# Investors' performance and trading behavior on the Norwegian stock market

by

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# Contents

# Chapter 1

# Introduction

This dissertation examines investors' performance and trading behavior on the Norwegian stock market. The extant literature has been focusing on institutional investors and much less has been studied on individual investors' performance and behavior, probably due to data limitation. With the availability of a unique and extensive monthly holding data set of all the investors on all the securities in a developed but under-investigated market, this dissertation provides intriguing results on individual investors' as well as other types of investors' trading behavior and performance. This study also derives interesting implications for future research. There are three papers in this dissertation and a brief summary of each paper is presented below.

## 1.1 Investor types and stock return volatility

This paper investigates how domestic individual investors, financial investors and foreign investors affect stock return volatility on the Norwegian stock market, using an extensive monthly holding data set of the number of shares held by each investor on each Norwegian stock from December 1992 to September 2007. Following the methodologies used in the literature, this paper finds surprising and interesting results: domestic individual investors and financial institutional investors dampen stock return volatility, and foreign investors exacerbate stock return volatility. While the result that individual investors reduce stock return volatility is similar to the implication of the findings in Sias (1996) and Malkiel and Xu (2003), it is inconsistent with the traditional assumption that individual investors are noise traders who make stocks more volatile. It is also striking that domestic financial institutional investors and foreign investors have opposite impact on stock return volatility, although we usually assume that institutional investors, regardless of geographical locations, have similar impact on the stock market.

We provides three explanations for investors' impact on stock return volatility: their trading style (momentum trading or contrarian trading), trading volume, and investment horizons.

There is both theoretical and empirical evidence that contrarian (negative feedback) trading reduces stock return volatility and momentum (positive feedback) trading increases stock return volatility. The analysis of investors' trading style shows that individual investors are contrarian traders and foreign investors are momentum traders, which is consistent with the result of their impact on return volatility. Domestic financial investors' trading is not much affected by lagged stock returns. By investigating investors' trading volume and investment horizons, we find that foreign investors trade the most and have the shortest investment horizons, individual investors trade the least and have the longest investment horizons, and financial investors lie in-between. These two explanations are also in line with the results of investors' impact on stock return volatility.

In summary, this paper shows that although it is likely that individual investors trade on noisy signals and make stocks more volatile, their trading behavior, such as contrarian trading style, lower trading volume and longer investment horizons, imposes negative impact on stock return volatility. Hence, the aggregate impact of individual investors depends on which factor dominates. The evidence in this paper shows that, even if Norwegian individual investors might have positive impact on return volatility, due to their noisy trading, the negative impact on return volatility from their trading behavior is stronger than their positive impact on return volatility. This paper has interesting implications for future theoretical research on investors' impact on stock return volatility. The existing models consider only one determinant of return volatility. For example, De Long et al. (1990b) focus on information while De Long et al. (1990a) consider positive feedback trading behavior. Since many factors, such as investors' information, trading style and trading volume, affect stock return volatility simultaneously, it is important to take into account more than one variable at the same time in order to get a more complete understanding. Hence, it would be very interesting to see how, for example, individual investors, who are noise traders and follow contrarian trading strategy, affect stock return volatility in a theoretical setting.

## 1.2 Investor timing ability between stock and bond markets

This paper examines whether some individual investors can successfully time the stock market, in the sense that they invest more in the stock market conditional on the forecast that the stock market will perform well in the subsequent period and reduce their equity portfolio holding when the stock market underperforms the bond market. While the previous studies mainly use equity data such as stock portfolio returns, this paper employs an extensive holding data set, which contains month-end shareholdings of all the stocks, mutual funds, and bonds for all the investors on the Norwegian financial market from December 1992 to June 2003. With the availability of both equity data and bond data, we are able to use a new and more natural method to check investors' timing ability by investigating whether their equity portfolio weight can forecast future stock market excess returns over future 1-, 3-, 6- and 12-month horizons. To derive reliable statistical references, we use the Newey and West (1987) autocorrelation- and heteroskedasticity-consistent covariance matrix to calculate standard errors, and employ the bootstrap technique in Kosowski et al. (2006) to overcome different issues, such as non-normality of market returns, small sample problems, and persistence in the portfolio weight levels. The results show that some individual investors can successfully time the market at 1 to 6 month horizons with the strongest results at the quarterly horizon.

If the market timing ability that we have uncovered for some of the investors is because they have true timing skill, and not driven by some form of biases in the way we measure timing ability, then this should translate into investors who have timing ability having higher performance than investors who can not time the market. Using three measures of portfolio performance: total portfolio returns, Sharpe ratio and risk adjusted Jensen's alpha, we show that investors with positive and significant timing ability have higher performance than that of investors with no or negative timing ability. This evidence indicates that our results that some individual investors can time the stock market are not spurious.

## 1.3 Performance persistence of individual investors

This paper examines whether some individual investors can outperform the market and can do so persistently, using monthly holding data of all the individual investors on all the Norwegian stocks over a sample of 11 years from December 1992 to June 2003. By using different measures of portfolio performance and various analysis methodologies, this paper finds that a sizable of individual investors exhibit economically and statistically significant performance persistence. Individual investors who have done well over the past two to five years outperform a passive benchmark for as long as the next three years. Unlike the evidence from the mutual fund and pension fund literature, the performance persistence exists not only for investors with poor performance but also for investors with top performance.

# Chapter 2

# Investor types and stock return volatility

**Abstract**
This paper examines the impact of domestic individual investors, financial investors and foreign investors on stock return volatility, at the individual security level. We find that foreign investors exacerbate stock return volatility, while domestic individual investors and financial investors dampen return volatility. The explanations are that foreign investors are momentum traders, trade the most and have the shortest investment horizon; individual investors are contrarian traders, trade the least and have the longest investment horizon; and financial investors fall somewhere in-between.

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## 2.1 Introduction

As a measure of risk, return volatility plays an essential role in many areas such as asset pricing, risk control, portfolio management, derivative pricing and the cost of capital. For example, many studies have shown that stock return volatility matters for asset pricing.[2] Furthermore, excess volatility could lead to a higher cost of capital, and thereby affect corporate investment and the fundamental value of the company (Froot et al. (1992)). Since stock price changes are driven by the arrival of new information and investors' trading processes that incorporate new information into stock prices, and since different types of investors may have heterogeneous information, belief, preferences, and trading behavior, it is important to understand how and why different types of investors affect stock return volatility. The extant literature has linked stock return volatility to investors' holdings. Hotchkiss and Strickland (2003) show that ownership structure is related to stock price volatility and to trading volume around the release of corporate information. Sias (1996) and Malkiel and Xu (2003) find evidence that institutional investors increase stock return volatility, using annual holding data. Brandt et al. (2010), using quarterly holding data, report the same result as in Sias (1996) and Malkiel and Xu (2003) for high priced stocks, but show that retail trading increases return volatility of low-priced stocks. Due to data limitation, the studies on investor composition and volatility have been focusing on either institutional investors or retail investors.[3]

The goal of this paper is to explore how the heterogeneity in investors' trading behavior affects stock return volatility.[4] Taking advantage of a unique and extensive Norwegian monthly holding data set with detailed information on investor types over a long sample period, this paper provides a more complete picture of how different types of investors affect stock return volatility and and a deeper understanding of why they have such an impact on return volatility. Focusing on domestic individual investors, domestic financial investors and foreign investors,[5] we find interesting and surprising results. First, domestic individual investors dampen stock return volatility. While this is consistent with the implication of Sias (1996) and Malkiel and Xu (2003), this result seems to contradict the traditional finance literature that considers individual investors as noise traders who increase stock return volatility (De Long et al. (1990b)). Second, although both domestic financial institutional investors and foreign investors are institutional

[2] Ang (2009), Goyal and Santa-Clara (2003), Bali et al. (2005), Wei and Zhang (2005), and Guo and Savickas (2007)

[3] Since there are only two types of investors, institutional investors and retail investors, in the US holding data, the retail holding = 1- institutional holding. Therefore, one can only study one of the two types of investors.

[4] We check both total return volatility and idiosyncratic volatility.

[5] Foreign investors are largely institutional investors. Grinblatt and Keloharju (2000), studying investor performance and behavior with Finish data, argue that foreign investors tend to be well capitalized foreign financial institutions that are generally, for example, mutual funds, hedge funds, and foreign investment banks. In addition, the transaction cost and investment cost would be very high for retail investors to invest directly in foreign markets.

investors, they have opposite impacts on stock return volatility. Domestic institutional investors have a negative impact on return volatility, which is similar to, but weaker than, individual investors', while foreign investors exacerbate stock return volatility. This is striking because we generally suppose institutional investors, regardless of geographical location, have similar trading behavior and would have a similar impact on the stock market. Dahlquist and Robertsson (2001) study the investment behavior of foreign investors on the Swedish stock market and document that foreign investors have characteristics similar to those of Swedish institutional investors.

This paper also provides other interesting findings. There is evidence that foreign investors' shareholdings are strongly affected by past oil prices. When regressing value-weighted and equal-weighted aggregate holdings of foreign investors on lagged oil prices, controlling for lagged market returns, foreign holdings are positively and significantly related to lagged oil prices. The magnitude is much stronger in the later part of the sample when oil prices have increased dramatically. However, since both holding and oil prices are persistent, the causality might go from holding to oil price. We argue that it is more likely that oil prices cause investors' trading than the other way around. This might indicate that the Norwegian stock market is exposed to extra risk through foreign investors' trading due to international oil prices. Another interesting finding is related to investors' trading behavior based on past positive and negative returns. By examining how investors' holding levels and changes in holdings are related to lagged positive returns and negative returns, we find that investors (individual investors and foreign investors) react stronger to negative returns than to positive returns, which might help us understand why volatility is negatively related to lagged returns.

This paper adds several contributions to the literature. First, this paper uses a more accurate measure of investors' holdings and therefore provides more reliable results. The annual or quarterly institutional holding data used in previous studies focus on "large" institutions with asset under management over \$100 million. In addition, institutional investors only report their holding positions which are more than 10,000 shares or \$200,000. The rest, including small institutions, holding position under report requirements, and other types of investors, is considered as individual investors. In contrast, the holding data employed in this study is not reported by investors themselves, but is registered (for all the investors who hold shares in the Norwegian stock market) by a company authorized by law. This holding data contains the number of shares of each stock held by each investor over the sample period. Second, using monthly holding data, instead of quarterly or annual frequencies employed in the extant literature, over a long sample period of 15 years, this paper is able to provide more precise evidence with stronger statistical power on the impact of investor types on stock return volatility.

Third and most importantly, this paper is the first to analyze how three types of investors affect stock return volatility in the same setting, due to the availability of the detailed information on investors. The existing studies either focus on institutional or individual investors in developed markets, or examine foreign investors in emerging markets. The comparisons of different types of investors in this paper can be done from two perspectives. The first one is to compare the two types of domestic investors: institutional investors and retail investors. The second perspective is to investigate whether the two types of institutional investors: domestic institutional investors and foreign (institutional) investors, have a similar impact on stock return volatility. These comparisons provide us with a deeper understanding of how volatility is affected by various investor groups. Assuming that we consider the domestic institutions and foreign investors as one group of institutional investors, we would find that the aggregate institutional investors increase stock return volatility, which would hide the negative impact of domestic institutional investors.

