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Which Past Returns Affect Trading Volume?

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Abstract

Anecdotal evidence and recent theoretical models argue that past stock returns affect subsequent stock trading volume. We study 3,000 individual investors over a 51 month period to test this prediction using linear panel regressions as well as negative binomial panel regressions and Logit panel regressions. We find that both past market returns as well as past portfolio returns affect trading activity of individual investors (as measured by stock portfolio turnover, the number of stock transactions, and the probability to trade stocks in a given month) and are thus able to confirm predictions of overconfidence models. However, contrary to intuition, the effect of market returns on subsequent trading volume is stronger for the whole group of investors. Using survey data of our investor sample, we present evidence that individual investors, on average, are unable to give a correct estimate of their own past realized stock portfolio performance. The correlation between return estimates and past realized returns is insignificant. For the subgroup of respondents, we are able to analyze the link between the ability to correctly estimate the past realized stock portfolio performance on the one hand and the dependence of trading volume on past returns on the other hand. We find that for the subgroup of investors that is better able to estimate the own past realized stock portfolio performance, the effect of past portfolio returns on trading volume is stronger. We argue that this finding might explain our results concerning the relation between past returns and subsequent trading volume.

Keywords: Individual Investors, Investor Behavior, Trading Volume, Stock Returns and Trading Volume, Overconfidence, Discount Broker, Online Broker, Online Banks, Panel Data, Count Data

JEL Classification Code: D8, G1

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Abstract

Anecdotal evidence and recent theoretical models argue that past stock returns affect subsequent stock trading volume. We study 3,000 individual investors over a 51 month period to test this prediction using linear panel regressions as well as negative binomial panel regressions and Logit panel regressions. We find that both past market returns as well as past portfolio returns affect trading activity of individual investors (as measured by stock portfolio turnover, the number of stock transactions, and the probability to trade stocks in a given month) and are thus able to confirm predictions of overconfidence models. However, contrary to intuition, the effect of market returns on subsequent trading volume is stronger for the whole group of investors. Using survey data of our investor sample, we present evidence that individual investors, on average, are unable to give a correct estimate of their own past realized stock portfolio performance. The correlation between return estimates and past realized returns is insignificant. For the subgroup of respondents, we are able to analyze the link between the ability to correctly estimate the past realized stock portfolio performance on the one hand and the dependence of trading volume on past returns on the other hand. We find that for the subgroup of investors that is better able to estimate the own past realized stock portfolio performance, the effect of past portfolio returns on trading volume is stronger. We argue that this finding might explain our results concerning the relation between past returns and subsequent trading volume.

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1 Introduction

Practitioners claim and anecdotal evidence suggests that past stock returns affect stock market trading volume. For example, a report from Deutsche Bank Research on the crisis of the German online brokerage market argues that "the declines in the equity markets have severely curbed the trading activities of these investors, eroding the online brokers' chief source of income."[1] Similarly, Deloitte & Touche's 2001 survey of online securities trading writes that "the decline in stock prices between Spring 2000 and Spring 2001 has led to slower growth of new online accounts and reduced trading volumes."[2]

The conjecture that past returns affect trading volume might be true, as Figures 1 and 2 suggest. These figures show the time series of the German market index DAX from January 1997 to March 2001 (end of month values) and the time series of the sum of stock transactions per month of a sample of individual investors from a German online broker.[3]

Why should past stock returns affect trading volume? Recently, theories have been proposed that are able to explain this link: High returns make investors overconfident and, as a consequence, these investors trade more subsequently.[4] However, these models are silent about the question *which* past returns affect trading volume: past stock market returns, past portfolio returns of individual investors, or both? Usually, only one risky asset is traded in theoretical models such that, in these models, past portfolio returns are

[1]Deutsche Bank Research, E-conomics, No. 26, April 19, 2002, www.dbresearch.com.

[2]Deloitte & Touche, Online Securities Trading 2001, www.deloitte.com.

[3]See Section 3 for details about the investor sample.

[4]See Section 2 for a discussion of overconfidence models.

equal to past market returns.[5] Figures 1 and 2 might be interpreted as evidence that past market returns affect the number of stock transactions of individual investors. Barber and Odean (2002) analyze a data set from a U.S. discount broker. They argue and find that high past portfolio returns induce individual investors to switch from phone-based to online trading. As a consequence, investors trade more subsequently. Statman, Thorley, and Vorkink (2004) find that market wide trading volume in the U.S. is related to past market returns. To summarize so far, empirical evidence suggests that *both* market returns and portfolio returns affect trading volume.[6]

The main goal of our study is to analyze the question *which* past returns affect trading volume of individual investors more comprehensively. Do past own stock portfolio returns or market returns have a stronger impact on the trading activity of investors? To do this, we study a panel data set of individual investors who have discount broker accounts over a 51 month period using various cross-sectional time-series regression models.

The results are useful for online brokers. As was discussed above, profits of online brokers are closely linked to the trading volume of investors. Thus, knowing how their customers behave and what the determinants of their trading activity are is necessary to, for example, optimize the online brokers' customer portfolio, the transaction fee structures, and the allocation of marketing expenditures.[7]

Our main results can be summarized as follows. Both past market returns as well as past portfolio returns affect trading activity of individual investors (as measured by stock portfolio turnover, the number of stock transactions, and the probability to trade stocks)

[5] See Section 2 for details.

[6] We present an in-depth discussion of these empirical studies in Section 3.

[7] See, for example, Zeithaml, Rust, and Lemon (2001) and Reinartz, Thomas, and Kumar (2005).

and are thus able to confirm predictions of overconfidence models. However, contrary to intuition, the effect of market returns on subsequent trading volume is stronger for the whole group of investors. Using survey data from our investor sample, we present evidence that individual investors, on average, are unable to give a correct estimate of their own past realized stock portfolio performance. The correlation between return estimates and past realized returns is negative but insignificant. For the subgroup of respondents, we are able to analyze the link between the ability to correctly estimate the past realized stock portfolio performance on the one hand and the dependence of trading volume on past returns on the other hand. We find that for the subgroup of investors that is better able to estimate the own past realized stock portfolio performance, the effect of past portfolio returns on trading volume is stronger. We argue that this finding might explain our results concerning the relation between past returns and subsequent trading volume. Furthermore, we support other studies that show that buy and sell transactions are driven by different factors.

Thus, the main contributions of our paper are:

- We present new tests of overconfidence models by analyzing a data set of individual investors using panel regression methodology,
- we are able to analyze *which* past returns affect trading volume, and
- we present an explanation based on an investor survey for the empirical finding that past market returns have a stronger impact on trading activity of individual investors compared to past portfolio returns.

The rest of the paper is organized as follows. The next section discusses related literature.

Section 3 describes our data set and the methodology we employ. Section 4 shows the results. Section 5 presents one interpretation of our results based on an investor survey. Section 6 analyzes whether our results are influenced by the investor's ability to correctly estimate the past realized stock portfolio performance. The last section discusses our results and concludes.

2 Related Literature

Why should past stock returns affect trading volume? In this section, we discuss overconfidence models that are able to explain this link more comprehensively.[8] These theories argue that high returns make investors overconfident and as a consequence these investors trade more subsequently. Daniel, Hirshleifer, and Subrahmanyam (1998) propose a model in which the degree of overconfidence, modeled as the degree of the underestimation of the variance of signals, is a function of past investment success. This modeling assumption is motivated by psychological studies that find biased self-attribution (see Wolosin, Sherman, and Till (1973), Langer and Roth (1975), Miller and Ross (1975), Schneider, Hastorf, and Ellsworth (1979)): People overestimate the degree to which they are responsible for their own success. Hirshleifer (2001) argues that "overconfidence and biased self-attribution are static and dynamic counterparts".[9] Benos (1998), Caballé and Sákovics (2003), Kyle and Wang (1997), Odean (1998b), and Wang (1998) incorporate this way of modeling overconfidence in different types of models such as those of Diamond and Verrecchia (1981), Hellwig (1980), Grossman and Stiglitz (1980), Kyle (1985), and Kyle (1989). These mod-

[8]For an in-depth discussion of various overconfidence models, their main predictions as well as several empirical tests of these models see Glaser, Nöth, and Weber (2004).

[9]Hirshleifer (2001), p. 1549.

els predict that overconfidence leads to high trading volume. Odean (1998b) calls this finding "the most robust effect of overconfidence". As long as past returns are a proxy for overconfidence, these models postulate a positive lead-lag relationship between past returns and trading volume. The intuition behind this link is as follows. High total market returns make (some) investors overconfident about the precision of their information. Investors mistakenly attribute gains in wealth to their ability to pick stocks. As a result they underestimate the variance of stock returns and trade more frequently in subsequent periods because of inappropriately tight error bounds around return forecasts.

Gervais and Odean (2001) analyze the link between past returns and trading volume more formally. They develop a multiperiod model in which traders learn about their ability. This learning process is affected by biased self-attribution. The investors in the model attribute past success to their own abilities which makes them overconfident. Accordingly, the degree of overconfidence dynamically changes over time. They predict that overconfidence is higher after market gains and lower after market losses. Gervais and Odean (2001) show that "greater overconfidence leads to higher trading volume" and that "this suggests that trading volume will be greater after market gains and lower after market losses".[10] However, it is important to note that Gervais and Odean (2001) analyze an economy in which only one risky asset is traded. Thus, in their model, the market return is identical to the portfolio returns of investors. Accordingly, the Gervais and Odean (2001) model makes no predictions about which past returns (market returns or portfolio returns) affect trading volume.[11]

[10] Gervais and Odean (2001), p. 2.

[11] There is, however, another interpretation. Although the price increases are market wide, investors mistakenly attribute gains in wealth to their ability to pick stocks. The implicit assumption behind this is that market returns and portfolio returns are correlated. This is true for our data set. The correlation is positive (0.4714) and highly significant (p-value of

Statman, Thorley, and Vorkink (2004) test the market trading volume prediction of formal overconfidence models using U.S. market level data. They find that market turnover, their measure of trading volume, is positively related to lagged market returns for months. Vector autoregressions and associated impulse response functions indicate that individual security turnover is positively related to lagged market returns as well as to lagged returns of the respective security. Kim and Nofsinger (2003) confirm these findings using Japanese market level data. They identify stocks with varying degrees of individual ownership to test the hypothesis and discover higher monthly turnover in stocks held by individual investors during the bull market in Japan. Barber and Odean (2002) test the prediction of overconfidence models using a data set from a U.S. discount broker. They analyze trading volume and performance of a group of 1,600 investors who switched from phone-based to online trading during the sample period. They find that those who switch to online trading perform well prior to going online and beat the market. Furthermore, they find that trading volume increases and performance decreases after going online. This finding is consistent with the prediction that high returns in the past make investors overconfident who, as a consequence, trade more subsequently. Barber and Odean (2002) thus conclude that "overconfident investors were more likely to go online and once online the illusion of control and the illusion of knowledge further increased their overconfidence. Overconfidence led them to trade actively...".[12]

Our study differs from the above mentioned papers in the following dimensions: We study a panel data set of individual investors using cross-sectional time-series regression models. Furthermore, we investigate whether market returns and portfolio returns have a different

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$p = 0.0000$) but far from perfect. See Section 3 for details.

