 |
| Number of unique ind. | = 169,929 | | Observations N = 636,594 | | | | N = 378,603 |
| | | | | **Private** | | | |
| $w^{act}$ | | 0.093 | 0.266 | 0 | 0 | 1 | 0.072 |
| $w^{corr,1}$ | $w^{mkt,1}$ | 0.063 | 0.257 | -0.016 | -0.070 | 0.904 | 0.055 |
| $w^{corr,2}$ | $w^{mkt,2}$ | 0.068 | 0.255 | -0.006 | -0.074 | 0.874 | 0.055 |
| Number of unique ind. | = 148,081 | | Observations N = 523,858 | | | | N = 257,237 |
| | | | | **Public** | | | |
| $w^{act}$ | | 0.182 | 0.360 | 0 | 0 | 1 | 0.134 |
| $w^{corr,1}$ | $w^{mkt,1}$ | 0.122 | 0.355 | -0.023 | -0.125 | 0.954 | 0.084 |
| $w^{corr,2}$ | $w^{mkt,2}$ | 0.093 | 0.363 | -0.010 | -0.277 | 0.960 | 0.074 |
| Number of unique ind. | = 40,462 | | Observations N = 112,736 | | | | N = 121,366 |

Table III: **Excess Trading**

The table reports summary statistics for trading activity in expertise stocks for the period 1996-2005. A stock is defined as an expertise stock for an individual if it has the same SIC code as the employer of that individual at year-end. Panels A and B include two different measures of trading activity in expertise stocks. The fraction of all trades that an individual trades in expertise stocks during a year is denoted as $tr_i$. The second measure, $er$ is equal to the average of $tr$ subtracted the average weight in expertise stocks across investors $w^{act}$. Details about $w^{act}$ are reported in Table II. Panel A includes holdings of previous and current company stocks, while in Panel B current and previous (10 years) employer and subsidiaries stocks are excluded. In panel B we split the individuals into two groups; individuals that work in a private (non-listed) company and individuals that work in a public (listed) company. Individuals in subsidiaries of public companies are included in that group.

| | **Two-digit SIC** | | | | |
|---|---|---|---|---|---|
| | Mean | Std. Dev. | Median | 5% | 95% |
| Panel A | **Not corrected for own-company stock** | | | | |
| | **All** | | | | |
| $tr$ | .327 | .445 | 0 | 0 | 1 |
| Number of unique ind. = 263,258 | | | Observations N = 782,653 | | |
| $w^{act}$ | .316 | | | | |
| $et$ | .011 | | | | |
| Panel B | **Corrected for previous and current employer stock** | | | | |
| | **All** | | | | |
| $tr$ | .117 | .291 | 0 | 0 | 1 |
| Number of unique ind. = 220,011 | | | Observations N = 562,512 | | |
| $w^{act}$ | .109 | | | | |
| $et$ | .008 | | | | |
| | **Private** | | | | |
| $tr$ | .097 | .265 | 0 | 0 | 1 |
| Number of unique ind. = 193,622 | | | Observations N = 466,668 | | |
| $w^{act}$ | .093 | | | | |
| $et$ | .004 | | | | |
| | **Public** | | | | |
| $tr$ | .212 | .378 | 0 | 0 | 1 |
| Number of unique ind. = 46,090 | | | Observations N = 95,844 | | |
| $w^{act}$ | .182 | | | | |
| $et$ | .030 | | | | |

## Table IV: **Determinants of Preference for Expertise Stocks**

The table reports the results of pooled cross-sectional regressions of excess weight in expertise stocks, as measured by $w_i^{corr}$. Excess weight is defined as in Equation (1). Industry experience is defined as the percentage of the last seven years that the individual has worked in the industry. General work experience is defined as number of years since ended education. The part time dummy is equal to one if the individual works less than 30 hours per week, and zero otherwise. Unemployed is a dummy equal to one if the individual has been unemployed one or more months during the last year, and zero otherwise. Listed is a dummy equal to one if the individual works in a listed company or a daughter of a listed company, and zero otherwise. Portfolio diversification is the logarithm of the number of stocks held by the investor at the end of the year. Numbers of stocks in industry is the number of listed companies in the industry. The local bias measure is defined as the fraction invested in companies headquartered within 100 km of the individual subtracted the fraction of the market within the same radius. The second column (Mean) shows the mean across all those years, calculated before logarithmic transformations. The period covered is 1996 to 2005. Huber-White robust standard errors allow for clustering of errors by individuals. The *t*-statistics are reported in parenthesis.