The final contribution is that we investigate investors' trading style, trading volume and investment horizon to provide explanations for the results, and make suggestions for future theoretical research. While individual investors are often supposed to increase stock return volatility since they are noise traders (De Long et al. (1990b)), we argue that although information is an important determinant of return volatility, there are other factors that play an important role in stock return volatility as well. The first explanation is trading style, momentum trading (positive feedback trading) or contrarian trading (negative feedback trading). De Long et al. (1990a) develop a model which shows positive feedback trading (momentum trading) increases stock return volatility. Avramov et al. (2006) present evidence that contrarian trading reduces volatility and momentum trading increases volatility. We hypothesize that retail investors are contrarian traders and foreign investors follow a momentum trading strategy, and find evidence supporting our hypotheses.

The second explanation is trading volume or trading turnover. Many studies show a positive correlation between trading volume and volatility (Schwert (1989) and Gallant et al. (1992)). Malkiel and Xu (2003) argue that the high trading turnover by institutional investors is the reason for a positive correlation between stock return volatility and lagged institutional ownership. We hypothesize that investors who increase volatility trade more than investors who decrease volatility. The results show that foreign investors, who exacerbate stock return volatility, trade the most; retail investors, who have the strongest negative impact on volatility, trade the least; and domestic financial institutions lie in between. This evidence is consistent with the idea that trading volume is one of the channels through which investors affect volatility. Third, it is likely that investors with short investment horizons induce higher volatility than investors with long investment horizons. Markowitz (1991) suggests that individual investors may make investment decision based on long-term horizon. Friedman (1995) also argues that institutional investors have plausible reasons to adopt short horizons comparing to individual investors. We document that retail investors, who reduce stock return volatility, have the longest investment horizons and foreign investors, who increase volatility, have the shortest horizons.

To sum up, we show that the negative impact of individual investors is a result of their contrarian trading strategy, low trading volume and long investment horizons. Although it is very likely that individual investors are noise traders and their noise trading increases return volatility, we argue that the aggregate impact is caused by both investors' information and their trading behavior. It seems that Norwegian individual investors' negative impact on return volatility, a result of their trading behavior, is stronger than the possible positive impact from their noise trading. While the extant models focus on one determinant of volatility, such as information, this paper provides an important implication for future theoretical research, that is, we would have a deeper understanding of investors' impact on return volatility by taking into account many factors, for example, information and trading style, simultaneously.

The rest of the paper proceeds as follows. Section 2 provides a short literature review. Section 3 describes the data and variable measurements, investigates the trend of aggregate idiosyncratic volatility, and presents descriptive statistics. The analysis of the impact of different types of investors on stock return volatility and various robustness tests are conducted in section 4 and section 5. Section 6 provides explanations for the results. Concluding remarks are offered in section 7.

## 2.2 Literature review

This paper is related to several strands of literature. First, there is evidence that investor heterogeneity affects investors' trading behavior and consequently has an impact on stock prices, though most of the studies focus on investor heterogeneity within institutional investors. Hotchkiss and Strickland (2003) show that institutional ownership composition is related to parameters of the market reaction to negative earnings announcements. When firms report earnings below analysts expectations, the stock price response is more negative for firms with higher levels of ownership by momentum or aggressive growth investors. Ownership structure is also related to trading volume and to stock price volatility on days around earnings announcements.

The studies most relevant to this paper are the ones examining how (institutional) investors' holdings affect future stock return volatility. Sias (1996) shows that the US institutional investors increase stock return volatility. He argues that this is surprising because institutional investors are supposed to stabilize stock return volatility. Campbell et al. (2001) document that idiosyncratic risk has been trended upward from 1962 to 1997, and Malkiel and Xu (2003) find that institutional investors' holding forecasts higher future idiosyncratic volatility. Brandt et al. (2010) show that idiosyncratic volatility goes down from 2004 to 2008 and therefore the positive trend in idiosyncratic volatility through the 1990s is not a trend, but rather an episodic phenomenon. They show that the higher idiosyncratic volatility is driven by greater trading of individual investors in low-priced stocks. They also find that institutional investors increase stock return volatility among high priced stocks.

Bennett et al. (2003) find evidence that firm-specific volatility is positively related to lag changes in institutional ownership, using quarterly institutional ownership data from 1983 to 1997. By examining the days where the absolute value of the Center for Research in Security Prices (CRSP) value weighted and equal-weighted return is greater than two percent, Dennis and Strickland (2002) investigate who buys when the stock market performs well and who sells during large market drop. They find that institutional investors sell more than individual investors when the stock market went down in value by more than two percent, and buy more when the stock market is up by more than two percent. They suggest that this momentum trading behavior of institutional investors contributes to stock market volatility. Dennis and Strickland (2004) show that firm-level volatility is positively related to increased institutional ownership.

Since in the US holding data investors are categorized into only two types, institutional investors and individual investors, the results from the above mentioned studies that institutional investors increase stock return volatility imply that individual investors reduce stock return volatility. This is surprising since individual investors are usually considered as noise traders who exacerbate stock return volatility. De Long et al. (1990b) develop a model which shows that noise traders make stocks more volatile. Foucault et al. (2011) provide evidence supporting the model of noise traders in De Long et al. (1990b). Using daily trading data on the French stock markets, Foucault et al. (2011) show that (some) individual investors, acting as noise traders, have a positive effect on return volatility. However, they state that although they find that some retail investors play the role of noise traders, they do not imply that all retail investors are noise traders nor that only retail investors are noise traders.

This study is also related to the literature on foreign investors. Little has been done on how foreign (institutional) investors affect stock return volatility in developed stock markets. Using Swedish data, Dahlquist and Robertsson (2001) document that foreign investors have similar stock preferences as domestic institutional investors. But they did not check whether they have similar effect on stock return volatility on the Swedish stock market. Several papers have examined how foreign investors affect stock return volatility in emerging markets. Bae et al. (2004) examine the impact of investibility, or the degree to which a stock can be foreign-owned, on emerging market volatility, and find a positive relation between return volatility and the investibility of individual stocks by foreign investors. Choe et al. (1999) show no evidence that foreign investors had a destabilizing effect on the Korea stock market using daily data from 1996 to 1997. Wang (2007) checks the impact of foreign holding on future stock return volatility on the indonesia stock market and documents a negative relationship between foreign ownership and future volatility of Indonesia stocks.

## 2.3 Data, variables and descriptive statistics

### 2.3.1 Data

This paper explores data on the Norwegian stock market from December 1992 to September 2007. The Norwegian stock market is a developed but under investigated market. At the end of June 2003, the Oslo Stock Exchange ranks 11th out of twenty-three European stock exchanges based on market capitalization and 12th based on the number of listed companies.[6] Thus, compared to other European exchanges, the Oslo Stock Exchange is close to the "median exchange" when it comes to market capitalization and number of shares listed. Looking at stock market turnover (measured as annualized electronic order book transactions), the exchange has the eighth highest turnover. Bohren et al. (1997) show that the intensity of seasoned equity offerings is comparable to that of active markets like the New York Stock Exchange. In short, the Oslo Stock Exchange is an established and mature market where liquidity and turnover are high enough to be an interesting laboratory to study investor behavior.

The main data set employed in this study is the month-end holding data on all the stocks held by all the investors that have ever invested in the Norwegian stock market over the sample period. Hence, this is a complete data set with the whole investor population. All the investors are categorized into 5 main types: domestic individual investors, financial institutional investors, non-financial corporate investors, state investors and foreign investors. We exclude non-financial corporate investors and state investors in this analysis, because the former might hold shares for corporate strategic purpose and the latter have strong political motive in their holdings.

The monthly holding data are provided by the Norwegian Central Securities Depository (NCSD).[7] NCSD is a Norwegian company authorized to register rights to securities. Companies listed on the Oslo Stock Exchange are required by law to report to a security register. During our sample period, all listed companies registered their shares with NCSD. All investors that invest in stocks registered at NCSD must have a NCSD-account. When securities are traded, NCSD performs the settlement by transferring the security from the seller's NCSD-account to the buyer's NCSD-account. The Norwegian Central Bank subsequently performs the cash settlement. The NCSD-registry is used by the Norwegian government for taxation of investors. Thus, the quality of the data is very high.

The other data sets, provided by OBI (Oslo Bors Information), include daily and monthly stock returns, monthly stock prices, monthly number of shares outstanding, monthly number of shares traded, monthly stock market capitalization, and adjustment factors for stock splits and stock mergers. We also obtain annual accounting data such as book market capitalization and

[6] See www.fese.eu.

[7] The Norwegian name for the Norwegian Central Securities Depository (NCSD) is VPS ASA—or better known as "Verdipapirsentralen." The description of the activities of the NCSD below borrows from www.vps.no/english.

book debt value. The monthly brent oil price is downloaded from Datastream.

### 2.3.2 Measures of stock return volatility and holdings

#### Measures of return volatility

This paper checks the impact of investors on both total return volatility and idiosyncratic return volatility. We use daily returns in each month to measure monthly return volatility.[8] Using nonoverlapping samples of daily data to estimate the monthly variance creates estimation error that is uncorrelated through time (Schwert (1989)). We apply the following 5 measures used in the literature. (1) The standard deviation of raw daily returns (square root of the sum of the squared demeaned daily returns) in that month (the standard measure of volatility); (2) The sum of absolute daily returns; (3) The square root of the sum of squared daily returns; (4) The standard deviation of the daily difference between stock return and the market return, and (5) The square root of the sum of squared errors from the market-model regression in each month. We focus on the standard measure of volatility (the first method) in the main analysis and use the others for robustness tests. Note that the last two methods measure idiosyncratic volatility.

#### Measures of investors' holdings

For each stock i in each month t, the holding ownership for investor type j, $H_{i,t}^{j}$ is the number of shares held by investor type j divided by the free float of stock i in month t.

$$H_{i,t}^{j} = \frac{\sum_{k=1}^{K^j} S_{i,t}^{k}}{FreeFloat_{i,t}}, \tag{2.1}$$

where $S_{i,t}^{k}$ is the number of shares held by investor k that belongs to investor type j, and j=individual investors, financial investors and foreign investors. In month t, stock i has $K^j$ investors in investor type j. $\sum_{k=1}^{K^j} S_{i,t}^{k}$ measures the aggregate shares of stock i held by investor type j in month t. We compute investors' holding ownership adjusted by free float. The definition of free float follows that of the MSCI return index, which defines free float as "total shares outstanding excluding shares held by strategic investors such as governments, corporations, controlling shareholders and management, and shares subject to foreign ownership restrictions".[9] We exclude the holding fraction of state investors, corporate investors, and large block holders with a minimum holding of X among individual investors, financial investors and foreign investors, where X=10%, 20%, 30%, 50% and 70%. We also measure holdings using the total number of shares outstanding.