[12] Barber and Odean (2002), p. 479.

impact on measures of trading activity and we are able to analyze which past returns have a stronger effect on volume. Moreover, we present an interpretation of our results using questionnaire data from our investor sample.

Furthermore, our study is part of the empirical literature that tests the prediction of overconfidence models that overconfidence leads to high trading volume by analyzing trading decisions of private investors. Odean (1999) analyzes trades of 10,000 individuals with U.S. discount brokerage accounts. He finds that these investors reduce their returns by trading and thus concludes that trading volume is excessive - a finding which is consistent with overconfidence models. Barber and Odean (2001) use gender as a proxy for overconfidence. In their paper, they summarize psychological studies that find a higher degree of overconfidence among men than among women. Thus, they partition their data set which consist of 35,000 households from a large discount brokerage house by means of gender and find that men trade more than women which is consistent with overconfidence models. Glaser and Weber (2004) measure various facets of overconfidence in a sample of online broker investors using a questionnaire. Thus, they are able to link measures of overconfidence and measures of trading volume for this group of individual investors. One finding of their study is that investors who think that they have above average investment skills (but who do not have above average returns) trade significantly more.

More generally, our paper is part of the literature on how trading activity is influenced by past price patterns. Odean (1998a) finds that investors show a strong preference for realizing winners rather that losers. This finding is called the disposition effect, the tendency to sell winners too early and ride losers too long.[13] Kumar and Dhar (2002) analyze

[13]See Shefrin and Statman (1985) and Weber and Camerer (1998) for further empirical and experimental evidence on the disposition effect.

the impact of price trends on trading decisions of individual investors and classify these investors as momentum or contrarian investors. Barber and Odean (2003) find that individual investors are more likely to be net buyers of attention-grabbing stocks (e.g. stocks with extreme positive or negative price movements) than institutional investors are. They find that investors tend to be net buyers of both the previous day's big winners and big losers. Barber, Odean, and Zhu (2003) find that individual investors buy and sell stocks with strong past returns. Grinblatt and Keloharju (2000) analyze the extent to which past returns determine the propensity to buy and sell. They find that foreign investors in Finland tend to be momentum investors whereas domestic individual investors tend to be contrarians. Grinblatt and Keloharju (2001) find that investors are reluctant to realize losses and that past returns and historical price patterns, such as being at a monthly high or low, affect trading. Huddart, Lang, and Yetman (2003) examine the relation between a stock's weekly trading volume and aspects of the stock's past price series. They document a substantial increase in volume when a stock trades above the highest or below the lowest price attained during a 52-week benchmark period ending 20 trading days before the current week.

3 Data Set and Methodology

This study is based on the combination of several data sets. The main data set consists of 563,104 buy and sell transactions as well as monthly portfolio positions of 3,079 individual investors from a German online broker in the period from January 1997 to mid April 2001. We consider all investors who trade via internet, had opened their account prior to January 1997, and had at least one transaction in 1997.[14] The second data set consists of demographic and other self-reported information (age, gender, income, investment strategy, investment experience), that was collected by the online broker at the time each investor opened her or his account. Data on the securities traded is obtained from Datastream, our third data source.

Table 1 presents descriptive statistics of the data set. The table shows descriptive statistics about age, the stock market investment experience (in years), the number of transactions in all security categories (sum over the period from January 1997 to mid April 2001), the number of stock transactions (sum over the period from January 1997 to mid April 2001), the number of warrant transactions (sum over the period from January 1997 to mid April 2001), the average of the monthly stock portfolio value (in EUR), the number of stocks in portfolio (time series average across investors), income (in EUR), the average of the monthly stock portfolio turnover from January 1997 to March 2001, the average of the monthly stock portfolio performance, the percentage of investors who describe their investment strategy as high-risk, the percentage of investors who use their account for retirement savings, and the percentage of female investors in our investor sample. The table contains means and medians of these variables as well as the number of observations of the respective variable. Income is reported within five ranges, where the top range is more than 102,258.38 EUR (200,000 Deutsche Mark (DEM)). We calculate means and medians using the midpoint of each range and 115,040.67 EUR (225,000 DEM) for the top range. Investment experience is reported within five ranges, where the top range is more than 15 years. We calculate means and medians using the midpoint of each range and 17.5

[14]See Glaser (2003) for descriptive statistics and further details. Not necessarily all orders are placed online but all investors traded via the internet at least once during our sample period. We consider all trades by these investors, i.e. we include the trades that were placed by telephone, for example.

years for the top range. Stock portfolio turnover in a given month is calculated as follows. We calculate the sum of the absolute values of purchases and sales per month for each investor and divide this sum by the respective end-of-month stock portfolio position. We calculate the monthly gross portfolio performance of each investor making the following simplifying assumptions. We assume that all stocks are bought and sold at the end of the month, and we ignore intra-month trading. Barber and Odean (2000) and Barber and Odean (2002) show that these simplifying assumptions do not bias the measurement of portfolio performance. The gross portfolio return R_{ht}^{gr} of investor h in month t is calculated as follows:

$$R_{ht}^{gr} = \sum_{i=1}^{S_{ht}} w_{iht} R_{it} \qquad \text{with} \qquad w_{iht} = \frac{P_{it} n_{iht}}{\sum_{i=1}^{S_{ht}} P_{it} n_{iht}} \tag{1}$$

R_{it} is the return of stock i in month t, S_{ht} is the number of stocks held by individual h in month t, P_{it} is the price of stock i at the beginning of month t, and n_{iht} is the number of stocks of company i held by investor h in month t. w_{iht} is the beginning-of-month-t market value of the holding of stock i of investor h divided by the beginning-of-month-t market value of the whole stock portfolio of investor h.

In Table 1, we exclude investors with less than 5 turnover observations to calculate the average of the monthly stock portfolio turnover and we exclude investors with stock positions in 12 or fewer months to calculate the average of monthly stock portfolio performance.

With the help of the year in which the account was opened, we are able to calculate the age and stock investment experience in our panel data set.[15] For example, the age of an investor who has opened an account in 1996 with an age of 39 is 41 years old in our panel

[15] 981 accounts were opened in 1994, 651 accounts were opened in 1995, and 1,447 accounts were opened in 1996.

data set in 1998.[16]

Our empirical model is specified as follows:

$$\text{Trading Activity}_{ht} = f(R^m_{t-1}, R^m_{t-2}, \ldots, R^m_{t-k}; R^p_{h,t-1}, R^p_{h,t-2}, \ldots, R^p_{h,t-j}; \mathbf{x}_h; \mathbf{y}_{ht}), \qquad (2)$$

with

- Trading Activity$_{ht}$: trading activity (i.e. stock portfolio turnover, number of stock transactions, probability to trade, number of stock purchases, number of stock sales) of investor h in month t.
- R^m_t: stock market return in month t.
- R^p_{ht}: stock portfolio return of investor h in month t.
- $\mathbf{x}_h$: control variables that vary across investors, but are constant for investor h over time (such as gender).
- $\mathbf{y}_{ht}$: control variables that vary across investors and over time (such as the stock portfolio value or age).

The separate analysis of buy and sell transactions is motivated as follows. There is evidence that buy and sell transactions are driven by different factors.[17] An investor who wants to buy a security has the choice between thousands of stocks whereas a sell decision only requires an analysis of the usually very few stocks in the investor's own portfolio (assuming that investors do not sell short). Furthermore, when investors buy a security

[16] The exact date of birth is unavailable.

[17] See, for example, Odean (1999), p. 1294, and Barber and Odean (2003).

they should consider the future performance of the stock they want to buy whereas they often consider past performance when they choose a security to sell as studies on the disposition effect show.[18] These studies suggest that there might be explanations for the decision to sell a stock, which are, for example, based on prospect theory (see Kahneman and Tversky (1979)). Another motivation is given by Coval, Hirshleifer, and Shumway (2002) who ignore all sales of shares in their study of performance persistence of individual investors. They argue that sales are often not strongly driven by specific analysis of or private information about the sold stock. Liquidity needs, or the reversing of a position taken long ago in order to diversify may motivate many sales. In contrast, they argue that the purchase of a particular stock is a relatively clear indication that the investor expects that stock to outperform the market. To summarize, dynamic overconfidence models predict that past returns make investors overconfident and that this overconfidence induces investors to trade. We therefore conjecture that the effect of overconfidence, i.e. the effect of past returns, is stronger when only buy transactions are considered due to the fact that, when selling a security the effect of overconfidence is mixed with a reference point dependent or liquidity based decision behavior of investors.

To analyze our data set we use linear panel regressions as well as negative binomial panel regressions and Logit panel regressions (see Greene (2003), Wooldridge (2002), Baltagi (2001), and Winkelmann (2003) for details). Nicolosi, Peng, and Zhu (2003) use an approach similar to ours. They investigate, among other things, whether security analysis ability, estimated from past trading experience, affects individual investors' future stock purchases. They run fixed-effect panel regressions of the number of purchases on several explanatory variables. They also include past portfolio performance and past market re-

[18] See Section 2.

turns as control variables. However, they only include one lag and focus on a different research question. Another related paper is the study of Grinblatt and Keloharju (2001). They analyze the determinants of the trading behavior of Finnish investors using Logit regressions. The dependent variable is a dummy variable that obtains the value of one when an investor sells a stock and zero when an investor does not sell a stock. They also include past return variables over various horizons. Besides past market returns they include, in contrast to our study, past market-adjusted stock returns. Thus, they are unable to measure the impact of past portfolio returns on the decision to sell. Another study that disentangles the influence of various past returns on measures of trading activity is the paper by Choe, Kho, and Stulz (1999). They analyze the impact of past market returns and past individual stock returns on order imbalance of stocks traded by various investor groups in Korea (see Choe, Kho, and Stulz (1999), Table 7). They do not include past portfolio returns in their regressions. Agnew (2005) analyzes how individuals react to market returns in one 401(k) plan using negative binomial regressions. She also includes several lagged market returns.

4 Past Returns and Trading Volume: Results

In this section we present the results on the relation between past returns and trading volume. We use several different trading volume measures. Subsection 4.1 presents the results on the relation between returns and turnover whereas Subsection 4.2 presents the results on the relation between returns and the number of stock transactions. Subsection 4.3 analyzes the relation between past returns and the probability to trade. Differences between buy and sell transactions are presented in Subsection 4.4. Subsection 4.5 discusses our robustness checks.