| LHS variable: | Excess weight in expertise stocks, as measured by $w_i^{corr}$ | | | | |
|---|---|---|---|---|---|
| | Mean | (1) | (2) | (3) | (4) |
| Industry experience | .718 | .0125 | .0210 | .0202 | .0127 |
| | | (7.9) | (12.3) | (11.9) | (8.0) |
| General work experience | 19.51 | | -.0003 | -.0004 | |
| | | | (-5.2) | (-5.9) | |
| Length of education | 12.41 | | -.0009 | -.0007 | |
| | | | (-4.4) | (-3.4) | |
| Part-time dummy | 0.110 | | -.0110 | -.0097 | |
| | | | (-7.2) | (-6.3) | |
| Unemployed dummy | 0.031 | | -.0121 | -.0115 | |
| | | | (-6.0) | (-5.6) | |
| ln Income | 471,319 | | .0187 | .0194 | |
| | | | (20.8) | (21.6) | |
| ln Gross wealth | 1,653,992 | | -.0162 | -.0123 | |
| | | | (-29.2) | (-20.1) | |
| Female | 0.184 | | .0158 | .0127 | |
| | | | (9.0) | (7.3) | |
| Listed company | 0.177 | | -.0071 | -.0018 | |
| | | | (-3.8) | (1.0) | |
| ln Value stock portfolio | 192,808 | | | .0009 | |
| | | | | (1.7) | |
| ln Portfolio diversification | 2.72 | | | -.0260 | |
| | | | | (-28.8) | |
| Numbers of stocks in industry | 9.81 | | | .0060 | |
| | | | | (26.2) | |
| Local bias | | | | | -.0097 |
| | | | | | (-5.8) |
| ln Excess trading | | | | | |
| Intercept | | .1758 | .1829 | .1790 | .1783 |
| | | (18.1) | (18.9) | (18.6) | (18.3) |
| Year and industry dummies | | Yes | Yes | Yes | Yes |
| N | | 636,594 | 627,477 | 627,477 | 634,606 |
| N (clusters) | | 171,500 | 169,669 | 169,669 | 171,018 |
| $R^2$ | | .114 | .120 | .126 | .115 |

## Table V: **Returns, Calendar-Time Portfolio Analysis**

The table shows results for four different calendar-time portfolios: Buys/sells in expertise stocks and buys/sells in non-expertise stocks. The portfolio returns in month $t$ for the buy (sell) portfolio, $R_{b,t}$ ($R_{s,t}$), is based on building a portfolio with one position in a stock for each occurrence of a purchase (sale) by an investor. The portfolio formation periods are 4, 12, and 24 months preceding month $t$. Panel A reports the average monthly excess (returns minus the 1-month risk-free interest rate, $R_f$) calendar-time portfolio return for individuals that are employed in an industry with at least one listed company. The OSE column shows the excess market return of the Oslo Stock Exchange. In Panel A each time period is weighted equally. In Panel B-E each trade is weighted equally. Panel B shows the average monthly returns for the buy portfolio, $R_{b,t}$, measured in basis points. Panel C shows the difference in average monthly trade-weighted returns between the buy and the sell expertise portfolios, $R_{b-s,e,t}$, measured in basis points. Panel D show the difference in average monthly trade-weighted returns between the buy expertise and non-expertise portfolios, $R_{b-s,t}$, measured in basis points. Panel E shows the difference between the expertise long-short portfolio and the non-expertise long-short portfolio, ($R_{b-s,e,t} - R_{b-s,ne,t}$). Risk-adjusted returns, alpha, is defined as the constant from a regression weighted by trades of the portfolio returns on the same risk factors as used by Carhart (1997). The $t$- statistics are based on Newey-West standard errors and correct for heteroscedasticity and serial correlation of residuals. We use three lags. The period covered is 1996 to 2005. ***,**,* Significant at the 1-, 5-, and 10-percent level, two-sided test.