[8]French, Schwert and Stambaugh (1987), Schwert (1989, 1990a, 1990b), and Schwert and Seguin (1991) rely primarily on daily return observations for the construction of monthly realized stock volatilities.

[9]See the link *http://www.mscibarra.com/eqb/pressreleases/archive/20001210_pr01.pdf*

### Equal- and value-weighted holding ownership

The equal- and value-weighted holding ownerships by different measures for each investor type are reported in Table 3.1. The first 5 columns present the holding ownership of individual investors (Ind), financial investors (Fin), and foreign investors (For), using different measures of free float. The last column reports the holding measure adjusted by the total number of shares outstanding.

Panel A reports the equal-weighted average of ownership holdings. The first 5 columns show that individual investors have the highest proportion of equal-weighted holdings and foreign investors have the lowest proportion. For example, when the free float measure excludes state investors, corporate investors and large block holders with a minimum holding fraction of 50%, individual investors hold 37.7% of the shares on average, financial investors hold 31.6% and foreign investors account for 30.7%. There is no big difference among investors' holdings when different measures of free float are used. We use the holding measure adjusted by the free float excluding state investors, corporate investors and large block holders with a minimum of 50% holdings for all the analyses. The results of using other measures of free float are qualitatively similar.

The last column reports the equal-weighted holdings of the 3 groups using the holding measure which divides the aggregate shares of each investor type by the number of shares outstanding. Naturally, these holding fractions are smaller than the ones using free float. Individual investors and foreign investors have similar holdings, about 20%, and financial investors have slightly higher, at 24%. The last row in Panel A of Table 3.1 reports the average free float for each measure. When requiring large block holders with a minimum holding of 10%, the equal-weighted free float is 48%. When the requirement of a minimum holding by large block holders is 70%, the equal-weighted free float becomes 59%.

Panel B reports the value-weighted average of ownership holdings. Different from Panel A, foreign investors are the largest investor group and individual investors are the smallest investor group when we value weight investors' holdings across stocks. The differences between different types of investors' holdings are dramatic. For example, when requiring large block holders with a minimum holding fraction of 50%, individual investors hold only 14.9%, financial investors 27.7%, while foreign investors have a share fraction of 57.6%, which is about 4 times of the proportion of individual investors and twice that of financial investors. The last column, which reports value-weighted holdings using the total number of shares outstanding, describes the same picture, though the magnitude is smaller. The last row in Panel B presents the value-weighted average of free floats, which are from 53.9% to 63.9% when the requirement of the minimum holding of large block holders ranges from 10% to 70%. The comparison between Panel A and Panel B indicates that, on average, foreign investors hold large stocks, individual investors hold small stocks and financial investors hold medium size stocks.

Figure 1 exhibits the equal-weighted average of monthly holdings (Panel A) and the value-weighted average of monthly holdings (Panel B) for domestic individual investors, financial institutional investors and foreign investors on the Norwegian stock market for a sample of 178 months from December 1992 to September 2007. In Panel A, before January 2004 (the 134th month), individual investors have the highest equal-weighted average of monthly holdings, while foreign investors have the lowest equal-weighted holdings in most of the months. However, since January 2004, individual investors' holdings have been declining dramatically over time and foreign investors are the counter parties that increase their holdings substantially. Financial investors have also reduced their holdings since January 2004, though to a lesser extent.

The value-weighted average of monthly holdings in Panel B presents a similar story. Foreign investors have been increasing their value-weighted average of holdings while domestic individual and financial investors have been decreasing their holdings. Consistent with the first two panels of Table 3.1, the fact that foreign investors have the largest value-weighted holdings but relatively smaller equal-weighted holdings indicates that they hold large stocks. The upward trend in foreign investors' holdings since January 2004, in both Panel A and Panel B, shows that foreign investors have increased their holdings in both large stocks and small stocks in the later part of the sample.

One potential explanation for the upward trend in holdings by foreign investors since January 2004 is oil prices. As plotted in Figure 3, oil prices have increased since January 2004, which corresponds to the period when foreign investors have increased their investment in the Norwegian stock market. We show in the next section that foreign investors' holdings are positively related to lagged oil prices, after controlling for lagged market returns. It is useful for Norwegian regulators to understand how Norwegian stocks, both oil related stocks and non-oil stocks, are influenced by oil prices. If oil prices are speculative in some periods, this might indicate that Norwegian stock market is exposed to more risk than other non-oil stocks dominated European markets.

### 2.3.3 Aggregate idiosyncratic volatility

Campbell et al. (2001) document a upward trend in idiosyncratic volatility in the US stock market from 1926 to 1997. Ang et al (2009) also find similar trends in other countries. However, Brandt et al. (2010) show that by 2003 volatility falls back to pre-1990s levels. Bekaert et al. (2010) examine aggregate idiosyncratic volatility in 23 developed equity markets, measured using various methodologies, and find no evidence of an upward trend when extending the sample to 2008. Using US data from 1926 to 1962, Brockman and YAN (2008) find a statistically significant downward trend in idiosyncratic volatility. By examining the Portuguese stock market, Sousa and Serra (2008) find no evidence of a statistically signicant rise in firm specific volatility. In contrast, they find that the ratio of firm-specific risk to total risk slightly decreases.

Although this paper is focusing on the cross sectional relation between investors' holdings and volatility, we follow the literature and briefly check whether the Norwegian stock market also exhibit such a upward trend in aggregate idiosyncratic volatility. Since the daily return data of Norwegian stocks starts from 1980, we have a time period of almost 30 years from March 1980 to June 2009, much longer than the holding data, to check the time series behavior of idiosyncratic volatility.

We adopt a similar measure of idiosyncratic volatility as the one in Campbell et al. (2001). Figure 2 exhibits the time series of annualized value weighted aggregate stock idiosyncratic volatility for a sample of 352 months from March 1980 to June 2009. There is no obvious upward trend as documented for the US stock market in Campbell et al. (2001). We do not go deeper into this issue since the focus of this paper is on the cross-sectional, rather than the aggregate time series, relation between investors' holding and future stock return volatility.

### 2.3.4 Descriptive statistics

#### Stock characteristics sorted on investors' holdings

We check how each type of investor's holdings are related to stock characteristics (size, price, volatility, return and turnover[10]). For each month, we sort stocks into quintiles based on one type of investor's holdings. We calculate the equal-weighted average of each variable for each portfolio, and then report the time series average of the variables in Table 3.2.

Panel A in Table 3.2 presents the mean and median of stock characteristics. The last column shows that there are 194 stocks on average. The two rows in Panel A indicate that all the variables are positively skewed. For example, the mean market capitalization is 3520 million NOK, while the median value is only 679 million NOK; the mean monthly return volatility is 0.178, while the median volatility is 0.136.

Panel B reports stock characteristics sorted on individual investors' holdings. Consistent with the literature, individual investors hold small stocks, with a monotonic negative relationship between individual holdings and stock size. Surprisingly, the volume "price" shows that the top portfolio with the highest individual holdings contains high priced stocks, at 104, which is only slightly lower than the bottom portfolio with the lowest individual holdings. This means that although individual investors prefer small stocks, they hold both high and low priced stocks. There is a seemingly negative relationship between individual holdings and stock return volatility. However, we can not infer any conclusive result from this bilateral relation since volatility is also highly correlated with other variables, such as market capitalization, which is related to return volatility. The last two columns show that stocks with higher individual holdings have lower turnover and higher returns, though the relationship is not monotonic.

[10]Trading turnover is the monthly trading volume divided by the number of shares outstanding.

Panel C reports stock characteristics sorted on the holdings of financial investors. There is no clear relationship between financial investors' holdings and size, although it is obvious that financial investors hold larger stocks comparing to individual investors. There is a positive and monotonic relation between financial investors' holdings and price, which indicates that domestic financial investors prefer high-priced stocks. Financial investors' holdings are negatively related to volatility, turnover and return.

Panel D sorts stocks on foreign investors' holdings. There is a strong positive and monotonic relationship between foreign holdings and stock market capitalization, consistent with the literature that foreign investors prefer large stocks. Comparing foreign investors with financial investors, financial investors hold much smaller stocks. The top portfolio with the highest foreign holdings has an average market capitalization of 11.3 billion NOK, while the top portfolio with the highest financial investors' holdings consists of stocks with an average market capitalization of 2.3 billion NOK. Dahlquist and Robertsson (2001) document that foreign investors have similar preferences as Swedish institutional investors. This is not exactly the case for the Norwegian stock market. The column "price" in Panel D shows that although foreign investors hold higher-priced stocks in general, they shy away from stocks with very high prices. The top portfolio with the highest foreign holdings has an average price of 100, which is lower than that of individual investors and financial investors, but the bottom portfolio with the lowest foreign holdings has a much higher price, at 144. There is a negative relationship between foreign holding and volatility, and a positive relationsip between foreign holding and turnover. There is no clear pattern between foreign holding and return.

Panel E presents the correlations between any two variables of investors' holdings and stock characteristics in the above panels. The first two columns report the correlations between individual investors' holdings and financial investors' holdings, between individual holdings and foreign holdings, and between financial holdings and foreign holdings, which are -0.467, -0.654 and -0.351, respectively. In line with the results in panels A and B, individual investors' holdings have a positive correlation, 0.167, with return volatility. The holdings of financial investors and foreign investors are negatively correlated with return volatility, at -0.173 and -0.022, respectively. Stock returns have a low correlation with the holdings of all the three types of investors, and a positive correlation of 0.104 with return volatility. Turnover also has a low correlation with the holdings of the three types of investors. Size has a high correlation with individual investors' holdings, at -0.626. The correlations between size and financial holdings and between size and foreign holdings are 0.223 and 0.465, respectively. Size is negatively related to volatility, at -0.402. Price is less correlated with volatility, at -0.389, comparing to size. In addition, the correlation between price and size is 0.424. Correlations among other variables are in general low.

In summary, this Table shows that individual investors prefer small stocks, foreign investors focus on large stocks and financial investors hold medium size stocks. However, there is a different story when we come to price. Individual investors prefer both high and low priced stocks, financial investors prefer high priced stocks, while foreign investors avoid stocks with very high prices. As for the relation between investors' holdings and volatility, it seems that stocks with higher individual holdings have higher volatility, while stocks with higher financial investors' holdings and foreign investors' holdings have lower volatility. This seems consistent with the traditional literature that individual investors, who are considered as noise traders, increase return volatility, while institutional investors (domestic and foreign institutions) decrease stock return volatility. However, it is very important to bear in mind that we can not infer any conclusive results from this table, since volatility is strongly related to size, which is again related to investors' holdings. For example, individual investors hold small stocks that in general have higher volatility. Therefore, it is important to control for size and other relevant variables when we investigate how investors' holdings affect future return volatility.

#### Holdings and stocks characteristics sorted on each stock characteristic

To have a better understanding of the relation between investors' holdings and stock characteristics, we sort stocks on each stock characteristic and report investors' holdings and other stock characteristics in Table 2.3.