4.1 Past Returns and Stock Portfolio Turnover

Table 3 presents ordinary least squares regressions (regression (1)) as well as random (regression (2)) and fixed effects (regression (3)) panel regressions. Dependent variable is the logarithm of monthly stock portfolio turnover. Explanatory variables are stock market investment experience, a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (six lags). Section 3 and Table 2 present definitions of the variables. These explanatory variables are known to affect financial decision making.[19] We use the natural logarithm of the stock portfolio value and the trading volume measures as these variables are positively skewed. Tests show, that we thus avoid problems like non-normality, non-linearity, and heteroscedasticity in the regression analysis (see Spanos (1986), chapter 21, especially, pp. 455-456, Davidson and McKinnon (1993), chapter 14, and Atkinson (1985), pp. 80-81). We include the OLS regression results to obtain an initial idea about the effect of our explanatory variables on turnover. Note, however, that the OLS estimator does not take into account that various observations come from the same individual, i.e. the OLS estimator does not consider the correlation across different error terms. Thus, the t-values are misleading. However, the OLS estimates are unbiased if the influence of omitted variables is uncorrelated with the included explanatory variables.

The main finding of this table (regressions (2) and (3)) is that both past market returns

[19] See, e.g., Barber and Odean (2001), Dorn and Huberman (2002), Glaser (2003), or Grinblatt and Keloharju (2001).

and past portfolio returns are significantly positively related to turnover at four lags. However, the effect of past market returns is stronger. The coefficients and the t-values are higher. This result does not depend on whether we use random effects of fixed effects.

The high t-values are not surprising given the large number of observations. Grinblatt and Keloharju (2001) present an in-depth discussion about this point in their study that is related to ours. They argue that "isolated t-statistics of less than three ... are unimpressive, even though such t-statistics represent statistical significance at the 1 percent level".[20] Table 3 shows that all past portfolio return variables with a lag greater than one have t-values below three.

We also find that stock market investment experience and age have a positive effect on turnover. Perhaps surprising, the turnover values of men are lower than those of women. This contradicts the findings of Barber and Odean (2001) who find that men trade more than women. However, our results are consistent with other studies analyzing the behavior of investors such as Dorn and Huberman (2002), Glaser (2003), and Grinblatt and Keloharju (2001). These studies show the sign and the significance of the gender variable depends on the specification of the regression.

Warrant traders trade significantly more stocks (as measured by higher turnover values). The warrant trader dummy variable might be interpreted as a measure of investor sophistication. Investors who describe their investment strategy as high-risk have higher turnover values and investors who use their accounts for retirement savings have lower turnover values. The higher the stock portfolio value, the lower the stock portfolio turnover. Note, that all time-invariant variables are eliminated from the fixed effects model (regression

[20]See Section 3 and Grinblatt and Keloharju (2001), p. 598.

(3)). This is also true for the age variable as the difference between age and investment experience is a constant for each investor in our data set (see Section 3). The low number of observations is due to the fact that only 2,998 investors in our data set trade stocks. Furthermore, the self-reported age and investment experience variables are only available for 2,552 and 2,386 investors, respectively (see Table 1 for details). The omission of these two variables and the inclusion of the income variable do not alter our results concerning past returns and trading volume. Our results hold for different sets of explanatory variables (see Subsection 4.5 for details and further robustness checks).

In our data set, 61,399 monthly turnover observations have the value 0. Thus, these observations drop out when we calculate the logarithm of turnover. A widely used measure to avoid this problem is to transform turnover as the logarithm of (1 + turnover). Table 4 presents ordinary least squares regressions (regression (1)) as well as random (regression (2)) and fixed effects (regression (3)) panel regressions. The dependent variable is the logarithm of (1 + monthly stock portfolio turnover). The number of observations increases. Again, we find that both past market returns and past portfolio returns are significantly positively related to turnover. As in Table 3, the effect of past market returns seems to be stronger. Note, however, that the adjusted R-squared values drop dramatically when the logarithm of (1 + turnover) is used as dependent variable. One interpretation of this finding might be that it is easier to explain the variation in the amount of turnover in a given month for a given investor compared to the investor's decision to trade at all in a given month. This observation motivates our Logit analysis of the determinants of the probability to trade in Subsection 4.3.

4.2 Past Returns and the Number of Stock Transactions

Table 5 and Table 6 present ordinary least squares regressions (regression (1)) as well as random (regression (2)) and fixed effects (regression (3)) panel regressions. Dependent variables are the logarithm of the number of stock transactions and the logarithm of (1 + the number of stock transactions) in a given month, respectively. Explanatory variables are, again, stock market investment experience, a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (six lags). The results are similar to those presented in the last subsection with a few exceptions. Age is negatively related to the number of transactions and the stock portfolio value is positively related to the number of transactions. Again, both past market returns and past portfolio returns are significantly positively related to the number of transactions and the effect of past market returns is stronger. However, in Table 5, only the first lag of the past portfolio return is significantly positive. Furthermore, the coefficient of lag 6 of the market return is significantly negative. This finding is consistent with Statman, Thorley, and Vorkink (2004) who find that a market turnover response as well as a security turnover response to a market return shock is positive for the first 6 months and turns negative after month 6 (see Statman, Thorley, and Vorkink (2004), Figure 2, Panel b), and Figure 3, Panel b)). The results are also related to Grinblatt and Keloharju (2000) who find that returns more than six months in the past have very little effect on the buy ratios of investors.

As the number of stock transactions has only non negative integer values, count data models are appropriate to analyze the data set. As the number of stock transactions is overdispersed (the variance (32,523) exceeds the mean (105)), Poisson regression models are inappropriate. The reason is that Poisson regression models assume equality of conditional mean and variance. We thus use negative binomial regressions (regression (1)) as well as random (regression (2)) and fixed effects (regression (3)) negative binomial panel regressions in Table 7 (see, for example, Winkelmann (2003) for details). The dependent variable is the number of stock transactions in a given month. In the negative binomial regression model, which is obtained by introducing unobserved heterogeneity into the Poisson model, the negative binomial distribution provides the probability of the number of event occurrences (the number of transactions in our case). This distribution allows for overdispersion. The findings of Table 7 strengthen our previous results. Both past market returns as well as past portfolio returns affect trading volume but the effect for past market returns is stronger. Note, that in negative binomial fixed effects panel regressions, time-invariant variables do not drop out, as "random effects" and "fixed effects" refer to the distribution of the dispersion parameter (see, for example, Winkelmann (2003)).

4.3 Past Returns and the Probability to Trade

Table 8 presents Logit regressions (regression (1)) as well as random (regression (2)) and fixed effects (regression (3)) Logit panel regressions. The dependent variable is an indicator variable that takes the value 1 if the investor trades in a given month and 0 otherwise. Explanatory variables are, as in the previous subsections, stock market investment experience, a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (six lags). The results of this table strengthen our previous findings. Past market returns as well as past portfolio performance have a positive affect on the probability to trade and this effect is stronger for market returns (larger coefficients, higher t-values). The other explanatory variables have the expected sign. Like Grinblatt and Keloharju (2001), we also ran the less sensible OLS specification (linear probability model). The results are similar to those shown in Table 8.

4.4 Past Returns and Trading Volume: Purchases versus Sales

Tables 9, 10, 11, and 12 present the regression results of Subsections 4.2 and 4.3 separately for buy and sell transactions. The main result of thus subsection is: Past returns have different effects on buy and sell transactions whereas there are almost no differences in the impact of other variables on buy and sell transactions. We are thus able to confirm prior research (see Odean (1999) and Barber and Odean (2003)). For example, Table 9 shows that past portfolio returns have a *negative* influence on the logarithm of the number of sales (regressions (5) and (6)). Note, that this finding does not contradict the disposition effect, as we analyze the influence of portfolio returns on the sell decision and not the return of a specific security on the decision to sell this specific security. Tables 10, 11, and 12 show that only the last one or two lags of portfolio returns positively affect the sell decision whereas all six lag of past market returns positively influence buy transactions.

Tables 9, 10, 11, and 12 also show that the effect of past returns on buy transactions is stronger than their impact on sell transactions. We are thus able to confirm predictions of dynamic overconfidence models that the effect of overconfidence, i.e. the effect of past returns, is stronger when only buy transactions are considered.

4.5 Robustness Checks

In this subsection, we discuss various robustness checks. We find that our regression results are robust. They hold for different sets of explanatory results. Especially, the omission of the investment experience and the age variable (which increases the number of observations) and the inclusion of the income variable (which decreases the number of observations) do not alter our main results. Furthermore, we ran regressions with different lag lengths. Past returns with lags larger than 6 have no or even negative effects on trading volume. The use of lag length 6 can be motivated by the study of Statman, Thorley, and Vorkink (2004) who find that a market turnover response to a market return shock is positive for the first six months and turns negative after month 6, but is indistinguishable from 0 (see Figure 2, Panel b)) and by the study of Grinblatt and Keloharju (2000) who find that returns more than six months in the past have very little effect on the buy ratios of investors. We also use different market indexes to capture market returns. Using different proxies for the market return does not change our main findings. When we control for potential autocorrelation (e.g. by including lagged trading volume or by running fixed and random effects linear regressions with AR(1) disturbances), our primary results are similar.

5 Do Investors Know Their Past Portfolio Returns? Evidence From an Investor Survey

In this section, we present survey evidence on investors' ability to give an estimate of their own past realized stock portfolio performance. In August and September 2001, our investor sample received an email from the online broker with a link to an online questionnaire. 215 investor answered the questionnaire.[21] Glaser and Weber (2004) show that there is no indication of a sample selection bias.

Among other questions which belong to another project (see Glaser and Weber (2004)), we asked the investors to give an estimate of their portfolio performance in the past (from January 1997 to December 2000):

> *Please try to estimate your past performance of your stock portfolio at your online broker. Please estimate the return of your stock portfolio from January 1997 to December 2000:*
>
> *[Answer] percent per year on average.*

Table 13 presents the results. Only 210 of 215 investors who answered at least one question answered the question presented above. The investors think, on average, that their own realized stock portfolio performance from January 1997 to December 2000 was about 15 % per year. There is a large variation in the answers to this questions. The answers range from -50% to $+120\%$.

Figure 3 plots the realized portfolio returns versus return estimates of the individual investors who answered the questionnaire. The correlation coefficient between return estimates and realized returns is -0.0693 with a t-value of 0.3424. Why is there no correlation between realized portfolio returns and return estimates? One interpretation is that investors do not have a good understanding of the concept "return". Another explanation is the way the online broker presents returns. Usually, the online broker presents gains

[21] See Glaser and Weber (2005) for details about this questionnaire.

and losses (with the buying price as the reference point) for every stock in the portfolio separately which makes it difficult to estimate the monthly or yearly stock portfolio performance.

The results in this subsection might be related to the experimental literature that shows that individuals in general are poor at recalling price changes when compared to recalling prices. Andreassen (1988) finds in an experiment that errors recalling price changes were significantly larger than those made in recalling prices. He argues that subjects pay greater attention to prices than to price changes.

To summarize, the main result of this section is that investors are unable to give a correct estimate of their own past realized stock portfolio performance.

6 Past Returns and Trading Volume: Dependence on Ability to Correctly Estimate Past Realized Returns

In this section, we analyze whether our results are influenced by an investor's ability to correctly estimate the past realized stock portfolio performance that was discussed in the previous section.