Panel A — **Average Monthly Returns (b.p.)**

| Holding Period | Expertise Buy | Expertise Sell | Non-Expertise Buy | Non-Expertise Sell | OSE Market-$R_f$ | N Months |
|---|---|---|---|---|---|---|
| 4 months | 39.1 | 50.5 | 55.7 | 58.2 | 73.0 | 116 |
| 1 year | 19.8 | 34.1 | 37.7 | 40.7 | 65.5 | 108 |
| 2 years | 14.6 | 26.2 | 18.3 | 18.6 | 47.1 | 96 |

Panel B — **Expertise Buys**

| Holding Period | Avg. Return (b.p.) | t-stat | Alpha (b.p) | t-stat | N Months |
|---|---|---|---|---|---|
| 4 months | -11.1 | -.08 | -71.4 | -1.13 | 116 |
| 1 year | -21.5 | -.16 | -44.1 | -.73 | 108 |
| 2 years | -1.0 | -.01 | -26.6 | -.48 | 96 |

Panel C — **Expertise Buys - Expertise Sells**

| Holding Period | Avg. Return (b.p.) | t-stat | Alpha (b.p) | t-stat | N Months |
|---|---|---|---|---|---|
| 4 months | -28.4* | -1.65 | -9.9 | -.82 | 116 |
| 1 year | -33.1** | -2.21 | -13.8 | -1.40 | 108 |
| 2 years | -22.7* | -1.72 | -13.4 | -1.46 | 96 |

Panel D — **Expertise Buys - Non-expertise Buys**

| Holding Period | Avg. Return (b.p.) | t-stat | Alpha (b.p) | t-stat | N Months |
|---|---|---|---|---|---|
| 4 months | -43.2 | -1.42 | -38.6* | -1.70 | 116 |
| 1 year | -28.5 | -1.16 | -14.2 | -.71 | 108 |
| 2 years | -20.5 | -.79 | -9.5 | -.48 | 96 |

Panel E — **(Expertise Buys - Expertise Sells)- (Non-expertise Buys - Non-expertise Sells)**

| Holding Period | Avg. Return (b.p.) | t-stat | Alpha (b.p) | t-stat | N Months |
|---|---|---|---|---|---|
| 4 months | -12.7 | -1.12 | -20.9* | -1.84 | 116 |
| 1 year | -10.5 | -1.26 | -8.9 | -1.12 | 108 |
| 2 years | -9.1 | -1.21 | -8.9 | -1.09 | 96 |

Table VI: **Returns, Control-Firm Analysis**

Average excess (returns minus the risk-free interest rate) returns in basis points are calculated for the 5, 10, 21, 42, and 84 trading days following purchases and sales in the dataset trades file. The fictitious benchmark consists of fictitious non-expertise trades from the same size/market-to-book category. Using a bootstrapped empirical distribution for the difference in returns following buys and following sells, the null hypothesis of zero difference in returns can be rejected with the given $p$-values. ***,**,* Significant at the 1-, 5-, and 10-percent level, two-sided test.

| | **Average Returns (b.p)** | | | | |
|---|---|---|---|---|---|
| | 1 week | 2 weeks | 4 weeks | 2 months | 4 months |
| Panel A | **Expertise Buys** | | | | |
| Expertise Buy | 2.8 | 20.7 | 42.5 | 52.4 | 59.3 |
| Fictitious (non-expertise) | 43.6 | 80.9 | 170.8 | 247.6 | 399.2 |
| Difference Buy- Fictitious | -40.8*** | -60.2*** | -128.3*** | -195.2*** | -339.9*** |
| $p$ | .00 | .00 | .00 | .00 | .00 |
| Panel B | **Expertise Buys - Expertise Sells** | | | | |
| Difference | -30.0*** | -44.1*** | -59.9*** | -39.7*** | -107.3*** |
| $p$ | .00 | .00 | .00 | .00 | .00 |
| Panel C | **Expertise Buys - Non-expertise Buys** | | | | |
| Difference | -27.3*** | -16.1*** | -42.7*** | -83.3*** | -173.7*** |
| $p$ | .00 | .00 | .00 | .00 | .00 |
| Panel D | **(Expertise Buys - Expertise Sells)- (Non-expertise Buys - Non-expertise Sells)** | | | | |
| Difference | -24.1*** | -22.6*** | -22.7*** | -27.3*** | -31.3 |
| $p$ | .00 | .00 | .00 | .00 | .10 |