Panel A of Table 2.3 sorts stocks on size. Consistent with Table 3.2, the 3 columns next to the last column show that individual investors prefer small stocks, foreign investors large stocks and financial investors medium size stocks. Large stocks, on average, have higher prices and lower volatility. However, there is no clear pattern between stock size and trading turnover, and between size and return. Panel B reports the results sorted on price. As we have shown in Table 3.2, individual investors prefer both high and low priced stocks and foreign investors shy away from high priced stocks. The top portfolio with the highest stock prices has an average price of 268 NOK. Among them, 37.7% of shares are held by individual investors and foregin investors hold the lowest proportion, 27.2%. Individual investors also prefer low priced stocks, 52.7% of shares in the bottom portfolio with lowest stock prices are held by individual investors. Price is positively related to size. Similar to size, price is negatively correlated to volatility.

Recall that there is no clear relationship between size and return, and between size and turnover in Panel A. It is interesting to note that there is a positive and monotonic relationship between price and return, and a negative and monotonic relation between price and turnover. The financial literature has paid more attention to size than price. It might be possible that price contains more information than what we have thought. Brandt (2010) show that the negative relation between stock price and idiosyncratic volatility is stronger and more robust than the size-volatility relation. In addition, since foreign investors prefer liquid stocks, the negative correlation between price and turnover might explain why foreign investors prefer large stocks but not high priced stocks. Panel C sorts stocks on volatility. As mentioned before, individual investors hold more volatile stocks than financial and foreign investors. The relationship between volatility and turnover is positive and monotonic, consistent with the existing evidence. There is also a positive and monotonic pattern between volatility and return.

Panel D reports results of sorting stocks on turnover. Interestingly, the column "mktcap" shows that both the top portfolio with the highest turnover and the bottom portfolio with the lowest turnover have small stocks, though the top portfolio contains relatively larger stocks relative to the bottom portfolio. That is why there is no clear relation between size and turnover in Panel A. Different from the size portfolios, the column "price" shows that the top portfolio, which has the highest turnover, contain stocks with lowest prices while the portfolio with the lowest turnover consists of stocks with highest prices. The 3 columns, next to the last column, show that while the top two portfolios with the highest turnover have more foreign investors than individual and financial investors, the bottom two portfolios with the lowest turnover have much higher holdings of individual investors than of financial investors and even higher than foreign investors. This is consistent with Table 3.2 in that stocks dominated by foreign investors have a higher trading volume than stocks dominated by individual and financial stocks. Panel E reports stock characteristics and investors' holdings sorted on returns. There is no clear relation between returns and other variables.

To sum up, this table provides consistent, but more interesting, elements comparing to Table 3.2. We show that there is no clear pattern between size and turnover, but price is negative correlated with turnover and the negative relation is monotonic. Since it is well documented that foregin investors prefer liquid stocks, this might explain why foreign investors shy away from high priced stocks. This could have interesting implications for corporate management and regulators. The monotonic relationship between price and returns/turnover, instead of between size and returns/turnover, might indicate that price deserves more attention.

## 2.4 Analysis

This section investigates how the domestic individual investors, financial investors and foreign investors affect stock return volatility at the stock level. Following the literature, we employ the Fama and MacBeth (1973) methodology and regress stock return volatility on lagged holdings. Since return volatility is also related to many other variables, we add various control variables in the analysis. It is well known that market capitalization is negatively correlated to volatility. Sias (1996) shows that the result of regressing return volatility on investors' holdings will be misleading, without controlling for stock size. Cheung and Ng (1992) show that future return volatility is also negatively related to stock prices. Brandt et al. (2010) find that price is more important than size in explaining volatility. We include turnover to control for the liquidity of stocks. Returns are included because of the well known negative relation between volatility and lagged returns.

There is evidence that growth options are an explanation for the increase in stock idiosyncratic volatility. Malkiel and Xu (2003) show that idiosyncratic volatility is positively associated with future growth opportunities. High market-to-book firms might have greater growth opportunities (Hotchkiss and Strickland (2003)). Hence, the book to market ratio is included in the analysis to control for firms' growth options. Cohen et al. (1976) show that the thinness of stocks, measured by stock price and floating supply, is also a determinant of volatility. We therefore include free float as a control variable. Finally, we add a dummy variable for the presence of state owners in one stock. State owners hold higher proportion of some large stocks. Since state owners are general passive investors, the stocks with the existence of state investors might have lower volatility than those without state owners, controlling for other factors. In each month, we assign 1 to stocks with the existence of state owners and 0 otherwise. We do not include a dummy for corporate investors since almost all stocks have corporate investors.

In order to compare the coefficients both across different types of investors and across different variables, we follow Bennett et al. (2003) and Brandt et al. (2010) and standardize the dependent variable and independent variables. For each cross-sectional regression, we subtract each observation by its cross-sectional average and divide the difference by its cross-sectional standard deviation. Therefore, each variable has mean 0 and standard deviation 1. The interpretation of the coefficient $\beta$ is that the expected standard deviation change in the dependent variable when there is one standard deviation change in the independent variable.

Since both volatility and holdings are persistent, the error terms will be correlated and the standard errors will be biased. We follow Brandt et al. (2010) to correct the standard errors for potential higher order serial correlation by using the Pontiff (1996) method and the Petersen (2009) technique. The t-statistics from these two different correction methods give the same statistical references. We only report the adjusted t values using Pontiff (1996), as Brandt et al. (2010) have done.

We employ the Fama and MacBeth (1973) regression as follows.

$$\begin{aligned} Vol_{i,t} = \beta_j Holding^j_{i,t-1} + \gamma_{vol} vol_{i,t-1} + \gamma_{ret} ret_{i,t-1} + \gamma_{TO} TO_{i,t-1} + \gamma_{size} size_{i,t-1} \\ + \gamma_{price} Price_{i,t-1} + \gamma_{B/M} B/M_{t-1} + \gamma_{Float} FreeFloat_{t-1} + \gamma_{dummy} StateDummy_t + \epsilon_{i,t}, \end{aligned} \tag{2.2}$$

where the dependent variable, $Vol_{i,t}$, is the logarithm value of return volatility of stock i in month t.[11] We use both the total return volatility (measure 1 in section 2.2) and the idiosyncratic volatility (measure 5 in section 2.2) in regression (2.2). The first independent variable,

[11] Recall that we document that stock return volatility is positively skewed. Andersen et al. (2001) also find that the distributions of the realized variances are skewed to the right. They show that the logarithms of the realized variances are approximately normal.

$Holding^j_{i,t-1}$, measures the holding fraction of stock i held by investor type j in month t, where j denotes individual investors, financial investors and foreign investors, respectively. The other independent variables in regression (2.2) are one month lagged volatility, stock return, turnover (trading volume/number of shares outstanding),[12] size (natural logarithm), price (natural logarithm), the book to market ratio, free float and a dummy variable for the presence of state investors. The regression (2.2) is performed for each month from December 1992 to September 2007. We then use the time series of each coefficient estimate to calculate the time series average of the coefficient.

$$\hat{\beta}_j = \frac{1}{T}\sum_{t=1}^{T}\hat{\beta^j_t}, \tag{2.3}$$

where $\hat{\beta^j_t}$ is the coefficient estimate on the holdings of investor type j in month t. We report the average coefficient, $\hat{\beta}_j$, on the holdings of investor type j, and the Pontiff (1996) method adjusted t values. We do the same for other independent variables.

The results are reported in Table 2.4. The first 3 columns report the regression results when the dependent variable is total return volatility (measure 1 in section 2.2) and the last 3 columns for the regression of the idiosyncratic volatility (measure 5 in section 2.2). The Pontiff (1996) adjusted t values are presented in parentheses in the rows below the coefficients. The first two rows in the first column show that individual investors have a negative impact on return volatility, -0.06, with a t-statistic of -5.3. The second column indicates that financial investors also have a significant and negative coefficient, -0.038, which is smaller in magnitude than that of individual investors. The result presented in the third column shows that foreign investors have a significant and positive impact on stock return volatility, with a coefficient of 0.1 and t value of 12.8. The last 3 columns, using the idiosyncratic volatility as dependent variable, present similar results. The coefficients on individual investors, financial investors and foreign investors are -0.054, -0.035 and 0.090, respectively, and all are significant at the 1% level. This panel shows that foreign investors exacerbate stock return volatility, while individual investors and financial investors dampen return volatility. However, since volatility and holding are persistent, it is possible that the causality also goes from volatility to holding. We will check whether volatility causes holdings in the next sub-section.

The coefficients on the control variables are consistent in all the regressions. Volatility is highly autocorrelated, with a coefficient of around 0.55 that is highly significant. The coefficient on lagged returns is negative, which indicates that high returns predict lower future volatility and lower returns predict higher future volatility. This is consistent with the existing evidence (Christie (1982) and Cheung and Ng (1992)). We will, in the later section, check the trading behavior of different types of investors conditional on lagged positive and negative returns, which

[12] We have tried to use both the number of shares outstanding and the free float to measure trading turnover. The results are very similar.

might strength our understanding of the asymmetric volatility puzzle. Turnover, size, and price also have negative impacts on future return volatility. Future return volatility is negatively related to a stock's free float, which is consistent with the thinness story of Cohen et al. (1976). The negative coefficient on the dummy variable shows that state investors reduce stock return volatility, keep everything else constant. Among all the control variables except lagged volatility, size, with a coefficient of -0.139, has the largest impact on return volatility.

In summary, this analysis shows that stocks with higher individual investor holdings have lower future stock return volatility, after controlling for other variables. Financial investors also have a negative impact on future volatility, though to a weaker extent. Foreign investors exacerbate stock return volatility. The results are striking for two reasons. One is that we would expect individual investors, who are usually considered as noise traders, have a positive instead of negative impact on future volatility. De Long et al. (1990b) have developed a model which shows that noise traders increase stock return volatility. However, our result that individual investors reduce stock return volatility is not necessary contradicting the noise trader model in De Long et al. (1990b). De Long et al. (1990b) only take into account information, while many other factors, in addition to information, also affect stock return volatility. For example, there is evidence that trading style affects return volatility. Momentum trading increases return volatility while contrarian traders reduce volatility (Avramov et al. (2006) and Koutmos and Saidi (2001)). If individual investors are contrarian ( Odean (1998) and Grinblatt and Keloharju (2000)), the contrarian trading of individual investors will induce a negative impact on return volatility. Hence, the aggregate impact of (individual) investors on stock return volatility depends on the combination of all the factors. Foucault et al. (2011) also find seemingly contradicting results to ours. They find that (some) individual investors are noise traders and increase stock return volatility. However, they state that they do not claim all individual investors are noise traders nor only individual investors are noise traders. Instead of focusing on a subset of individual investors as Foucault et al. (2011) have done, we use the whole population of individual investors. The second striking result is that domestic financial institutional investors and foreign investors, both as institutional investors, have opposite impacts on stock return volatility. We generally consider institutional investors have similar preference and trading behavior. Dahlquist and Robertsson (2001) have shown that foreign (institutional) investors have similar preferences to those of Swedish institutional investors.