Table 14 presents ordinary least squares regressions (regressions (1) and (4)) as well as random (regressions (2) and (5)) and fixed effects (regressions (3) and (6)) panel regressions. The dependent variable is the logarithm of monthly stock portfolio turnover. Explanatory variables are a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (two lags).[22]

We run the regressions for two subgroups of investors who answered the questionnaire. To create these groups we first calculate the absolute difference between the past realized stock portfolio performance and the return estimate. Group 1 contains the 50 % of investors with a difference between realized and estimated performance that is below the median of all respondents. Group 2 contains the 50 % of investors with a difference between realized and estimated performance that is above the median of all respondents.

The main (and intuitive) result is that the own past realized stock portfolio performance only significantly affects trading volume of investors who know their own past realized stock portfolio performance. For this subgroup, the effect of past portfolio performance is stronger than the effect of past market returns. Only for the subgroup of investors that does not know its past realized stock portfolio performance, past market returns remain significant.

7 Discussion and Conclusion

In this study, we analyze a panel data set of individual investors who have discount broker accounts over a 51 month period using cross-sectional time-series regression models to investigate the relationship between past returns and trading volume. We find that both past market returns and past portfolio returns affect trading volume of individual investors and are thus able to confirm predictions of overconfidence models. Contrary to intuition, the effect of market returns on subsequent trading volume is stronger for the

[22]We exclude investment experience and past portfolio returns with lags higher than two to increase the number of observations and the degrees of freedom.

whole group of investors. Using survey data from our investor sample, we present evidence that individual investors, on average, are unable to give a correct estimate of their own past realized stock portfolio performance. The correlation between return estimates and past realized returns is negative but insignificant. For the subgroup of respondents, we are able to analyze the link between the ability to correctly estimate the past realized stock portfolio performance on the one hand and the dependence of trading volume on past returns on the other hand. We find that for the subgroup of investors that is better able to estimate their own past realized stock portfolio performance, the effect of past portfolio returns on trading volume is stronger. We argue that this finding might explain our results concerning the relation between past returns and subsequent trading volume.

But why do past *market* returns predict trading volume of investors? This finding seems to be robust as other studies present similar results. Statman, Thorley, and Vorkink (2004) find that "not only does that impact of past market returns on a typical security's trading activity survive the inclusion of lagged security returns in the same regression, it appears that the lagged market return impact is actually larger" (Statman, Thorley, and Vorkink (2004), p. 22). Nicolosi, Peng, and Zhu (2003) also find in their regressions that the impact of past market returns on stock purchases is stronger than the effect of past portfolio returns (see Nicolosi, Peng, and Zhu (2003), Table 2). Choe, Kho, and Stulz (1999) find that past market returns affect the order imbalance of stocks traded by individual investors in Korea.

One explanation of why past market returns should affect trading activity is that high past market returns might increase differences of opinion. Theoretically, differences of opinion can arise due to differences in prior beliefs or due to differences in the way investors interpret public information. Modeling differences of opinion is mainly motivated by mere plausibility: differences of opinion are present in every day life (see, for example, Harris and Raviv (1993)). Varian (1989), Harris and Raviv (1993), and Kandel and Person (1995) show that differences of opinion help explain high levels of trading volume and that a higher degree of differences of opinion leads to a higher degree of trading volume. There are studies which show empirically that differences in opinion creates trading volume. Bamber, Barron, and Stober (1999) and Antweiler and Frank (2004) are two examples. Bamber, Barron, and Stober (1999) measure differential interpretations using data on analysts' revisions of forecasts of annual earnings after the announcement of quarterly earnings. They find that differential interpretations explain a significant amount of trading. Antweiler and Frank (2004) study the effect of more than 1.5 million messages posted on Yahoo! Finance and Raging Bull about the 45 companies in the Dow Jones Industrial Average and the Dow Jones Internet Index. They find that disagreement among the posted Internet messages is associated with increased trading volume.

In their survey of CFO stock return expectations, Graham and Harvey (2003) show that past market returns are related to differences of opinion. High past (absolute) returns lead to higher differences of opinion.[23] This result helps to explain why we find that high past market returns lead to high trading volume.

Another explanation might be that investors act "as if" they know past market returns. Barber and Odean (2003) analyze buying behavior of individual investors and find that investors buy attention-grabbing stocks, for example stocks that exhibit high trading

[23] Although Graham and Harvey (2003) find that both large negative and positive returns affect differences of opinion, we argue that negative returns that are associated with differences of opinion do not lead to the same level of trading activity as positive returns in connection with differences of opinion. Negative returns are associated with paper losses and investors usually are reluctant to realize these paper losses. See Shefrin and Statman (1985), Odean (1998a), and Weber and Camerer (1998).

volume. They argue that (among other things) abnormal trading volume serves as a proxy for an unobserved attention-grabbing event. However, they are not claiming that investors pay attention to a stock because of its trading volume. However, an unusually high trading volume might be an indicator that investors are paying attention to the stock. A similar mechanism might be at work in the case of past market returns and subsequent trading activity.

Future research should further investigate explanations for the stylized fact that past market returns affect trading volume of investors.

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Table 1: **Descriptive Statistics of Investor Sample**

This table shows descriptive statistics about age, the stock market investment experience (in years), the number of transactions in all security categories (sum over the period from January 1997 to mid April 2001), the number of stock transactions (sum over the period from January 1997 to mid April 2001), the number of warrant transactions (sum over the period from January 1997 to mid April 2001), the average of the monthly stock portfolio value (in EUR), the number of stocks in portfolio (time series average across investors), income (in EUR), the average of the monthly stock portfolio turnover from January 1997 to March 2001, the average of the monthly stock portfolio performance (see Section 3 for details), the percentage of investors who describe their investment strategy as high-risk, the percentage of investors who use their account for retirement savings, and the percentage of female investors in our investor sample. The table contains means and medians of these variables as well as the number of observations of the respective variable. Income is reported within five ranges, where the top range is more than 102,258.38 EUR (200,000 Deutsche Mark (DEM)). We calculate means and medians using the midpoint of each range and 115,040.67 EUR (225,000 DEM) for the top range. Investment experience is reported within five ranges, where the top range is more than 15 years. We calculate means and medians using the midpoint of each range and 17.5 years for the top range. We exclude investors with less than 5 turnover observations to calculate the average of the monthly stock portfolio turnover and we exclude investors with stock positions in 12 or fewer months to calculate the average of the monthly stock portfolio performance.

No. of accounts		3,079
Age	Mean	40.86
	Median	39
	Observations	2,552
Investment experience	Mean	5.50
	Median	7.5
	Observations	2,386
Transactions	Mean	182.89
	Median	103
	Observations	3,079
Stock transactions	Mean	105.45
	Median	54
	Observations	2,998
Warrant transactions	Mean	87.60
	Median	27
	Observations	1,650
Stock portfolio value (EUR)	Mean	36,622.87
	Median	15,679.79
	Observations	2,964
Number of stocks in portfolio	Mean	6.76
	Median	5.17
	Observations	2,964
Income (EUR)	Mean	52,149.05
	Median	38,346.89
	Observations	1,128
Stock portfolio turnover	Mean	1.36
	Median	0.33
	Observations	2,874
Stock portfolio performance	Mean	0.0054
	Median	0.0057
	Observations	2,793
High risk investment strategy	%	12.02
Retirement savings	%	3.73
Female investors	%	4.81

Table 2: **Definition of Variables**

This table summarizes and defines dependent and independent variables of the regression analysis in this paper and presents their respective data source.

Variables	Data source	Description
Investment experience	Self-reported data collected by the online broker at the time each investor opened the account.	Stock market investment experience in years.
Gender (dummy)	Self-reported data collected by the online broker at the time each investor opened the account.	Dummy variable that takes the value 1 if the investor is male.
Age	Self-reported data collected by the online broker at the time each investor opened the account.	Age of investor.
Retirement saving (dummy)	Self-reported data collected by the online broker at the time each investor opened the account.	Dummy variable that takes the value 1 if the account is used for retirement savings.
High risk (dummy)	Self-reported data collected by the online broker at the time each investor opened the account.	Dummy variable that takes the value 1 if the investment strategy is characterized as high risk.
Warrant trader (dummy)	Transaction and portfolio data	Dummy variable that switches to the value 1 if the investor trades warrants for the first time (in a given month) in the period form January 1997 to March 2001.
Number of stock transactions	Transaction and portfolio data	Number of stock transactions (Sum in a given month).
Turnover	Transaction and portfolio data	Stock portfolio turnover in a given month.
Stock portfolio value	Transaction and portfolio data	Stock portfolio value in a given month.
Portfolio return	Transaction and portfolio data	Stock portfolio performance in a given month.
Market Return	Datastream	Return of the German market index DAX in a given month.

Table 3: **Past Returns and Turnover**

This table presents ordinary least squares regressions (regression (1)) as well as random (regression (2)) and fixed effects (regression (3)) panel regressions. Dependent variable is the logarithm of monthly stock portfolio turnover. Explanatory variables are stock market investment experience, a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (six lags). Absolute value of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

Dependent variable	ln(stock portfolio turnover)		
	Ordinary least squares (1)	Random effects (2)	Fixed effects (3)
Investment experience	0.004	0.015	0.074
	(1.55)	(3.08)***	(9.17)***
Gender (dummy; men=1)	-0.215	-0.200	
	(5.29)***	(1.99)**	
Age	0.006	0.013	
	(7.13)***	(6.30)***	
Warrant trader (dummy)	0.297	0.197	0.135
	(18.45)***	(7.40)***	(3.85)***
High risk strategy (dummy)	0.068	0.109	
	(3.14)***	(2.01)**	
Retirement savings (dummy)	-0.448	-0.441	
	(11.46)***	(4.79)***	
ln(stock portfolio value)	-0.487	-0.651	-0.739
	(84.92)***	(83.36)***	(77.20)***
Market return (lag 1)	1.157	1.115	1.107
	(8.79)***	(9.96)***	(9.88)***
Market return (lag 2)	0.419	0.446	0.430
	(3.15)***	(3.94)***	(3.80)***
Market return (lag 3)	0.918	1.017	1.002
	(6.78)***	(8.84)***	(8.71)***
Market return (lag 4)	0.610	0.719	0.740
	(4.59)***	(6.36)***	(6.55)***
Market return (lag 5)	-0.256	-0.148	-0.060
	(1.93)*	(1.31)	(0.52)
Market return (lag 6)	0.130	0.121	0.190
	(0.97)	(1.06)	(1.65)*
Portfolio return (lag 1)	0.545	0.533	0.568
	(8.12)***	(9.26)***	(9.84)***
Portfolio return (lag 2)	0.082	0.116	0.155
	(1.20)	(1.96)*	(2.61)***
Portfolio return (lag 3)	0.133	0.120	0.153
	(1.90)*	(2.00)**	(2.54)**
Portfolio return (lag 4)	0.127	0.144	0.172
	(1.80)*	(2.39)**	(2.86)***
Portfolio return (lag 5)	-0.068	-0.051	-0.040
	(0.98)	(0.86)	(0.68)
Portfolio return (lag 6)	0.078	0.078	0.104
	(1.11)	(1.29)	(1.72)*
Constant	3.445	4.580	
	(47.81)***	(32.76)***	
Observations	34,410	34,410	34,410
Groups		1,817	1,817
(Adjusted) R-squared overall	0.2077	0.2042	0.1895
R-squared within		0.1948	0.1957
R-squared between		0.3581	0.3315