## Table VII: **Multivariate Calendar Returns**

The table shows the coefficient estimates and $t$-values (in parentheses) from pooled OLS (trade-weighted) regressions with Driscoll-Kray standard errors. The table reports the monthly return in basis points. The regressions include all expertise buys and sells. The portfolio formation period is 12 months preceding month $t$. In Regression (3) only trades performed by investors holding more than five stocks are included. In Regression (4) only trades performed by investors with at least 16 years of education are included. A trade is defined as local if it is a trade in a company headquartered within 100 km of the individual. In Regression (5) only local trades are included. Portfolio diversification is the logarithm of the number of stocks held by the investor. Excess weight is measured by $w_i^{corr}$, defined in Equation (1). The individuals are grouped into three groups based on how large the excess weight in expertise stocks is. ln(trades+1) is defined as the logarithm of the number of trades during a year. Industry experience is defined as the percentage of the last seven years that the individual has worked in the industry. Risk-adjusted for the same factors as in Equation (2). Extra socio are the variables that are included in Table IV. ***,**,* Significant at the 1-, 5-, and 10-percent level, two-sided test.

| LHS variable: | | | | | Returns | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Trades | All | All | # stocks > 5 | Long educ | Local | All | All | All | All |
| Buy | -13.8 | -14.1 | -25.2** | -16.2 | -18.8 | -13.7 | -19.0* | -19.0* | -18.4* |
| | -1.40 | -1.42 | -2.12 | -1.53 | -1.60 | -1.41 | -1.89 | -1.82 | -1.85 |
| ln (Portfolio | | -4.8 | | | | | | 7.0 | -6.7 |
| Diversification) | | -.51 | | | | | | .51 | -.52 |
| Local | | | | | | -47.7 | | -45.4 | -38.3 |
| | | | | | | -1.19 | | -1.16 | -1.03 |
| Excess weight | | | | | | | | 7.1 | -25.6 |
| | | | | | | | | .17 | -.63 |
| ln (Trade+1) | | | | | | | -16.5 | -16.2 | -23.5 |
| | | | | | | | -1.27 | -1.04 | -1.42 |
| Industry experience | | | | | | | | | 58.8 |
| | | | | | | | | | 1.15 |
| Risk-adjusted? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Extra socio? | No | No | No | No | No | No | No | No | Yes |
| Constant | -30.3 | -30.9 | -31.0 | -10.0 | -55.0 | -10.0 | -26.8 | -9.8 | -93.1 |
| | -.50 | -.52 | -.58 | -.16 | -.74 | -.19 | -.45 | -.19 | -1.47 |
| Obs | 2,820,955 | 2,820,955 | 877,817 | 680,704 | 1,160,859 | 2,805,223 | 2,820,955 | 2,805,223 | 2,767,311 |
| $R^2$ | .236 | .237 | .240 | .245 | .266 | .244 | .238 | .247 | .248 |

# Internet Appendix to Do Individual Investors Have Asymmetric Information Based on Work Experience?*

Trond M. Døskeland and Hans K. Hvide

*Citation format: Trond M. Døskeland and Hans K. Hvide (201X), Internet Appendix to "Do Individual Investors Have Asymmetric Information Based on Work Experience?", Journal of Finance [vol #], [pages], http://www.afajof.org/IA/201X.asp. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the authors of the article.

This Internet Appendix includes additional material to the paper "Do Individual Investors Have Asymmetric Information Based on Work Experience?".

- **Appendix A: Summary Statistics for Transactions**
- **Appendix B: Excess Weight and Industries**
- **Appendix C: Excess Weight given more than one stock**
- **Appendix D: Correlation Matrix**
- **Appendix E: Education, Control-Firm Analysis**
- **Appendix F: Local trades, Control-Firm Analysis**

## Appendix A: Trades

Table AI: **Summary Statistics for Transactions**

The table reports summary statistics for the transactions of the sample. In Panel A we report the number of transaction for different calendar-time portfolios, while in Panel B we report the value of trades for the different calendar-time portfolios. The figures are reported in billion NOK.