### 2.4.1 Causation from volatility to holding

The previous subsection has shown that investors' holdings affect future stock return volatility. It is interesting to check whether the causation also goes from volatility to holdings. Using the Fama and MacBeth (1973) method, we regress changes in holding of one type of investor on lagged volatility and the other control variables in the main analysis. We also regress the holding level of one type of investor on lagged volatility, controlling for lagged holding level and other variables. As in the analysis that uses both the total return volatility and the idiosyncratic volatility in the previous subsection, we employ both measures of volatility. The results are reported in Panel B of Table 2.4.

The first three columns report the coefficient estimates and the Pontiff (1996) adjusted t values on lagged total return volatility, while the last three columns report the results on lagged idiosyncratic volatility. The last two rows, which present the results of using changes in holdings as dependent variable, show that when stock return volatility is higher, individual investors increase their holdings while foreign investors decrease their holdings. However, the first two rows, which report the results of using holding levels as dependent variable, show that all the three types of investors' holdings are not affected by lagged return volatility. This might indicate that although volatility affects some investors' trading behavior, the changes in holdings of individual and foreign investors, caused by lagged return volatility, are not so large that it affects the aggregate holding levels. Lagged volatility does not affect financial investors' trading behavior. This analysis shows that investors' holdings are not strongly affected by lagged volatility.

## 2.5 Robustness tests

The analysis in the previous section finds that individual investors and financial investors dampen return volatility while foreign investors increase return volatility. In this section, we provide various tests to check whether these results are robust.[13] We use the same control variables as in the main analysis in regression (2.2), the same Pontiff (1996) correction for the error terms, and standardize all the variables (both dependent and independent variables). For brevity reason, we only report the coefficient and t statistics on investors' holdings, which is the focus of this paper.

### 2.5.1 Restrictions on foreign holdings and short sales

Restrictions were imposed on foreign holdings in the Norwegian market and were not lifted until January 1995.[14] To check whether the impact of foreign investors and other types of investors on stock return volatility have changed after the restriction was lifted, we divide the whole sample into 2 sub-samples. We also examine whether the abolition of the short-sales constraint in January 1997 matters for investors' impact on stock return volatility. We redo the Fama and MacBeth (1973) regression for subsamples before and after January 1995, and before and after

[13] In most cases, we regress the total stock return volatility on holdings of individual investors, financial investors and foreign investors, respectively.

[14] See more detailed information on this in Bohren and Odegaard (2001)

January 1997.

The results are reported in Panel A of Table 2.5. The first two columns present the coefficients and Pontiff (1996) adjusted t statistics (in the parentheses) on the lagged investors' holdings before and after the abolition of the restriction on foreign holdings in January 1995. The last two columns report the results for the subsamples before and after the abolition of the short sales constraint in January 1997. Before the abolition of the restriction on foreign holdings, individual investors investors have no impact on future stock return volatility, with a small and insignificant coefficient of -0.0101. Individual investors also have insignificant impact, with a coefficient of -0.0149 and t statistics of -1.6339, on return volatility before the lift of the short sales constraint in January 1997.[15] The negative impact of individual investors on return volatility in the period after January 1995 and January 1997 is consistent with the evidence in the main analysis. Financial investors have a consistently negative and significant coefficients on holdings, and foreign investors have a similar positive and significant impact on return volatility, in all the 4 subsamples. However, though foreign investors have a positive impact on return volatility before the abolition of foreign holding constraints, the magnitude is much smaller than the coefficient in the later period. We will examine this further in a later section.

### 2.5.2 Small vs. large stocks and low- vs. high- priced stocks

It is possible that the same type of investors have different impacts for stocks with different size and price. Brandt et al. (2010) find that individual investors increase return volatility among low-priced stocks, while institutional investors increase volatility for stocks with high prices. We note some differences between the Norwegian data and the US data used in Brandt et al. (2010). Brandt et al. (2010) find that price matters more for volatility than size does since the coefficient on price is much higher than the coefficient on size in the regression of volatility on holdings and stock characteristics. This is not the case in our data. Table 2.4 shows that the coefficients on size are much higher than the coefficients on price in all the regressions. Brandt et al. (2010) also document a link between low-priced stocks and individual holding and trading, which is different in our analysis. As shown in Table 3.2, the top quintile with the highest individual holdings has high-priced stocks.

We redo the Fama and MacBeth (1973) regressions for small stocks (the 50% stocks smaller than the median), large stocks (the 50% stocks larger than the median), low-priced stocks (the 50% stocks with the price below the median), and high-priced stocks (the 50% stocks with the price above the median). The results are presented in Panel B of Table 2.5.

The first two columns report the coefficients and t-statistics (in parentheses) on lagged investors' holdings for low and high priced stocks, and the last two columns for small and large

[15] In the next section, we check why individual investors have small and insignificant coefficients on return volatility before January 1995 and before January 1997.

stocks. Domestic individual investors and financial institutional investors have a negative impact on return volatility of both small and large stocks and both low and high priced stocks, and all the coefficients are significant at the 1% level. The same story applies to foreign investors. For both small stocks and large stocks, and for both high-priced stocks and low-priced stocks, foreign investors have similar positive and significant impact on future return volatility. This shows that all the three types of investors have their consistent effects on stocks with different size and difference prices.

### 2.5.3 Tests using quarterly and annual frequencies

Sias (1996) and Malkiel and Xu (2003) use annual holding data and Brandt et al. (2010) employ quarterly holding data to check the relation between institutional investor holdings and stock return volatility. To reconcile our results with previous studies and to check whether our previous evidence still holds for lower holding data frequency, we use quarterly and annual frequencies in this subsection to redo the Fama and MacBeth (1973) regression for domestic individual investors, financial institutional investors and foreign investors. The results are presented in Panel A of Table 2.6. The findings that individual investors and financial investors reduce volatility while foreign investors increase volatility remain the same. All the Pontiff (1996) adjusted t-statistics are significant at the 1% level, except that the coefficient on financial investors with annual frequency is significant at the 5% level. This analysis shows that our results are robust for different data frequencies.

### 2.5.4 Tests using other measures of stock return volatility

We apply the other three measures of stock return volatility, measures 2, 3 and 4 (the idiosyncratic volatility) in section 2.2, which are not studied in the main analysis. The results, which are reported in Panel B of Table 2.6, are very similar to the ones using the measures of volatility reported in Table 2.4. This demonstrates that the results we get in the main analysis are robust to the measure of total return volatility and idiosyncratic volatility.

### 2.5.5 Regressing volatility on changes in holdings

If investors can affect stock return volatility, then not only holding levels, but changes in holdings might also be able to predict future return volatility. However, it is likely that changes in holdings have much less power than holding levels, since investors' information, trading behavior and other characteristics are more likely to be reflected in holding levels than in changes in holdings. Rubin (2007) shows that ownership level proxies for group-specific trading behavior. Gompers and Metrick (2001) study how institutional investors' demand for stock characteristics affects stock returns. They find that the level of institutional holdings forecasts returns better than the change in holdings, since the change in holdings reflect only a small fraction of institutional trade and is a much noisier measure. We expect changes in holdings to have low or even no power to forecast future return volatility. We redo the Fama and MacBeth (1973) regression, but replace investors' holding levels with changes in holdings. We use monthly changes in holdings, as well as quarterly and annual changes in holdings, which reflect larger preference changes than monthly changes in holdings.

The results are presented in Panel C of Table 2.6. The pontiff (1996) adjusted t values are reported in parentheses in the rows below the coefficients. The first column, which presents the coefficients on monthly changes in holdings, shows that all the coefficients are very small and insignificant. Falkenstein (1996) argues that if variation in variables across firms is much greater than the variation in variables within firms over the sample period, there will be a significant loss of power. He shows that the loss in power from using within-firm changes in the explanatory variables is signicant.

The last 2 columns, which use quarterly and annual changes in holdings to forecast future return volatility, provide the consistent results for individual investors and foreign investors as in the main analysis. However, the magnitude and statistical power of the coefficients are much lower than the ones using holding levels. Changes in holdings of financial investors can not predict subsequent stock return volatility, no matter which data frequency we use. The analysis in this subsection shows that changes in holdings contain less information and provide much weaker or insignificant results than the levels of investors' holdings.

### 2.5.6 Use additional control variables

There are other variables that might affect stock return volatility. Capital structure is an important determinant of stock return volatility. Christie (1982) shows that return volatility is an increasing function of financial leverage. Dennis and Strickland (2004) also find a positive relation between leverage and total and idiosyncratic volatility. In addition, return on asset (ROA) could affect stock return volatility. As ROA increases, firm-level uncertainty decreases (Gaspar and Massa (2006)). Sousa and Serra (2008) show that firm idiosyncratic volatility is negatively related with ROA. Furthermore, whether firms pay a dividend or not might matter for stock return volatility. Rubin and Smith (2009) study the effect of a firm's dividend policy on the relation between the levels of institutional ownership and stock return volatility. They find that institutional ownership is negatively related to volatility among non-dividend paying stocks, and institutional ownership is positively related to volatility among dividend paying stocks. We hence conduct the Fama and MacBeth (1973) analysis in regression (2.2) by adding these three variables: capital structure (the book value of debt divided by the market value of equity in the previous year), ROA and a dummy variable of 1 for dividend payment stocks and of 0 otherwise, as controls in the regression.

The coefficients on holdings of all the three types of investors, -0.055 for individual investors, -0.0413 for financial investors, and 0.1007 for foreign investors, are significant and very similar to the ones in the main analysis in Panel A of Table 2.4. We have also divided stocks into dividend paying group and non dividend paying group. Investors' impact on return volatility remains similar. Therefore, the impact of the three types of investors on return volatility is robust to various control variables.

### 2.5.7 Oil price, investors' holdings and the impact on volatility

Norway is an oil producing country and has a high proportion of its GDP from annual oil revenue. Hence, it is likely that oil prices affect the holdings and trading behavior of investors, especially of foreign investors. When oil prices are high, many oil related Norwegian stocks and probably the entire Norwegian stock market will perform well. Therefore, international investors might be more interested in the Norwegian stock market due to demands such as hedging, speculating or rebalancing. Figure 3 exhibits the monthly price chart of Brent Crude oil during the sample period from December 1992 to September 2007. Panel A, which presents monthly oil prices, shows that the oil prices have increased dramatically in the second sub period, especially in the last one fourth of the sample. Interestingly, this graph corresponds fairly well to foreign investors' holdings in Figure 1, in the sense that foreign investors' holdings and oil prices increase at the same time. We examine how investors' holdings are related to past oil prices, controlling for lagged market returns. We use oil prices instead of oil returns because foreign investors are more likely to be attracted to the Norwegian stock market due to high oil prices than when the oil returns are high but oil prices are low. Panel B of Figure 3 exhibits the time series of monthly oil returns, which behave like a random variable throughout the sample period.