Table 4: **Past Returns and Turnover**

This table presents ordinary least squares regressions (regression (1)) as well as random (regression (2)) and fixed effects (regression (3)) panel regressions. Dependent variable is the logarithm of (1 + monthly stock portfolio turnover). Explanatory variables are stock market investment experience, a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (six lags). Absolute value of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

Dependent variable	ln(1+ stock portfolio turnover)		
	Ordinary least squares (1)	Random effects (2)	Fixed effects (3)
Investment experience	0.003	0.018	0.047
	(6.14)***	(13.38)***	(24.82)***
Gender (dummy; men=1)	-0.044	-0.053	
	(4.73)***	(1.75)*	
Age	0.0004	0.003	
	(1.94)*	(4.64)***	
Warrant trader (dummy)	0.104	0.099	0.073
	(27.52)***	(14.09)***	(8.41)***
High risk strategy (dummy)	0.043	0.043	
	(8.01)***	(2.64)***	
Retirement savings (dummy)	-0.092	-0.096	
	(10.76)***	(3.49)***	
ln(stock portfolio value)	-0.044	-0.092	-0.119
	(35.66)***	(49.73)***	(55.46)***
Market return (lag 1)	0.309	0.280	0.287
	(10.13)***	(10.45)***	(10.72)***
Market return (lag 2)	0.150	0.119	0.120
	(4.86)***	(4.39)***	(4.43)***
Market return (lag 3)	0.308	0.282	0.278
	(9.92)***	(10.33)***	(10.23)***
Market return (lag 4)	0.160	0.142	0.157
	(5.28)***	(5.33)***	(5.86)***
Market return (lag 5)	0.005	0.015	0.070
	(0.15)	(0.55)	(2.58)***
Market return (lag 6)	-0.050	-0.032	0.019
	(1.63)	(1.19)	(0.70)
Portfolio return (lag 1)	0.153	0.174	0.191
	(9.62)***	(12.39)***	(13.57)***
Portfolio return (lag 2)	0.060	0.079	0.091
	(3.71)***	(5.55)***	(6.37)***
Portfolio return (lag 3)	0.042	0.067	0.082
	(2.58)***	(4.65)***	(5.69)***
Portfolio return (lag 4)	0.025	0.046	0.056
	(1.59)	(3.26)***	(4.03)***
Portfolio return (lag 5)	0.037	0.047	0.050
	(2.31)**	(3.37)***	(3.59)***
Portfolio return (lag 6)	0.010	0.017	0.023
	(0.67)	(1.22)	(1.68)*
Constant	0.605	0.837	
	(38.37)***	(20.89)***	
Observations	63,925	63,925	63,925
Groups		1,853	1,853
(Adjusted) R-squared overall	0.0479	0.0386	0.0231
R-squared within		0.0581	0.0607
R-squared between		0.0385	0.0165

Table 5: **Past Returns and Stock Transactions**

This table presents ordinary least squares regressions (regression (1)) as well as random (regression (2)) and fixed effects (regression (3)) panel regressions. Dependent variable is the logarithm of the number of stock transactions in a given month. Explanatory variables are stock market investment experience, a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (six lags). Absolute value of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

Dependent variable	ln(number of stock transactions)		
	Ordinary least squares (1)	Random effects (2)	Fixed effects (3)
Investment experience	0.010	0.034	0.098
	(7.08)***	(11.54)***	(19.79)***
Gender (dummy; men=1)	-0.112	-0.074	
	(4.37)***	(1.19)	
Age	-0.003	-0.003	
	(5.45)***	(2.21)**	
Warrant trader (dummy)	0.273	0.230	0.122
	(26.99)***	(13.92)***	(5.64)***
High risk strategy (dummy)	0.083	0.114	
	(6.03)***	(3.38)***	
Retirement savings (dummy)	-0.192	-0.138	
	(7.83)***	(2.41)**	
ln(stock portfolio value)	0.168	0.168	0.139
	(47.02)***	(35.01)***	(23.68)***
Market return (lag 1)	0.478	0.604	0.670
	(5.80)***	(8.77)***	(9.73)***
Market return (lag 2)	0.057	0.159	0.183
	(0.68)	(2.29)**	(2.64)***
Market return (lag 3)	0.292	0.449	0.467
	(3.45)***	(6.34)***	(6.61)***
Market return (lag 4)	0.030	0.169	0.235
	(0.37)	(2.43)**	(3.38)***
Market return (lag 5)	0.003	0.124	0.281
	(0.04)	(1.77)*	(3.99)***
Market return (lag 6)	-0.403	-0.341	-0.197
	(4.78)***	(4.85)***	(2.79)***
Portfolio return (lag 1)	0.065	0.080	0.106
	(1.53)	(2.25)**	(2.98)***
Portfolio return (lag 2)	-0.037	-0.017	-0.001
	(0.86)	(0.47)	(0.04)
Portfolio return (lag 3)	-0.022	-0.023	-0.004
	(0.49)	(0.63)	(0.12)
Portfolio return (lag 4)	-0.008	-0.016	-0.011
	(0.18)	(0.44)	(0.30)
Portfolio return (lag 5)	-0.058	-0.050	-0.059
	(1.35)	(1.37)	(1.60)
Portfolio return (lag 6)	-0.017	-0.021	-0.018
	(0.39)	(0.55)	(0.48)
Constant	-0.598	-0.969	
	(13.21)***	(11.16)***	
Observations	36,130	36,130	36,130
Groups		1,819	1,819
(Adjusted) R-squared overall	0.0889	0.0818	0.0399
R-squared within		0.0622	0.0670
R-squared between		0.1445	0.0507

Table 6: **Past Returns and Stock Transactions**

This table presents ordinary least squares regressions (regression (1)) as well as random (regression (2)) and fixed effects (regression (3)) panel regressions. Dependent variable is the logarithm of (1 + the number of stock transactions) in a given month. Explanatory variables are stock market investment experience, a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (six lags). Absolute value of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

Dependent variable	ln(1+ number of stock transactions)		
	Ordinary least squares (1)	Random effects (2)	Fixed effects (3)
Investment experience	0.010	0.034	0.062
	(9.61)***	(13.39)***	(18.72)***
Gender (dummy; men=1)	-0.019	-0.026	
	(1.09)	(0.42)	
Age	-0.003	-0.002	
	(7.86)***	(1.63)	
Warrant trader (dummy)	0.282	0.227	0.172
	(39.86)***	(17.59)***	(11.36)***
High risk strategy (dummy)	0.102	0.108	
	(10.23)***	(3.25)***	
Retirement savings (dummy)	-0.126	-0.118	
	(7.85)***	(2.10)**	
ln(stock portfolio value)	0.166	0.157	0.143
	(72.85)***	(46.91)***	(38.15)***
Market return (lag 1)	0.780	0.758	0.773
	(13.65)***	(16.17)***	(16.49)***
Market return (lag 2)	0.430	0.404	0.412
	(7.45)***	(8.53)***	(8.71)***
Market return (lag 3)	0.582	0.551	0.552
	(10.01)***	(11.55)***	(11.58)***
Market return (lag 4)	0.430	0.421	0.445
	(7.57)***	(9.01)***	(9.52)***
Market return (lag 5)	0.214	0.257	0.329
	(3.72)***	(5.41)***	(6.88)***
Market return (lag 6)	-0.229	-0.178	-0.113
	(3.99)***	(3.77)***	(2.37)**
Portfolio return (lag 1)	0.178	0.205	0.220
	(5.98)***	(8.34)***	(8.93)***
Portfolio return (lag 2)	0.104	0.126	0.136
	(3.46)***	(5.08)***	(5.45)***
Portfolio return (lag 3)	0.077	0.103	0.115
	(2.53)**	(4.11)***	(4.59)***
Portfolio return (lag 4)	0.014	0.037	0.044
	(0.46)	(1.49)	(1.80)*
Portfolio return (lag 5)	0.026	0.033	0.031
	(0.89)	(1.33)	(1.26)
Portfolio return (lag 6)	0.015	0.012	0.014
	(0.52)	(0.49)	(0.56)
Constant	-0.910	-1.069	
	(30.85)***	(13.32)***	
Observations	63,925	63,925	63,925
Groups		1,853	1,853
(Adjusted) R-squared overall	0.1207	0.1116	0.0832
R-squared within		0.0736	0.0748
R-squared between		0.1868	0.1216

Table 7: **Past Returns and Stock Transactions**

This table presents negative binomial regressions (regression (1)) as well as random (regression (2)) and fixed effects (regression (3)) negative binomial panel regressions. Dependent variable is the number of stock transactions in a given month. Explanatory variables are stock market investment experience, a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (six lags). Absolute value of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

Dependent variable	Number of stock transactions		
	Negative binomial regression (1)	Random effects (2)	Fixed effects (3)
Investment experience	0.023	0.021	0.024
	(11.92)***	(8.49)***	(8.92)***
Gender (dummy; men=1)	-0.068	0.028	0.036
	(2.03)**	(0.61)	(0.71)
Age	-0.006	-0.002	-0.002
	(9.30)***	(2.46)**	(1.52)
Warrant trader (dummy)	0.552	0.317	0.298
	(41.03)***	(20.77)***	(18.59)***
High risk strategy (dummy)	0.172	0.089	0.078
	(9.18)***	(3.64)***	(2.94)***
Retirement savings (dummy)	-0.444	-0.023	0.031
	(13.84)***	(0.49)	(0.59)
ln(stock portfolio value)	0.358	0.229	0.218
	(78.85)***	(47.89)***	(43.85)***
Market return (lag 1)	1.126	1.173	1.155
	(10.15)***	(15.46)***	(15.18)***
Market return (lag 2)	0.545	0.717	0.697
	(4.92)***	(9.13)***	(8.85)***
Market return (lag 3)	1.068	0.913	0.899
	(9.47)***	(11.48)***	(11.28)***
Market return (lag 4)	0.527	0.641	0.633
	(4.70)***	(8.23)***	(8.12)***
Market return (lag 5)	0.186	0.287	0.283
	(1.66)*	(3.66)***	(3.61)***
Market return (lag 6)	-0.409	-0.372	-0.375
	(3.60)***	(4.83)***	(4.86)***
Portfolio return (lag 1)	0.218	0.318	0.320
	(4.01)***	(8.36)***	(8.38)***
Portfolio return (lag 2)	0.033	0.184	0.187
	(0.59)	(4.62)***	(4.68)***
Portfolio return (lag 3)	-0.020	0.137	0.142
	(0.35)	(3.38)***	(3.48)***
Portfolio return (lag 4)	-0.023	0.038	0.042
	(0.41)	(0.93)	(1.01)
Portfolio return (lag 5)	-0.001	0.076	0.079
	(0.01)	(1.81)*	(1.90)*
Portfolio return (lag 6)	-0.070	0.061	0.066
	(1.28)	(1.48)	(1.59)
Constant	-2.738	-2.848	-2.796
	(46.44)***	(40.13)***	(36.75)***
Observations	63,925	63,925	63,623
Groups		1,853	1,811