| Panel A | **Number of Trades** | | | |
|---|---|---|---|---|
| Year | Expertise Trade | | Non-expertise Trade | |
| | Buy | Sell | Buy | Sell |
| 1996 | 5,730 | 4,136 | 73,649 | 57,618 |
| 1997 | 9,160 | 8,299 | 95,931 | 95,679 |
| 1998 | 7,889 | 5,656 | 79,685 | 72,101 |
| 1999 | 12,480 | 10,887 | 113,887 | 120,026 |
| 2000 | 23,209 | 19,896 | 233,303 | 221,158 |
| 2001 | 24,397 | 20,547 | 263,951 | 218,965 |
| 2002 | 18,281 | 14,145 | 203,541 | 168,648 |
| 2003 | 18,240 | 18,466 | 201,971 | 191,292 |
| 2004 | 23,106 | 20,328 | 270,785 | 249,943 |
| 2005 | 32,986 | 26,462 | 351,747 | 326,605 |
| Total | 175,478 | 148,822 | 1,888,440 | 1,722,035 |

| Panel B | **Value of Trades, NOK billion** | | | |
|---|---|---|---|---|
| Year | Expertise Trade | | Non-expertise Trade | |
| | Buy | Sell | Buy | Sell |
| 1996 | .5 | .6 | 8.3 | 8.5 |
| 1997 | .8 | 1.1 | 14.1 | 15.3 |
| 1998 | .8 | .8 | 9.2 | 9.6 |
| 1999 | 1.4 | 1.4 | 17.4 | 15.8 |
| 2000 | 2.6 | 2.3 | 28.1 | 29.1 |
| 2001 | 2.4 | 2.5 | 31.5 | 31.5 |
| 2002 | 1.6 | 1.5 | 19.9 | 19.7 |
| 2003 | 1.5 | 1.4 | 23.8 | 23.2 |
| 2004 | 2.5 | 2.5 | 38.4 | 39.0 |
| 2005 | 5.5 | 5.5 | 81.3 | 82.3 |
| Total | 19.6 | 19.4 | 272.6 | 273.3 |

# Appendix B: Excess Weight and Industries

Table AII: **Excess Weight and Industries**

The table reports average estimates for the excess weight in expertise stocks sorted by industries for 1996 to 2005. The industries are listed with SIC codes in parenthesis. The Companies column shows the average number of companies listed on the OSE within this sector. The benchmark $w^{mkt,1}$ represents the actual weight less the expertise sectors share of total equity owned by individual investors ($w^{mkt,1}$), and the benchmark $w^{mkt,2}$ measures the actual weight less the expertise sectors share of total outstanding equity. The next columns show the excess weight $w^{corr,1}$ for the different sectors. Own-company stock holdings by employees in listed and subsidiaries and holdings in previous employer for the last 10 years are excluded.