We regress both equal-weighted monthly holdings and value weighted monthly holdings of individual, financial and foreign investors on one month lagged oil prices, controlling for lagged market returns. We employ the Pontiff (1996) method to correct for standard errors due to the persistence of investors' holdings and oil prices. The results, which are reported in Panel A of Table 2.7, show that foreign investors increase their holdings when previous oil prices are high while domestic individual and financial investors do the opposite. Since both oil prices and investors' holdings are persistent, the causality might go the other direction, from investors' holdings to oil prices. However, it is more reasonable to argue that oil prices cause investors' trading behavior than the other way around. The positive correlation between oil prices and foreign investors' holdings might indicate that the Norwegian stock market is affected by foreign investors to a stronger extent than other European stock markets, due to oil price movements.

We are interested in examining whether investors' impact on return volatility is related to oil prices. Since we do not have good data on industry codes to figure out which stocks are oil related and which ones are not, we distinguish these two types of stocks by checking how sensitive they are to oil shocks. For each stock i, we regress its monthly return on contemporaneous and two lagged oil returns.

$$r_{i,t} = \alpha + \beta_0 r_{oil,t} + \beta_1 r_{oil,t-1} + \beta_2 r_{oil,t-2} + \epsilon_{i,t}, \tag{2.4}$$

$\sum_{k=0}^{2} \beta_k$ measures the sensitivity of one stock to oil shocks. We also try other measures of oil sensitivity, for example, regress monthly stock returns on contemporaneous oil returns. The results remain similar.

Since stocks' oil sensitivity might matter for their return volatility and investors' impact on return volatility might be different conditional on stocks' oil sensitivity, we redo the Fama and MacBeth (1973) analysis in regression (2.2) by adding two more explanatory variables. One is the dummy variable for oil sensitivity, which is 1 if one stock's sensitivity to oil returns is above the median and 0 otherwise. The second new explanatory variable is the interaction term of the dummy variable for oil sensitivity and investors' holdings. The coefficients and the Pontiff (1996) adjusted t-statistics on investors' holdings and these two new explanatory variables are reported in Panel B of Table 2.7.

The coefficients on investors' holdings in the first column, which are for stocks with low oil sensitivity, are negative for individual investors and financial investors, and positive for foreign investors. The next column, which reports the coefficients on the interaction term, shows that conditional on stocks that are more oil related, individual investors decrease stock return volatility, while financial investors and foreign investors have a positive impact on return volatility. The total impact of investors' holdings on return volatility of stocks with high oil sensitivity is the sum of the coefficient on investors' holdings and the coefficient on the interaction term. Individual investors have a strong negative impact on return volatility, with a coefficient estimate of -0.1 (-0.052+(-0.0481)). Financial investors have a weaker negative impact on return volatility, at -0.021 (0.0518-0.0308), comparing to that of individual investors. Foreign investors have a significant and positive total coefficient of 0.13 (0.1065+0.0240). The last column shows that stocks with higher oil sensitivity have slightly higher future return volatility.

We also divide all the stocks into oil related stocks (with high oil sensitivity) and non-oil stocks (with low oil sensitivity) to check how investors affect return volatility of these two groups of stocks. We sort stocks on lagged oil sensitivity into two portfolios and conduct the Fama and MacBeth (1973) analysis for each portfolio. If the oil price is one of the reasons for foreign investors' investment in the Norwegian stock market, then foreign investors might have stronger impact on oil related stocks. The results are presented in Panel C of Table 2.7. The last two rows show that foreign investors have a much stronger positive impact on return volatility for stocks with high oil sensitivity than stocks with low sensitivity, 0.0738 vs. 0.0481, as expected. It seems that individual investors are the trading counter-party of foreign investors for stocks with high oil sensitivity, with a large negative coefficient of -0.0804. Financial investors have a small and insignificant impact on return volatility for stocks with high oil sensitivity. This is consistent with the results in Panel B that while financial investors in general have a negative impact on return volatility, they have a positive impact on return volatility for stocks with high oil sensitivity. To check whether these results are due to investors' different holding levels on oil-related stocks and non-oil stocks, we calculate the average holdings of the three types of investors in these two oil sensitivity portfolios. All the three types of investors have similar holding levels in oil-related stocks and non-oil stocks, though individual investors have slightly higher holdings while financial investors have slightly lower holdings on oil related stocks.

Since there is a strong upward trend in the oil price in the later sub period of the sample (from January 2004), we divide the whole period into before and after January 2004 sub-periods to check whether investors have different impact on return volatility in these two sub-periods. In Panel D, we report how investors' equal-weighted and value weighted holdings are related to lagged oil prices, controlling for lagged market returns, in the two sub-periods. Surprisingly, column 1 shows that, before January 2004, equal-weighted foreign investors' holdings are negatively related to past oil prices, though the coefficient is very small, while the equal-weighted holdings of individual investors are positively related to past oil prices. The second column shows that foreign investors increase their value-weighted holdings while domestic individual and financial investors decrease their value-weighted holdings when past oil prices were higher before January 2004. These two columns indicate that while foreign investors increase their holdings on large stocks conditional on higher lagged oil prices, they decrease their holdings, though marginally, on small stocks before the oil price started to increase in 2004.

The last 2 columns in Panel D report how investors' holdings are affected by lagged oil prices when oil prices have increased dramatically since January 2004. While the correlation between equal-weighted foreign holdings and 1 month lagged oil prices and the correlation between value-weighted foreign holdings and 1 month lagged oil prices, reported in columns 1 and 2 of Panel D, are -0.0156 and 0.068 before January 2004, in which the oil prices were low, these correlations become significantly larger, at 0.215 and 0.207 (in columns 3 and 4), after January 2004. This shows that, when oil prices are high, foreign investors increase their holdings in both large and small stocks and the extent is substantial. It seems that individual investors are the ones selling small stocks to foreign investors, since individual investors' equal-weighted holdings are strongly negatively correlated with lagged oil price, with a coefficient of -0.1998. This might explain why the equal-weighted holdings of individual investors have reduced dramatically in the late sub period as exhibited in Figure 1. In both sub periods, financial investors are the main players who sell large stocks to foreign investors, and this corresponds to the declining value-weighted holdings of financial investors and the symmetric pattern between the value-weighted holdings of financial and foreign investors in Panel B of Figure 1. This is not surprising since individual investors hold more smaller stocks while financial investors hold relatively larger stocks.

Panel E reports the impact of investors' holdings on stock return volatility for stocks with high and low oil sensitivity before and after January 2004. The results show that foreign investors have a stronger positive impact on return volatility for stocks with high oil sensitivity than for stocks with low oil sensitivity both before and after January 2004. Foreign investors' positive impact on stocks with high oil sensitivity is also stronger when oil prices were higher after January 2004 (0.091) than when oil prices were lower before January 2004 (0.0678).

In short, Table 2.7 analyzes how oil prices affect investors' holdings and whether investors' impact on return volatility is different for stocks with high and low oil return sensitivity. The results show that foreign investors invest more in the Norwegian stock market, and the positive impact on return volatility is stronger, when oil prices are high in the later period of the sample. They also have a stronger positive impact on return volatility for stocks with high oil sensitivity than for stocks with low oil sensitivity.

### 2.5.8 Sub-types of foreign investors and individual investors

In this subsection, we check the sub groups of foreign investors and individual investors. Foreign investors consist of both nominee accounts[16] with unknown identities and the known identities (non-nominee) accounts. To examine whether foreign investors' positive impact is mainly driven by the nominee accounts, we redo the Fama and MacBeth (1973) regression for foreign investors with unknown (nominee) accounts and known (non-nominee) accounts, respectively. There are also Norwegian investors who live abroad and are considered foreign investors. It is possible that the positive impact of foreign investors is caused by Norwegian foreign investors instead of foreign investors from other countries. We therefore also divide foreign investors into Norwegian foreign investors and non-Norwegian foreign investors and investigate their separate impact on return volatility.

The results are reported in Panel A of Table 2.8. The first 2 columns show that foreign investors with known identities and with nominee accounts have a similar significant and positive impact on return volatility, with coefficients of 0.0349 and 0.0309, respectively. The last 2 columns indicate that Norwegian foreign investors have no impact on return volatility, with an extremely small and statistically insignificant coefficient on future return volatility. The Non-Norwegian foreign investors have a positive and significant impact on return volatility, as documented in the previous analyses. This means that the positive impact of foreign investors on return volatility is driven by international investors, rather than Norwegian investors who reside abroad.

[16] An account in which the named holder holds the assets in it on behalf of another (the beneficiary). In the stock market, the most common use of nominee accounts is where execution-only brokers act as nominees for their clients. The shares are registered in the name of the broker, but the client has beneficial ownership of them. See http://www.finance-glossary.com/define/nominee-account/2006/0/N.

It is also likely that the positive impact of foreign investors on return volatility is driven by large international institutions. We therefore divide foreign investors into large and small foreign investors, requiring a minimum average portfolio value of K million NOK, where K=50, 100, 500, and 1000. The results are reported in Panel B of Table 2.8. Regardless of the requirement of the minimum portfolio value, both large and small foreign investors have a significant and positive impact on volatility.

Grinblatt and Keloharju (2000) show that large individual investors are more sophisticated than small individual investors in the Finnish stock market. If this is the case in the Norwegian stock market, then large individual investors and small individual investors might have different impacts on stock return volatility. To define which individual investors are large investors, we calculate the time series average of stock portfolio value for each investor and define one investor as a large investor if her portfolio value is larger than X million NOK, where X=0.5, 1, 5 and 10.

The results of the impact of large and small individual investors on return volatility are presented in Panel C of Table 2.8. The first two columns show that while large individuals with a minimum of 0.5 million NOK and 1 million NOK have a negative impact on volatility, the magnitudes are much smaller than small individual investors. The third column, in which large individual investors have a minimum portfolio value of 5 million NOK, shows that large individuals have an insignificant impact on return volatility. When the minimum portfolio value is required to be 10 million NOK, large individual investors have a significant and positive impact on return volatility, though the magnitude of coefficient is small.

The four columns in the first row of Panel C show that when individual investors have higher portfolio value, their negative impact on volatility decreases and the impact becomes positive when the minimum portfolio value is required to be 10 million NOK. The last two rows show that small individual investors in all the 4 columns have negative and significant coefficients. If large individual investors are more sophisticated, as documented in Grinblatt and Keloharju (2000), then the negative impact of small individual investors on return volatility might indicate that individual investors trade on noisy information and/or suffer from behavioral biases.

### 2.5.9 Volatility of portfolios double sorted on market capitalizations and holdings

This subsection employs a different method to check whether investors' holdings have predictive power for future stock return volatility by sorting stocks on investors' holdings and forming portfolios. If one type of investor has a positive impact on stock return volatility, then the stock portfolio with higher holdings of this type of investor should have higher return volatility. However, it is important to bear in mind that stock market capitalization is an important determinant of volatility. Sias (1996) examines stock return volatility by sorting stocks both on institutional investors' holdings alone and sorting stocks on size and holdings. He shows that the results could be misleading, without controlling for stock market capitalization. We therefore double sort stocks on both size and investors' holdings, following Sias (1996).