Table 8: **Past Returns and the Probability to Trade**

This table presents Logit regressions (regression (1)) as well as random (regression (2)) and fixed effects (regression (3)) Logit panel regressions. Dependent variable is an indicator variable that takes the value 1 if the investor trades stocks in a given month and 0 otherwise. Explanatory variables are stock market investment experience, a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (six lags). Absolute value of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

		Prob(trade)	
	Logit	Random effects	Fixed effects
	(1)	(2)	(3)
Investment experience	0.013	0.023	0.074
	(5.50)***	(2.87)***	(6.90)***
Gender (dummy; men=1)	0.088	0.108	
	(2.11)**	(0.63)	
Age	-0.006	-0.005	
	(6.84)***	(1.42)	
Warrant trader (dummy)	0.487	0.549	0.422
	(28.49)***	(14.04)***	(8.49)***
High risk strategy (dummy)	0.204	0.163	
	(8.35)***	(2.31)**	
Retirement savings (dummy)	-0.204	-0.298	
	(5.32)***	(2.53)**	
ln(stock portfolio value)	0.318	0.373	0.337
	(54.47)***	(34.20)***	(26.86)***
Market return (lag 1)	1.781	2.038	2.043
	(12.80)***	(13.21)***	(13.19)***
Market return (lag 2)	1.205	1.340	1.332
	(8.62)***	(8.64)***	(8.56)***
Market return (lag 3)	1.410	1.588	1.571
	(10.02)***	(10.19)***	(10.04)***
Market return (lag 4)	1.289	1.452	1.484
	(9.40)***	(9.53)***	(9.69)***
Market return (lag 5)	0.618	0.680	0.802
	(4.48)***	(4.42)***	(5.13)***
Market return (lag 6)	-0.222	-0.287	-0.178
	(1.61)	(1.87)*	(1.15)
Portfolio return (lag 1)	0.521	0.700	0.732
	(7.07)***	(8.44)***	(8.71)***
Portfolio return (lag 2)	0.411	0.574	0.598
	(5.55)***	(6.89)***	(7.11)***
Portfolio return (lag 3)	0.285	0.413	0.445
	(3.84)***	(4.96)***	(5.30)***
Portfolio return (lag 4)	0.059	0.140	0.160
	(0.82)	(1.73)*	(1.97)**
Portfolio return (lag 5)	0.180	0.271	0.273
	(2.51)**	(3.37)***	(3.37)***
Portfolio return (lag 6)	0.089	0.124	0.131
	(1.27)	(1.56)	(1.64)
Constant	-3.114	-3.806	
	(42.52)***	(14.81)***	
Observations	63,925	63,925	61,940
Groups		1,853	1,759

Table 9: **Past Returns and Stock Transactions: Purchases versus Sales**

This table presents ordinary least squares regressions (regressions (1) and (4)) as well as random (regressions (2) and (5)) and fixed effects (regressions (3) and (6)) panel regressions. Dependent variable is the logarithm of the number of stock purchases (regressions (1), (2), and (3)) and the logarithm of the number of stock sales (regressions (4), (5), and (6)) in a given month, respectively. Explanatory variables are stock market investment experience, a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (six lags). Absolute value of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

Dependent variable	ln(number of stock purchases)			ln(number of stock sales)		
	Ordinary least squares (1)	Random effects (2)	Fixed effects (3)	Ordinary least squares (4)	Random effects (5)	Fixed effects (6)
Investment experience	0.009	0.028		0.008	0.019	0.075
	(6.40)***	(10.86)***		(5.53)***	(7.55)***	(13.71)***
Gender (dummy; men=1)	-0.122	-0.096		-0.076	-0.056	
	(4.81)***	(1.79)*		(2.84)***	(1.16)	
Age	-0.001	0.000	0.118	-0.003	-0.004	
	(2.25)**	(0.05)	(22.58)***	(4.79)***	(4.07)***	
Warrant trader (dummy)	0.207	0.169	0.062	0.210	0.186	0.079
	(20.65)***	(10.86)***	(2.78)***	(19.58)***	(12.18)***	(3.32)***
High risk strategy (dummy)	0.058	0.086		0.057	0.085	
	(4.31)***	(2.99)***		(4.06)***	(3.32)***	
Retirement savings (dummy)	-0.161	-0.132		-0.184	-0.104	
	(6.58)***	(2.73)***		(6.73)***	(2.28)**	
ln(stock portfolio value)	0.131	0.097	0.037	0.149	0.171	0.187
	(36.74)***	(20.82)***	(6.04)***	(38.46)***	(34.89)***	(27.73)***
Market return (lag 1)	0.229	0.361	0.443	0.262	0.396	0.513
	(2.81)***	(5.14)***	(6.32)***	(2.96)***	(5.13)***	(6.64)***
Market return (lag 2)	-0.022	0.040	0.042	0.141	0.292	0.374
	(0.27)	(0.57)	(0.59)	(1.59)	(3.79)***	(4.86)***
Market return (lag 3)	0.314	0.424	0.435	0.261	0.338	0.346
	(3.74)***	(5.89)***	(6.06)***	(2.87)***	(4.28)***	(4.40)***
Market return (lag 4)	0.089	0.242	0.319	0.041	-0.004	0.026
	(1.08)	(3.43)***	(4.52)***	(0.46)	(0.05)	(0.33)
Market return (lag 5)	0.047	0.175	0.383	-0.087	-0.043	0.103
	(0.57)	(2.47)**	(5.37)***	(0.97)	(0.55)	(1.31)
Market return (lag 6)	-0.212	-0.172	0.002	-0.191	-0.237	-0.127
	(2.55)**	(2.40)**	(0.03)	(2.13)**	(3.04)***	(1.62)
Portfolio return (lag 1)	0.041	0.056	0.093	-0.084	-0.081	-0.069
	(0.97)	(1.54)	(2.54)**	(1.90)*	(2.10)**	(1.78)*
Portfolio return (lag 2)	0.020	0.027	0.054	-0.145	-0.135	-0.136
	(0.48)	(0.74)	(1.45)	(3.19)***	(3.40)***	(3.40)***
Portfolio return (lag 3)	-0.088	-0.070	-0.042	-0.063	-0.089	-0.090
	(2.01)**	(1.86)*	(1.10)	(1.35)	(2.18)**	(2.21)**
Portfolio return (lag 4)	-0.010	-0.000	0.009	-0.016	-0.026	-0.035
	(0.23)	(0.01)	(0.25)	(0.34)	(0.64)	(0.85)
Portfolio return (lag 5)	-0.068	-0.058	-0.069	-0.040	-0.045	-0.062
	(1.62)	(1.59)	(1.86)*	(0.86)	(1.09)	(1.51)
Portfolio return (lag 6)	-0.039	-0.019	-0.001	-0.080	-0.082	-0.085
	(0.91)	(0.51)	(0.04)	(1.73)*	(2.04)**	(2.10)**
Constant	-0.503	-0.527		-0.725	-1.099	
	(11.14)***	(6.89)***		(14.94)***	(15.09)***	
Observations	29,167	29,167	29,167	24,788	24,788	24,788
Groups		1,752	1,752		1,783	1,783
(Adjusted) R-squared overall	0.0693	0.0607	0.0044	0.0800	0.0783	0.0476
R-squared within		0.0332	0.0433		0.0726	0.0775
R-squared between		0.1069	0.0057		0.1102	0.0532

Table 10: **Past Returns and Stock Transactions: Purchases versus Sales**

This table presents ordinary least squares regressions (regressions (1) and (4)) as well as random (regressions (2) and (5)) and fixed effects (regressions (3) and (6)) panel regressions. Dependent variable is the logarithm of (1+ the number of stock purchases) (regressions (1), (2), and (3)) and the logarithm of (1+ the number of stock sales) (regressions (4), (5), and (6)) in a given month, respectively. Explanatory variables are stock market investment experience, a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (six lags). Absolute value of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

Dependent variable	ln(1+ number of stock purchases)			ln(1+ number of stock sales)		
	Ordinary least squares (1)	Random effects (2)	Fixed effects (3)	Ordinary least squares (4)	Random effects (5)	Fixed effects (6)
Investment experience	0.008	0.030	0.063	0.007	0.020	0.034
	(9.27)***	(14.25)***	(22.04)***	(9.50)***	(10.45)***	(12.98)***
Gender (dummy; men=1)	-0.021	-0.022		-0.028	-0.038	
	(1.43)	(0.45)		(2.00)**	(0.84)	
Age	-0.002	0.001		-0.003	-0.004	
	(4.95)***	(0.53)		(9.58)***	(4.18)***	
Warrant trader (dummy)	0.199	0.165	0.117	0.217	0.169	0.122
	(33.44)***	(15.15)***	(8.97)***	(38.94)***	(16.64)***	(10.02)***
High risk strategy (dummy)	0.065	0.065		0.079	0.093	
	(7.72)***	(2.46)**		(10.03)***	(3.75)***	
Retirement savings (dummy)	-0.094	-0.096		-0.098	-0.086	
	(7.02)***	(2.17)**		(7.82)***	(2.06)**	
ln(stock portfolio value)	0.119	0.088	0.066	0.116	0.142	0.142
	(61.70)***	(30.79)***	(20.32)***	(64.70)***	(53.48)***	(47.15)***
Market return (lag 1)	0.563	0.539	0.554	0.534	0.537	0.549
	(11.70)***	(13.29)***	(13.67)***	(11.89)***	(14.25)***	(14.57)***
Market return (lag 2)	0.175	0.146	0.154	0.377	0.378	0.387
	(3.61)***	(3.57)***	(3.76)***	(8.31)***	(9.92)***	(10.16)***
Market return (lag 3)	0.475	0.441	0.441	0.298	0.295	0.298
	(9.71)***	(10.69)***	(10.70)***	(6.52)***	(7.69)***	(7.79)***
Market return (lag 4)	0.506	0.487	0.511	0.008	0.021	0.040
	(10.56)***	(12.04)***	(12.62)***	(0.18)	(0.56)	(1.07)
Market return (lag 5)	0.265	0.294	0.371	-0.009	0.032	0.081
	(5.49)***	(7.17)***	(8.96)***	(0.20)	(0.85)	(2.11)**
Market return (lag 6)	-0.117	-0.081	-0.011	-0.244	-0.201	-0.157
	(2.43)**	(1.98)**	(0.27)	(5.42)***	(5.28)***	(4.11)***
Portfolio return (lag 1)	0.166	0.200	0.219	0.092	0.095	0.101
	(6.62)***	(9.40)***	(10.28)***	(3.93)***	(4.79)***	(5.10)***
Portfolio return (lag 2)	0.104	0.134	0.147	0.033	0.032	0.035
	(4.10)***	(6.22)***	(6.82)***	(1.41)	(1.61)	(1.74)*
Portfolio return (lag 3)	0.084	0.120	0.135	0.011	0.010	0.015
	(3.29)***	(5.50)***	(6.21)***	(0.46)	(0.52)	(0.73)
Portfolio return (lag 4)	0.014	0.045	0.056	0.006	0.005	0.006
	(0.56)	(2.14)**	(2.66)***	(0.24)	(0.23)	(0.30)
Portfolio return (lag 5)	0.028	0.046	0.048	-0.005	-0.020	-0.025
	(1.11)	(2.20)**	(2.25)**	(0.22)	(1.01)	(1.26)
Portfolio return (lag 6)	0.012	0.026	0.031	0.000	-0.022	-0.025
	(0.50)	(1.22)	(1.46)	(0.02)	(1.15)	(1.30)
Constant	-0.690	-0.691		-0.696	-0.986	
	(27.78)***	(10.75)***		(30.01)***	(16.32)***	
Observations	63,925	63,925	63,925	63,925	63,925	63,925
Groups		1,853	1,853		1,853	1,853
(Adjusted) R-squared overall	0.0930	0.0797	0.0449	0.0998	0.0750	0.0769
R-squared within		0.0475	0.0496		0.0750	0.0758
R-squared between		0.1575	0.0681		0.1426	0.1016