| Two-digit SIC code | Market | | | Bias | |
|---|---|---|---|---|---|
| | Companies | $w^{mkt,1}$ | $w^{mkt,2}$ | $w^{corr,1}$ | N |
| Fishing, fish farming, incl. services (5) | 2.7 | .018 | .004 | .167 | 3,490 |
| Oil and gas extraction, incl. serv. (11) | 25.0 | .124 | .221 | .138 | 42,886 |
| Mining of metal ores (13) | 1.6 | .004 | .001 | .022 | 330 |
| Food products and beverages (15) | 7.6 | .062 | .040 | .212 | 22,423 |
| Textile products (17) | 1.0 | .001 | .000 | .051 | 755 |
| Wood and wood products (20) | 3.5 | .013 | .015 | .208 | 6,679 |
| Pulp, paper and paper products (21) | 3.0 | .011 | .014 | .091 | 4,905 |
| Publishing, printing, reproduction (22) | 6.3 | .043 | .044 | .099 | 15,787 |
| Chemicals and chemical products (24) | 5.6 | .082 | .166 | .342 | 21,326 |
| Rubber and plastic products (25) | 1.0 | .004 | .001 | .013 | 810 |
| Other non-metallic mineral prod. (26) | 1.7 | .005 | .007 | .006 | 5,028 |
| Basic metals (27) | 4.4 | .050 | .108 | .005 | 10,963 |
| Fabricated metal products (28) | 1.3 | .004 | .001 | .021 | 8,799 |
| Machinery and equipment (29) | 9.5 | .040 | .018 | .058 | 15,998 |
| Office machinery and computers (30) | 1.5 | .004 | .001 | .076 | 859 |
| Electrical machinery and apparatus (31) | 3.9 | .010 | .004 | .021 | 5,652 |
| Radio, TV, communication equip (32) | 8.3 | .032 | .014 | .160 | 4,301 |
| Instruments, watches and clocks (33) | 6.3 | .012 | .006 | .020 | 5,459 |
| Motor vehicles, trailers, semi-tr.(34) | 1.6 | .001 | .001 | .010 | 1,707 |
| Other transport equipment (35) | 3.9 | .021 | .021 | .224 | 25,130 |
| Furniture, manufacturing (36) | 3.1 | .013 | .003 | .020 | 4,980 |
| Electricity, gas and water supply (40) | 3.1 | .006 | .007 | .032 | 12,793 |
| Water supply (41) | 1.0 | .001 | .000 | -.001 | 296 |
| Construction (45) | 2.8 | .018 | .003 | -.003 | 55,871 |
| Motor vehicle services (50) | 1.0 | .000 | .000 | -.000 | 1,243 |
| Wholesale trade, commision trade (51) | 14.9 | .035 | .012 | .025 | 68,385 |
| Retail trade, repair personal goods (52) | 5.1 | .017 | .006 | .009 | 44,314 |
| Hotels and restaurants (55) | 1.3 | .010 | .001 | -.009 | 13,666 |
| Land transport, pipeline transport (60) | 2.5 | .010 | .003 | .013 | 16,025 |
| Water transport (61) | 39.6 | .077 | .095 | .172 | 19,292 |
| Air transport (62) | 2.3 | .003 | .007 | .065 | 8,326 |
| Post and telecommunications (64) | 5.2 | .028 | .046 | .118 | 17,828 |
| Real estate activities (70) | 6.5 | .007 | .008 | .007 | 16,455 |
| Renting of machinery and equip. (71) | 1.0 | .004 | .002 | .017 | 832 |
| Computers and related activities (72) | 19.5 | .062 | .019 | .223 | 33,387 |
| Research and development (73) | 3.4 | .013 | .005 | .017 | 10,392 |
| Other business activities (74) | 9.0 | .020 | .007 | .007 | 96,519 |
| Cultural and sporting activities (92) | 2.1 | .003 | .001 | .005 | 12,703 |
| Total | | | | 0.074 | 636,594 |

Table  reports the means of actual weights, market weights, and deviations from market weights across industries, and shows that industry outliers do not drive our finding of an expertise bias. While our first measure of excess weight, $w_i^{act}$ is positively correlated with $w_i^{mkt}$, the second measure of bias, $w_i^{corr}$ is quite consistent across industries. Sector 74 (other business activities) picks up all the non-identifiable companies. The excess weight in this sector is almost equal zero. That suggests that there is no systematic bias in our results.

# Appendix C: Excess Weight given more than one stock

Table AIII: **Excess Weight given more than one stock**

The table reports summary statistics for different measures of excess weight in expertise stocks at year-end for the period 1996-2005. An investor has to hold more than one stock. A stock is defined as an expertise stock for an individual if it has the same SIC code as the employer of that individual at year-end. Panels A and B include three different measures of expertise bias. $w^{act}$ is defined as the average weight in expertise stocks across investors. $w^{corr,1}$ is equal to $w^{act}$ subtracted the average market weight of the industry, calculated as individual holdings in that industry relative to total individual holdings across all industries. $w^{corr,2}$ is equal to $w^{act}$ subtracted the average market weight of the industry, calculated as market capitalization of that industry relative to the market capitalization of the OSE. We describe results based on a five-digit mapping of SIC codes in addition to a two-digit mapping. The sample consists of individual-years where the individual has at least NOK 5000 in stock holdings and works in an industry with at least one listed company. We split the individuals into two groups; individuals that work in a private (non-listed) company and individuals that work in a public (listed) company. Individuals in subsidiaries of public companies are included in that group. Panel A includes holdings of previous and current company stocks, while in Panel B current and previous (10 years) employer and subsidiaries stocks are excluded.