For each month t, we sort stocks into size quintiles based on stock market capitalization at t-1, and within each size quintile, we further sort stocks into holding quintiles based on the fraction of shares held by each type of investor at t-1. We calculate the equal-weighted portfolio returns, using stock monthly return at t, for each of the 25 portfolios in each month, and then compute, for each portfolio, the monthly standard deviation of the time series portfolio returns. We report both portfolio volatility and ownership holdings for the 25 portfolios in Table 2.9. The first 5 columns report portfolio volatility and the last 5 columns present the equal-weighted average of ownership holdings for each portfolio.

Panel A reports return volatility of portfolios sorted on market capitalization and individual investors' holdings. The last portfolio with the smallest stock size in column 5 shows that stocks with the highest individual investors' holdings have much lower monthly volatility than the portfolio with the lowest individual investors' holdings, 0.076 vs. 0.147. The middle 3 size portfolios also indicate that stocks with higher individual investors' holdings have lower return volatility than stocks with lower individual investors' holdings. These 4 size portfolios support the evidence derived from the Fama and MacBeth (1973) analysis that higher individual investors' holdings predict lower future return volatility. However, the portfolio with the largest stock size in column 1 does not support the previous evidence, which might be due to the fact that foreign investors are the biggest players in the large stocks.

Panel B reports the volatility of portfolios sorted on size and financial investors' holdings. Similar to Panel A, except the largest size portfolio, stocks with higher financial holdings have lower return volatility. Panel C presents the results of sorting stocks on size and foreign holdings. Except the largest size portfolio, stocks with higher foreign holdings have higher volatility, consistent with the results from the Fama and MacBeth (1973) analysis. For the portfolio with the largest stock size in column 1, the lower volatility of stocks with higher foreign investors' holdings is puzzling. Since state investors have a negative impact on return volatility, documented in Table 2.4, the reason that large stocks with higher foreign holdings have lower volatility might be that large stocks with high foreign holdings have also high state holdings and this reduces stock return volatility.

To sum up, all the robustness tests in this section support the results from the main analysis that domestic individual investors and financial investors dampen future return volatility, and foreign investors have a positive impact on stock return volatility.

## 2.6 Explanations

### 2.6.1 Theories and evidence

There are many explanations for why and in which way investors affect stock return volatility. Information is definitely one of the determinants. However, as in Dennis and Strickland (2004), we do not investigate which types of investors are informed and whether investors' impacts on return volatility is stabilizing or destabilizing.

In this section, we consider three potential determinants of stock return volatility: investors' trading style, trading volume and investment horizons. The first one is trading strategy, momentum trading (positive feedback trading) or contrarian trading (negative feedback trading). De Long et al. (1990a) develop a model showing that positive feedback trading increases stock return volatility. Avramov et al. (2006) provide evidence that contrarian trading decreases volatility and momentum trading increases stock return volatility. Koutmos and Saidi (2001) show that positive feedback trading may lead to excess volatility. Based on our results, we hypothesize that individual investors are contrarian traders, foreign investors are momentum traders and domestic institutional investors have a trading strategy in between, probably contrarian trading.

Trading volume is the second explanation. Many studies have shown a positive correlation between contemporaneous trading volume and volatility (Schwert (1989) and Gallant et al. (1992)). Schwartz and Shapiro (1992) show that institutions turn over their portfolios and trade more often than individuals do. For example, mutual funds typically have to trade when exogenous shocks of cash withdrawals or infusions occur as they are committed to provide funds to unit holders on demand and to comply with their stated investment policy. In some instances, institutional porotfolio turnover may be driven by agency problems (window dressing). Dennis and Strickland (2002) show that higher level of institutional investors is associated with higher level of trading turnover. We hypothesize that investors who increase volatility have higher trading volume and investors who decrease volatility have lower trading volume.

Furthermore, it is reasonable to expect that investment horizons, as a measure of trading frequency, affect stock return volatility. Keep everything else equal, shorter investment horizons would increase stock return volatility and vice versa. There is evidence that shareholders' investment horizons matter for firms' investment and performance. Stein (1989), Shleifer and Vishny (1990), and Bebchuk and Stole (1993) model how shareholders' short-term focus can lead to suboptimal investment behavior. Froot et al. (1992) argue that many hold the view that shorter horizons for stockholders lead inevitably to shorter horizons for managers when they evaluate investment opportunities. Gaspar et al. (2005) investigate how investment horizons of a firm's institutional shareholders impact the market for corporate control. They find that target firms with short-term shareholders are more likely to receive an acquisition bid but get lower premiums, and bidder firms with short-term shareholders experience signicantly worse abnormal returns around the merger announcement, as well as higher long-run underperformance. Moreover, industry practitioners seem to devote considerable attention to investor horizon considerations, and many firms implement investor relation activities aimed at attracting long-term investors to their shareholder base.

Markowitz (1991) suggests that individual investors may make investment decisions based on long-term horizons. Friedman (1995) argue that institutional investors, who compete among one another for the business of ultimate savers, systematically adopt a time horizon that is too short and there are plausible reasons to think that institutional capital is less patient than individuals own capital. We check whether individual investors, who dampen return volatility, have the longest investment horizon, and foreign investors, who exacerbate stock return volatility, have the shortest investment horizon.

### 2.6.2 Trading strategy

#### Fama and MacBeth (1973) analysis

We regress both changes in holding and holding levels of each type of investor in month t on lagged returns from month t-1 to t-k, where k=1, 2, 3, and 6, and other control variables, which are the same as in the main analysis.

$$H_{i,t}^{j} = \beta_1^{j} ret_{i,t-k,t-1} + controls + \epsilon_{i,t}, \tag{2.5}$$

$$\Delta H_{i,t}^{j} = \beta_2^{j} ret_{i,t-k,t-1} + controls + u_{i,t}, \tag{2.6}$$

where $H_{i,t}^{j}$ is the aggregate fraction of shares of stock i held by investor type j in month t, and $\Delta H_{i,t}^{j}$ measures the change in holding ownership of stock i by investor type j from month t-1 to month t, where j = individual investors, financial investors and foreign investors. $ret_{i,t-k,t-1}$ measures cumulative stock returns from month t-k to month t-1, where k=1, 2, 3 and 6 and is corresponding to the horizon in Grinblatt and Keloharju (2000). We follow the Fama and MacBeth (1973) analysis in the previous sections, standardize both the dependent variable and the independent variables, and employ the Pontiff (1996) method to correct for standard errors.

The results are reported in Panel A of Table 2.10 for changes in holdings in regression 2.5 and in Panel B of Table 2.10 for holding levels in regression 2.6. The 4 columns exhibit the coefficients and t statistics (in parentheses) on past returns from month t-1 to t-k, where k=1, 2, 3, and 6. Panel A and Panel B provide consistent results that individual investors are contrarian investors and foreign investors are momentum investors. All the coefficients on lagged returns are negative and significant for individual investors, and are positive and significant for foreign investors. This means that individual investors sell when past returns are high and buy when past returns are low, while foreign investors increase their holdings when stock prices go up and decrease their holdings when stock prices go down. These results are consistent with our hypotheses that trading style is one of the channels that foreign investors increase return volatility and individual investors reduce return volatility. Both panels indicate that financial investors' holdings are not affected by past returns, except when we regress changes in holdings on past returns up to 6 months, which has a positive coefficient with a t-statistic of 1.95.

These results on investors' trading style are consistent with Grinblatt and Keloharju (2000), who show that foreign investors are momentum traders, individual investors are contrarian traders and financial investors fall in between, using Finnish data. There is other evidence that individual investors follow a contrarian trading strategy. Kaniel et al. (2008) show that individuals tend to buy stocks following declines in the previous month and sell following price increases. Barber et al. (2007) analyze all the trading activity on the Taiwan Stock Exchange and show that Taiwanese individual investors are selling winners at a faster rate than losers. Odean (1998) finds that investors at a US brokerage house are reluctant to realize loses. Calvet et al. (2009) also show that individuals in Sweden are selling winning stocks. All these studies present evidence that is consistent with contrarian investment strategies of Norwegian individual investors.

It is possible that investors react differently to positive returns and negative returns. Hence, we separate returns into positive and negative ones and regress changes in holdings of each type of investor on both positive and negative lagged returns. The results, reported in Panel C, show that, for individual investors, the negative coefficients on both positive and negative returns are negative, and, for foreign investors, the coefficients on both positive and negative returns are positive, consistent with the evidence in Panel A and Panel B. However, the coefficients on negative returns are much larger in absolute value and more significant than those on positive returns for past returns up to 2 months. This shows that investors react stronger when recent stock prices go down than when recent stock prices go up, which might strengthen our understanding of the asymmetric volatility puzzle that volatility is negatively related to lagged returns. Consistent with this result, Hotchkiss and Strickland (2003) find that when firms report lower than forecasted earnings, the increase in variance is greater for firms with a high proportion of momentum investors. When we regress changes in holdings on past returns up to 6 months, the coefficients (in absolute terms) on positive returns are similar to, or even larger than, the coefficients on negative returns. This might indicate that it takes longer time for investors to react on positive shocks than negative shocks, since investors are more concerned and react faster when prices go down.

Interestingly, the middle 4 rows show that financial investors react differently on positive returns and negative returns. While they behave as momentum traders when past returns are positive, they act as contrarian investors when past returns are negative. The opposite trading behavior on past positive and negative returns explains the small and insignificant coefficients on lagged returns in Panel A and Panel B where we do not distinguish positive returns from negative returns.

Recall that Panel B of Table 2.8 shows that large individual investors have a weaker negative or even positive impact on stock return volatility, comparing to small individual investors. We check whether large and small individual investors also have different trading behavior conditional on lagged returns. As in Table 2.8, we require large individual investors to have a minimum portfolio value of X million NOK, where X=0.5, 1, 5 and 10. The results of coefficients on lagged returns for small and large individual investors are reported in Panel A of Table 2.11. The results, using both changes in holdings and holding levels, show that large individual investors have much weaker contrarian trading behavior and their impact becomes insignificant when large individual investors have a minimum portfolio value of 5 and 10 million NOK. The magnitude of the negative coefficients on lagged returns for large individual investors is decreasing when the required minimum portfolio value is larger. Grinblatt and Keloharju (2000) also find that large Finnish individual investors are less contrarian, comparing to small individual investors.

We have shown in Panel A of Table 2.5 that individual investors have insignificant impact on return volatility before January 1995 and before January 1997. We check whether this is related to individual investors' trading style, by regressing individual investors' changes in holdings on one month lagged returns, controlling for other variables, before and after January 1995. We show that individual investors' trading is not significantly affected by lagged returns, with a coefficient of -0.044 and t statistics of -1.615, before January 1995. In contrast, the coefficient and t statistics on lagged returns for individual investors in the period after January 1995 are -0.056 and -4.713. We also check individual investors' trading style conditional on lagged returns before and after January 1997. The coefficient for the sub-period before January 1997 is -0.038, with a statistics of -1.872, which is marginally significant. The coefficient for the sub-period after January 1997 is much larger and more significant, at -0.062, with a t statistics of -4.772. This analysis shows that individual investors' contrarian trading is related to their negative impact on return volatility. When there is no contrarian trading in one period, the negative impact on return volatility disappears. Panel A of Table 2.5 also shows that foreign investors have weaker positive impact on return volatility before the abolition of foreign holding constraints in January 1995 than in the period after January 1995. The regressions of foreign holdings on lagged stock returns show that while foreign investors are momentum traders after the lift of foreign holding constraints in January 1995, their holdings are not affected by lagged returns before January 1995. This means that foreign investors' impact on return volatility might be related to their momentum trading style.