Table 11: **Past Returns and Stock Transactions: Purchases versus Sales**

This table presents negative binomial regressions (regressions (1) and (4)) as well as random (regressions (2) and (5)) and fixed effects (regressions (3) and (6)) negative binomial panel regressions. Dependent variable is the number of stock purchases (regressions (1), (2), and (3)) and the number of stock sales (regressions (4), (5), and (6)) in a given month, respectively. Explanatory variables are stock market investment experience, a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (six lags). Absolute value of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

Dependent variable	Number of stock purchases			Number of stock sales		
	Negative binomial regression	Random effects	Fixed effects	Negative binomial regression	Random effects	Fixed effects
	(1)	(2)	(3)	(4)	(5)	(6)
Investment experience	0.023	0.025	0.030	0.023	0.024	0.028
	(11.03)***	(8.66)***	(9.46)***	(9.93)***	(7.74)***	(8.09)***
Gender (dummy; men=1)	-0.075	0.067	0.087	-0.051	-0.100	-0.116
	(2.04)**	(1.26)	(1.48)	(1.27)	(1.68)*	(1.72)*
Age	-0.005	-0.000	0.000	-0.009	-0.008	-0.007
	(6.10)***	(0.40)	(0.22)	(10.94)***	(6.62)***	(5.65)***
Warrant trader (dummy)	0.497	0.306	0.291	0.625	0.411	0.379
	(33.77)***	(17.19)***	(15.37)***	(38.63)***	(21.12)***	(18.20)***
High risk strategy (dummy)	0.150	0.051	0.034	0.197	0.166	0.152
	(7.32)***	(1.77)*	(1.07)	(8.82)***	(5.34)***	(4.35)***
Retirement savings (dummy)	-0.394	-0.112	-0.061	-0.508	-0.128	-0.071
	(11.15)***	(2.11)**	(0.98)	(12.68)***	(2.11)**	(0.97)
ln(stock portfolio value)	0.333	0.181	0.158	0.400	0.309	0.309
	(66.62)***	(32.50)***	(27.14)***	(70.08)***	(49.65)***	(46.72)***
Market return (lag 1)	1.045	1.127	1.104	1.244	1.351	1.332
	(8.70)***	(12.88)***	(12.59)***	(9.19)***	(14.14)***	(13.91)***
Market return (lag 2)	0.261	0.339	0.309	0.917	1.065	1.048
	(2.14)**	(3.78)***	(3.44)***	(6.88)***	(10.64)***	(10.45)***
Market return (lag 3)	1.145	0.927	0.906	0.952	0.766	0.753
	(9.29)***	(10.22)***	(9.98)***	(6.98)***	(7.54)***	(7.40)***
Market return (lag 4)	0.923	1.035	1.019	-0.032	-0.103	-0.108
	(7.60)***	(11.50)***	(11.31)***	(0.24)	(1.06)	(1.11)
Market return (lag 5)	0.373	0.511	0.503	-0.072	-0.084	-0.083
	(3.06)***	(5.67)***	(5.58)***	(0.53)	(0.85)	(0.84)
Market return (lag 6)	-0.270	-0.280	-0.282	-0.599	-0.631	-0.634
	(2.18)**	(3.16)***	(3.18)***	(4.37)***	(6.47)***	(6.49)***
Portfolio return (lag 1)	0.298	0.406	0.413	0.154	0.221	0.217
	(4.96)***	(9.40)***	(9.52)***	(2.35)**	(4.62)***	(4.55)***
Portfolio return (lag 2)	0.129	0.249	0.259	-0.070	0.065	0.062
	(2.11)**	(5.48)***	(5.67)***	(1.03)	(1.30)	(1.24)
Portfolio return (lag 3)	0.027	0.235	0.246	-0.079	-0.012	-0.014
	(0.44)	(5.13)***	(5.35)***	(1.16)	(0.24)	(0.26)
Portfolio return (lag 4)	-0.032	0.081	0.091	-0.007	0.010	0.009
	(0.52)	(1.73)*	(1.94)*	(0.11)	(0.19)	(0.18)
Portfolio return (lag 5)	0.032	0.118	0.129	-0.044	-0.008	-0.010
	(0.53)	(2.50)**	(2.72)***	(0.66)	(0.15)	(0.18)
Portfolio return (lag 6)	-0.022	0.094	0.104	-0.104	0.019	0.020
	(0.36)	(1.98)**	(2.19)**	(1.56)	(0.38)	(0.38)
Constant	-3.122	-2.601	-2.454	-3.912	-3.574	-3.583
	(48.37)***	(31.34)***	(27.19)***	(53.92)***	(38.87)***	(35.10)***
Observations	63,925	63,925	63,041	63,925	63,925	62,928
Groups		1,853	1,751		1,853	1,776

Table 12: **Past Returns and the Probability to Trade: Purchases versus Sales**

This table presents Logit regressions (regressions (1) and (4)) as well as random (regressions (2) and (5)) and fixed effects (regressions (3) and (6)) Logit panel regressions. Dependent variable is an indicator variable that takes the value 1 if the investor buys stocks in a given month and 0 otherwise (regressions (1), (2), and (3)) and an indicator variable that takes the value 1 if the investor sells stocks in a given month and 0 otherwise (regressions (4), (5), and (6)) in a given month, respectively. Explanatory variables are stock market investment experience, a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (six lags). Absolute value of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

	Prob (stock purchase)			Prob (stock sale)		
	Logit	Random effects	Fixed effects	Logit	Random effects	Fixed effects
	(1)	(2)	(3)	(4)	(5)	(6)
Investment experience	0.014	0.040	0.006	0.017	0.040	0.040
	(5.67)***	(5.66)***	(0.56)	(7.01)***	(5.95)***	(3.57)***
Gender (dummy; men=1)	0.067	-0.028		-0.022	-0.053	
	(1.60)	(0.13)		(0.52)	(0.43)	
Age	-0.005	0.001		-0.009	-0.020	
	(5.37)***	(0.29)		(9.98)***	(5.24)***	
Warrant trader (dummy)	0.429	0.485	0.369	0.574	0.592	0.399
	(25.43)***	(12.64)***	(7.60)***	(33.06)***	(14.77)***	(7.96)***
High risk strategy (dummy)	0.159	0.068		0.232	0.222	
	(6.71)***	(0.78)		(9.68)***	(2.82)***	
Retirement savings (dummy)	-0.214	-0.114		-0.283	-0.387	
	(5.50)***	(0.82)		(6.83)***	(3.72)***	
ln(stock portfolio value)	0.286	0.282	0.206	0.317	0.479	0.545
	(49.16)***	(26.68)***	(16.44)***	(52.00)***	(41.62)***	(38.60)***
Market return (lag 1)	1.603	1.836	1.834	1.844	2.222	2.252
	(11.68)***	(12.05)***	(11.97)***	(13.01)***	(14.02)***	(14.11)***
Market return (lag 2)	0.553	0.562	0.527	1.381	1.655	1.678
	(4.00)***	(3.66)***	(3.42)***	(9.62)***	(10.33)***	(10.41)***
Market return (lag 3)	1.257	1.412	1.373	0.855	1.004	0.999
	(9.00)***	(9.12)***	(8.83)***	(5.92)***	(6.23)***	(6.16)***
Market return (lag 4)	1.602	1.845	1.853	-0.095	-0.135	-0.113
	(11.71)***	(12.13)***	(12.12)***	(0.68)	(0.86)	(0.72)
Market return (lag 5)	0.794	0.945	1.060	-0.002	0.032	0.095
	(5.79)***	(6.17)***	(6.83)***	(0.01)	(0.20)	(0.59)
Market return (lag 6)	-0.225	-0.252	-0.143	-0.707	-0.809	-0.755
	(1.65)*	(1.66)*	(0.93)	(5.02)***	(5.13)***	(4.73)***
Portfolio return (lag 1)	0.554	0.773	0.828	0.473	0.595	0.579
	(7.63)***	(9.49)***	(10.06)***	(6.39)***	(7.14)***	(6.88)***
Portfolio return (lag 2)	0.361	0.529	0.577	0.279	0.349	0.330
	(4.94)***	(6.47)***	(7.01)***	(3.74)***	(4.17)***	(3.92)***
Portfolio return (lag 3)	0.397	0.568	0.621	0.107	0.124	0.114
	(5.41)***	(6.92)***	(7.49)***	(1.41)	(1.46)	(1.33)
Portfolio return (lag 4)	0.080	0.185	0.232	0.058	0.075	0.059
	(1.11)	(2.30)**	(2.86)***	(0.77)	(0.89)	(0.69)
Portfolio return (lag 5)	0.195	0.304	0.331	0.045	0.021	-0.012
	(2.73)***	(3.79)***	(4.10)***	(0.59)	(0.25)	(0.14)
Portfolio return (lag 6)	0.102	0.172	0.211	0.102	0.055	0.019
	(1.45)	(2.17)**	(2.65)***	(1.39)	(0.66)	(0.23)
Constant	-3.278	-3.748		-3.680	-5.085	
	(44.82)***	(15.88)***		(48.48)***	(21.39)***	
Observations	63,925	63,925	62,501	63,925	63,925	62,760
Groups		1,853	1,736		1,853	1,769

Table 13: **Return Estimates**

We asked the investors to give an estimate of their portfolio performance in the past (from January 1997 to December 2000):

> *Please try to estimate your past performance of your stock portfolio at your online broker. Please estimate the return of your stock portfolio from January 1997 to December 2000: [Answer] percent per year on average.*

This table presents the answers to this question (mean, median, standard deviation, skewness, kurtosis, minimum, maximum, and various percentiles).