| | | | **Two-digit SIC** | | | |
|---|---|---|---|---|---|---|
| | Benchmark | Mean | Std. Dev. | Median | 5% | 95% |
| Panel A | **Not corrected for own-company stock** | | | | | |
| | | | **All** | | | |
| $w^{act}$ | | .195 | .341 | 0 | 0 | .996 |
| $w^{corr,1}$ | $w^{mkt,1}$ | .152 | .314 | -.003 | -.074 | .891 |
| $w^{corr,2}$ | $w^{mkt,2}$ | .156 | .325 | -.011 | -.067 | .911 |
| Number of unique ind. = 111,589 | | | Observations N = 417,205 | | | |
| | | | **Private** | | | |
| $w^{act}$ | | .092 | .238 | 0 | 0 | .780 |
| $w^{corr,1}$ | $w^{mkt,1}$ | .066 | .224 | -.049 | -.072 | .689 |
| $w^{corr,2}$ | $w^{mkt,2}$ | .061 | .228 | -.016 | -.068 | .715 |
| Number of unique ind. = 90,071 | | | Observations N = 313,964 | | | |
| | | | **Public** | | | |
| $w^{act}$ | | .507 | .410 | .563 | 0 | 1 |
| $w^{corr,1}$ | $w^{mkt,1}$ | .416 | .392 | .440 | -.085 | .973 |
| $w^{corr,2}$ | $w^{mkt,2}$ | .446 | .398 | .490 | -.055 | .964 |
| Number of unique ind. = 33,726 | | | Observations N = 103,241 | | | |
| Panel B | **Corrected for previous and current employer stock** | | | | | |
| | | | **All** | | | |
| $w^{act}$ | | .100 | .257 | 0 | 0 | .904 |
| $w^{corr,1}$ | $w^{mkt,1}$ | .058 | .248 | -.006 | -.173 | .763 |
| $w^{corr,2}$ | $w^{mkt,2}$ | .062 | .248 | -.016 | -.099 | .822 |
| Number of unique ind. = 108,961 | | | Observations N = 388,576 | | | |
| | | | **Private** | | | |
| $w^{act}$ | | .082 | .225 | 0 | 0 | .706 |
| $w^{corr,1}$ | $w^{mkt,1}$ | .055 | .212 | -.005 | -.074 | .627 |
| $w^{corr,2}$ | $w^{mkt,2}$ | .051 | .215 | -.016 | -.069 | .644 |
| Number of unique ind. = 88,401 | | | Observations N = 295,666 | | | |
| | | | **Public** | | | |
| $w^{act}$ | | .160 | .334 | 0 | 0 | 1 |
| $w^{corr,1}$ | $w^{mkt,1}$ | .066 | .336 | -.012 | -.277 | .910 |
| $w^{corr,2}$ | $w^{mkt,2}$ | .098 | .329 | -.025 | -.125 | .917 |
| Number of unique ind. = 32,306 | | | Observations N = 92,910 | | | |

# Appendix D: Correlation Matrix

Table AIV: **Correlation Matrix**

The table shows the correlation matrix of the independent variables in Table 4 in the paper.

| **Variable** | **Correlation matrix** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $N=627,477$ | Ind.exp. | Gen. exp. | Educ. | Part | Unem. | Inc. | Wea. | Wo | List. | Sto. | Div. | N.ofS. |
| Industry experience | 1.00 | | | | | | | | | | | |
| General work experience | .327 | 1.00 | | | | | | | | | | |
| Length of Education | -.053 | -.193 | 1.00 | | | | | | | | | |
| Part-time dummy | -.108 | -.022 | -.101 | 1.00 | | | | | | | | |
| Unemployed | -.109 | -.046 | -.044 | .035 | 1.00 | | | | | | | |
| ln Income | .155 | .151 | .240 | -.388 | -.110 | 1.00 | | | | | | |
| ln Gross Wealth | .196 | .351 | .108 | -.102 | -.074 | .400 | 1.00 | | | | | |
| Female | -.028 | .011 | -.085 | .248 | .010 | -.273 | -.207 | 1.00 | | | | |
| Listed company | .031 | -.026 | .056 | -.104 | -.034 | .155 | -.037 | -.042 | 1.00 | | | |
| ln Value stock portfolio | .067 | .139 | .087 | -.026 | -.029 | .210 | .484 | -.091 | .095 | 1.00 | | |
| ln Portfolio Diversification | .038 | .056 | .097 | -.049 | -.021 | .163 | .280 | -.131 | .120 | .547 | 1.00 | |
| Numbers of stocks in industry | -.012 | -.023 | .096 | -.118 | -.030 | .216 | .045 | -.062 | .132 | .049 | .058 | 1.00 |