Number of observations	210
Mean	14.93 %
Standard deviation	13.11 %
Skewness	2.01
Kurtosis	24.33
Minimum	−50 %
1st percentile	−15 %
5th percentile	0 %
10th percentile	5 %
25th percentile	10 %
Median	15 %
75th percentile	20 %
90th percentile	27 %
95th percentile	35 %
99th percentile	41 %
Maximum	120 %

Table 14: **Past Returns and Turnover: Dependence on Ability to Correctly Estimate Past Realized Returns**

This table presents ordinary least squares regressions (regressions (1) and (4)) as well as random (regressions (2) and (5)) and fixed effects (regressions (3) and (6)) panel regressions. Dependent variable is the logarithm of monthly stock portfolio turnover. Explanatory variables are a gender dummy, a warrant trader dummy, a high-risk investment strategy dummy, a retirement savings dummy, the logarithm of the monthly stock portfolio value as well as past stock market and portfolio returns (two lags). We run the regressions for two subgroups of investors who answered the questionnaire. To create these groups we first calculate the absolute difference between the the past realized stock portfolio performance and the return estimate. Group 1 contains the 50 % of investors with a difference between realized and estimated performance that is below the median of all respondents. Group 2 contains the 50 % of investors with a difference between realized and estimated performance that is above the median of all respondents. See Section 5 for details. Absolute value of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

	Group 1: Investors know past portfolio performance			Group 2: Investors do not know past portfolio performance		
	Ordinary least squares (1)	Random effects (2)	Fixed effects (3)	Ordinary least squares (4)	Random effects (5)	Fixed effects (6)
Gender (dummy; men=1)	0.393	0.530		-0.777	-0.125	
	(2.23)**	(1.63)		(3.14)***	(0.21)	
Age	0.007	0.019	0.100	0.008	0.013	0.087
	(2.31)**	(2.89)***	(2.97)***	(1.78)*	(1.34)	(2.57)**
Warrant trader (dummy)	0.121	0.128	-0.019	0.236	0.060	-0.088
	(1.86)*	(1.23)	(0.12)	(3.29)***	(0.55)	(0.63)
High risk strategy (dummy)	0.468	0.623		-0.130	0.095	
	(4.31)***	(2.59)***		(1.18)	(0.33)	
Retirement savings (dummy)	-0.727	-0.843		-0.595	-0.590	
	(4.36)***	(2.35)**		(3.09)***	(1.29)	
ln(stock portfolio value)	-0.593	-0.721	-0.853	-0.521	-0.644	-0.728
	(24.76)***	(23.21)***	(20.36)***	(22.35)***	(20.23)***	(18.29)***
Market return (lag 1)	0.689	0.614	0.621	0.836	0.911	0.959
	(1.30)	(1.28)	(1.30)	(1.58)	(1.92)*	(2.00)**
Market return (lag 2)	-0.492	-0.568	-0.554	0.896	0.927	0.909
	(0.92)	(1.17)	(1.14)	(1.63)	(1.89)*	(1.85)*
Portfolio return (lag 1)	0.582	0.496	0.505	0.292	0.241	0.218
	(1.94)*	(1.82)*	(1.86)*	(1.35)	(1.24)	(1.11)
Portfolio return (lag 2)	0.515	0.465	0.474	0.214	0.245	0.276
	(1.73)*	(1.73)*	(1.77)*	(0.97)	(1.23)	(1.38)
Constant	3.959	4.499	2.679	4.283	4.584	2.279
	(14.08)***	(9.47)***	(1.97)**	(12.59)***	(6.65)***	(1.74)*
Observations	1594	1594	1594	1481	1481	1481
Groups		77	77		81	81
(Adjusted) R-squared overall	0.3253	0.3254	0.2631	0.2831	0.2797	0.1816
R-squared within		0.2602	0.1278		0.2264	0.2293
R-squared between		0.5617	0.1913		0.4847	0.2662

Figure 1: **Time series of the DAX from January 1997 to March 2001 (End of Month Values)**

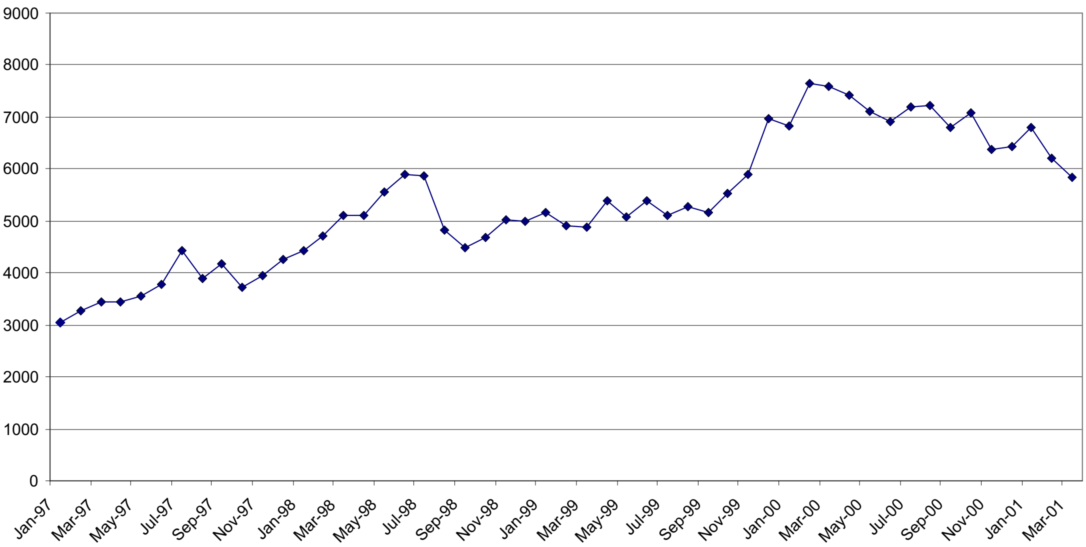


Figure 2: **Time Series of the Number of Stock Transactions**

This figure plots the time series of the sum of stock transactions of a sample of about 3,000 individual investors of a German online broker each month (see Section 3 for details about the investor sample). Time period is January 1997 to March 2001.

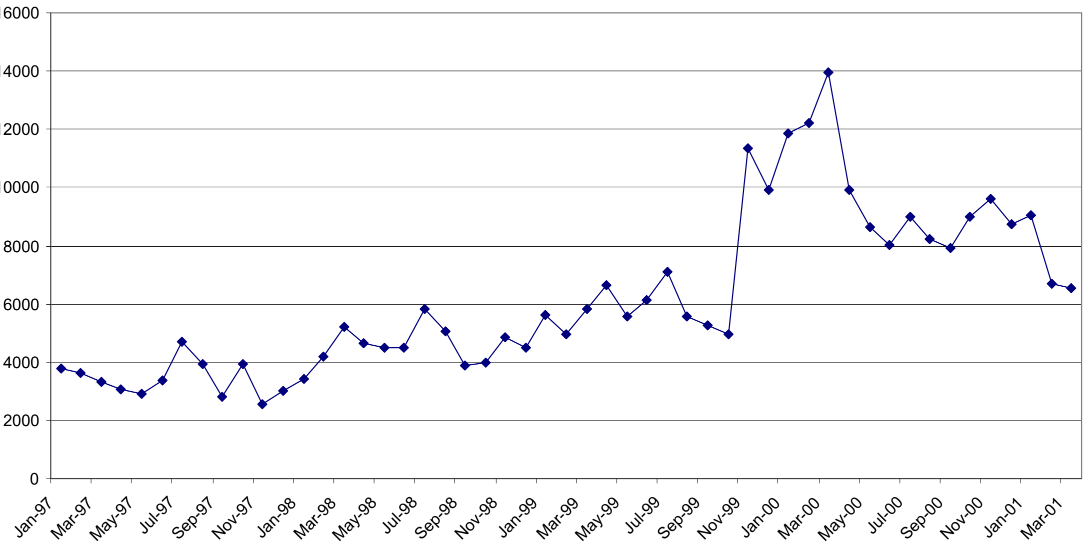
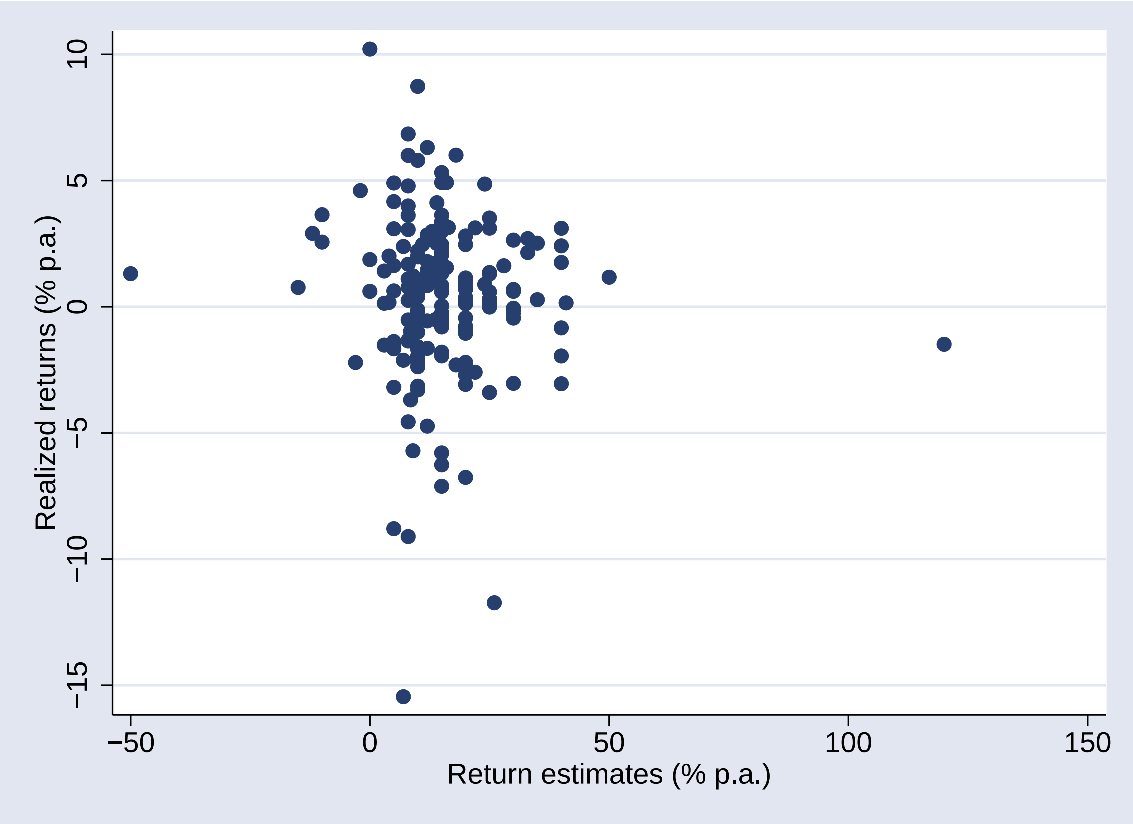


Figure 3: **Return Estimates and Realized Returns**

This figure plots the realized portfolio returns versus return estimates of the individual investors who answered the questionnaire.



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