# Appendix E: Education, Control-Firm Analysis

Table AV: **Returns, Control-Firm Analysis**

Average excess (returns minus the risk-free interest rate) returns in basis points are calculated for the 5, 10, 21, 42, and 84 trading days following purchases and sales in the dataset trades file. Only trades performed by investors with more than 16 years of education are investigated. The fictitious benchmark consists of fictitious non-expertise trades from the same size/market-to-book category. Using a bootstrapped empirical distribution for the difference in returns following buys and following sells, the null hypothesis of zero difference in returns can be rejected with the given *p*-values. ***,**,* Significant at the 1-, 5-, and 10-percent level, two-sided test.

| | **Average Returns (b.p)** | | | | |
|---|---|---|---|---|---|
| | 1 week | 2 weeks | 4 weeks | 2 months | 4 months |
| Panel A | | | **Expertise Buys** | | |
| Expertise Buy | 33.7 | 58.5 | 118.1 | 88.4 | 64.1 |
| Fictitious (non-expertise) | 41.6 | 71.8 | 150.6 | 186.2 | 319.1 |
| Difference Buy- Fictitious | -7.9 | -13.3** | -32.5*** | -97.8*** | -255.0*** |
| *p* | .11 | .04 | .00 | .00 | .00 |
| Panel B | | | **Expertise Buys - Expertise Sells** | | |
| Difference | -15.2** | -29.6*** | -48.1*** | -67.1*** | -100.8*** |
| *p* | .03 | .00 | .00 | .00 | .00 |
| Panel C | | | **Expertise Buys - Non-expertise Buys** | | |
| Difference | -.8 | -1.9 | 3.4 | -30.8** | -76.3*** |
| *p* | .86 | .76 | .72 | .03 | .00 |
| Panel D | | | **(Expertise Buys - Expertise Sells)- (Non-expertise Buys - Non-expertise Sells)** | | |
| Difference | -10.5 | -17.0 | -24.6 | -45.6* | -58.9* |
| *p* | .17 | .10 | .11 | .06 | .06 |

# Appendix F: Local Trades, Control-Firm Analysis

Table AVI: **Returns, Control-Firm Analysis**

Average excess (returns minus the risk-free interest rate) returns in basis points are calculated for the 5, 10, 21, 42, and 84 trading days following purchases and sales in the dataset trades file. Only trades in a company that is headquartered within 100 kilometers of the residence of the investor are investigated. The fictitious benchmark consists of fictitious non-expertise trades from the same size/market-to-book category. Using a bootstrapped empirical distribution for the difference in returns following buys and following sells, the null hypothesis of zero difference in returns can be rejected with the given $p$-values. ***,**,* Significant at the 1-, 5-, and 10-percent level, two-sided test.

| | **Average Returns (b.p)** | | | | |
|---|---|---|---|---|---|
| | 1 week | 2 weeks | 4 weeks | 2 months | 4 months |
| Panel A | | | **Expertise Buys** | | |
| Expertise Buy | -12.7 | -30.5 | -53.9 | -219.2 | -503.0 |
| Fictitious (non-expertise) | 31.1 | 54.0 | 103.5 | 118.5 | 190.8 |
| Difference Buy- Fictitious | -43.8*** | -84.5*** | -157.4*** | -337.7*** | -693.8*** |
| $p$ | .00 | .00 | .00 | .00 | .00 |
| Panel B | | | **Expertise Buys - Expertise Sells** | | |
| Difference | -12.9*** | -29.0*** | -48.2*** | -79.0*** | -138.0*** |
| $p$ | .00 | .00 | .00 | .00 | .00 |
| Panel C | | | **Expertise Buys - Non-expertise Buys** | | |
| Difference | -.4 | .6 | -1.7 | -33.8*** | -87.5*** |
| $p$ | .90 | .89 | .80 | .00 | .00 |
| Panel D | | | **(Expertise Buys - Expertise Sells)- (Non-expertise Buys - Non-expertise Sells)** | | |
| Difference | -3.6 | -9.9 | -12.5* | -22.3 | -32.2 |
| $p$ | .43 | .13 | .18 | .08 | .11 |