### Grinblatt and Keloharju (2000) measure of trading style

In this subsection, we follow the method in Grinblatt and Keloharju (2000) to examine investors' investment styles related to past returns, by using "buy ratio" – the number of shares bought divided by the sum of the number of shares bought and the number of shares sold. The difference is that Grinblatt and Keloharju (2000) use daily frequency and 16 finnish large stocks, while we use monthly frequency and all the stocks in the Norwegian stock market.

In each month t, we sort stocks on past returns into quartiles and calculate the equal-weighted cross-sectional average of buy ratio for each portfolio. The difference between the average buy ratio in the top quartile (with the highest past return) and the average buy ratio in the bottom quartile (with the lowest past returns) is the measure of investment style in month t. If the difference for investor type j in month t is positive, then investor type j is considered as momentum trader in month t, since the buy ratio for past winning stocks is higher than the buy ratio for past losing stocks. On the other hand, investor type j with a negative value of the difference between buy ratio in the top and bottom quartile, is considered as contrarian.

The investment style for each type of investor is determined by the fraction of months for which the buy ratio is positive. If the fraction for one investor type is larger than 0.5, this type of investor is considered as momentum trader. If the fraction is less than 0.5, then this type of investor is considered as contrarian. We measure trading style conditional on returns up to 6 months in the past, as Grinblatt and Keloharju (2000) have done. The past returns for month t are the cumulative monthly returns from month t-m to t-1, where m=1, 2, 3 and 6.

Panel B of Table 2.11 presents the fraction of months with positive buy ratio and its p-value for individual investors, financial institutions and foreign investors. The columns (-m, -1) indicate that the fraction is computed conditional on past returns from month t-m to t-1. The first row and the third row show that individual investors are contrarian traders and foreign investors are momentum traders. These results are significant with p-values of zero. The second row shows that the fraction of months for positive buy ratio is less than 0.5 for financial investors when using returns in the past one or two months, but is insignificant at the 5% significance level. Financial investors become momentum investors when conditioning on past returns up to 6 months. These results are largely consistent with the results in Grinblatt and Keloharju (2000) and those from regression analysis of trading strategy in the previous subsection.

To sum up, the analysis of investors' trading style provides supportive evidence to our hypotheses that foreign investors, who increase stock return volatility, are momentum traders, and individual investors, who have the strongest negative impact on return volatility, are contrarian traders. The trading behavior of financial investors, who have a weaker negative impact on return volatility, is less affected by lagged stock returns. We also show that individual investors and foreign investors have consistent trading behavior conditional on lagged positive and negative returns. However, both types of investors react stronger to negative returns than to positive returns, which might shed some light on why stock return volatility is negatively related to lagged returns. When individual investors have a small and insignificant impact on return volatility before January 1995, their contrarian trading behavior disappears in the same period. Similarly, the smaller positive impact of foreign investors on return volatility before January 1995 might be because foreign investors did not have momentum trading behavior at that time. All these results indicate that trading style is one of the explanations for investors' impact on return volatility.

### 2.6.3 Trading volume

In this subsection, we check whether foreign investors, who increase stock return volatility, trade more than the other types of investors that decrease stock return volatility. Due to the unavailability of trading data, we use monthly changes in holdings of one investor to proxy this investor's trading. For each stock i in each month t, we calculate the net traded shares, the number of shares held in month t minus the number of shares held in month t-1, adjusting for stock split/merge, for each investor. The total trading of investor type j on stock i in month t is the sum of the absolute value of the net traded shares of stock i in month t by all the investors in investor type j, divided by the free float or the number of shares outstanding in month t-1.

$$TotTrade^{j}_{i,t} = \frac{\sum_{k=1}^{K^j} |\Delta S^k_{i,t}|}{SHS_{i,t-1}}, \tag{2.7}$$

where $\Delta S^k_{i,t}$ is the change in holding shares of stock i from month t-1 to month t by investor k who belongs to investor type j, and j denotes individual investors, financial investors and foreign investors. $\sum_{k=1}^{K^j} |\Delta S^k_{i,t}|$ measures the aggregate number of shares net traded by all the investors in type j. There are $K^j$ investors in type j. $SHS_{i,t-1}$ measures free float or the number of shares outstanding of stock i in month t-1.

In addition to investigating the total trading of each investor type, we also check total trading per holding, which is investors' total trading divided by their proportion of holding. The intuition is as follows. Even though investor type A is less active trader than investor type B, if investor type A holds much larger fraction of holdings than investor type B, the total trading of investor type A might be higher than that of investor type B. We therefore examine whether the high total trading of one type of investor is due to their high holdings or their active trading. For example, assume both individual investors and foreign investors hold 30% of one group of stocks (e.g. small stocks) and individual investors trade less than foreign investors, the total trading of individual investors will be lower. However, even if individual investors trade the least on average, if they hold much higher holding than other types of investors, the total trading of individual investors might be higher. The total trading per holding reveals how active each type of investor is given one unit of holding. We report both total trading and total trading per holding for all the three types of investors.

In each month t, we sort stocks on market capitalizations into 3 portfolios and calculate equal-weighted average of total trading of individual, financial and foreign investors for each portfolio. We then compute the time series average of total trading for each size portfolio. The same procedure is used for total trading per holding. Table 2.12 reports total trading and total trading per holding for individual, financial and foreign investors. The total trading is adjusted by free float in Panel A, while by the number of shares outstanding in Panel B. The last row in Panel A shows that, on average, individual investors have the lowest total trading, at 0.063, while foreign investors have the highest trading, at 0.144. Financial investors fall in a middle ground, at 0.106. When we look at investors' total trading for each size portfolio, the first 3 rows in Panel A show that while individual investors have the lowest total trading for the medium and large size portfolios, they have the highest total trading for the small size portfolio. Since individual investors hold most small stocks, we check whether the highest total trading of individual investors in small stocks is due to their high holding or because of their active trading.

The last 3 columns of Panel A present total trading per unit of holding. For the small size portfolio, the total trading per holding of individual investors is 0.145, while the numbers for financial and foreign investors are 0.176 and 0.389. Foreign investors are more than twice as active as individual investors in small stocks. This shows that the high total trading of individual investors among small stocks is due to their high holding, not because they are the most active traders.

For all the size portfolios, individual investors have the lowest total trading per holding. The last 3 columns in the last row of Panel A show that the average total trading per holding for individual investors is 0.194, while the numbers are 0.317 and 0.426 for financial and foreign investors, respectively. The results in Panel B, where total trading is adjusted by the number of shares outstanding, are consistent with the ones in Panel A. In line with our evidence, Hotchkiss and Strickland (2003) find that volume is significantly higher when firms have a higher proportion of momentum investors, and lower when there are higher proportion of low turnover investors.

In summary, this table shows that individual investors, who reduce stock return volatility, have the lowest trading volume and are the least active traders, while foreign investors, who increase stock return volatility, have the highest trading volume and are the most active traders. Financial investors fall in between. The evidence is consistent with Gompers and Metrick (2001) and Schwartz and Shapiro (1992), who show that institutions tend to trade much more than retail investors. This analysis indicates that investors' trading volume is one of the determinants of their impact on return volatility.

### 2.6.4 Investment horizons

We check investors' ownership duration by counting how many months each investor has been participating in the Norwegian stock market over a sample of 178 months from December 1992 to September 2007. We split investors into categories (m, n], conditional on the number of months they hold shares of Norwegian stocks over the same period, where (m, n]=(0,6], (6,12],..., and (144, 178], and indicates that investors have been invested in the Norwegian stock market for longer than m months, but shorter than or equal to n months. The results are reported in Panel A of Table 2.13. The last column shows that there are 792, 578 individual investors that have held at least one share of Norwegian stocks over the whole sample period. The total number of financial investors and foreign investors are 1198 and 102,158, respectively. The first column of Panel A indicates that the numbers of individual investors that have been participating in the Norwegian stock market for a very short time period, less than or equal to 6 months, are 71441, 123 and 27621 for individual, financial and foreign investors. To make it easier to understand and compare, we present the percentage of investors in each investment horizon category for each type of investor in Panel B. The first column of Panel B shows that while there are 9.01% of individual investors that have less than or equal to 6 months holdings, there are 27.04% of foreign investors, 3 times as large as the percentage of individual investors. The last column presents the percentage of investors that have longer than 60 months holdings. While the percentage of individual investors with longer than 5 years holdings is 60%, the percentage is 49% for financial investors and only 24% for foreign investors.

Going though all the columns, it is clear that individual investors have lower percentage in shorter investment horizon categories while higher percentage in longer investment horizons, and foreign investors have the shortest investment horizons. Financial investors have shorter investment horizons than individual investors, but still much longer comparing to foreign investors.

However, the results in panels A and B might be biased. Recall that foreign investor hold more Norwegian stocks in the later period of the sample (from 2004 to September 2007). If more foreign investors enter the Norwegian stock market late or at the end of the sample period, there will be higher percentage of foreign investors with shorter investment horizons. We therefore require investors to have been in the sample before January 2000 in order to be included in this analysis. To avoid miscounting holding period of investors that have been participating in the Norwegian stock market before the beginning of the sample (December 1992) and were about to exit the market during the early period of the sample, we also require investors to be in the data after January 1995. Panels C and D report the number and percentage of investors in different investment horizon categories for investors that have been participating in the Norwegian stock market during the period from January 1995 to January 2000.

The last column in Panel C shows that the total number of individual investors has decreased from 792,578 in Panel A to 486,261, while the numbers of financial investors and foreign investors have dropped from 1198 and 102,158 to 756 and 41,922, respectively. The first column in Panel D shows that while there are 1.98% individual investors that have investment horizons less than 6 months, the percentage for foreign investors is as high as 10.77%, more than 5 times the percentage of individual investors. 2.91% financial investors have a less than 6 months holding period. The last column in Panel D presents the percentage of investors with investment horizons longer than 60 months. While there are 80.32% of individual investors, only 47.66% of foreign investors have been investing in the Norwegian market for longer than 60 months, conditional on the requirement that they have to be in the market during the period from January 1995 to January 2000. The percentage of financial investors that have longer than 60 months investment horizon is 66.01%, between that of individual investors and foreign investors.

Panels C and D provide consistent results as in panels A and B. This indicates the evidence that foreign investors have the shortest investment horizons, and domestic individual investors have the longest holding period on the Norwegian stock market is robust to the timing of entry and exit. In line with our results, Dennis and Strickland (2002) argue that individual investors, who may make decisions on long-term criteria, would be less likely to react during short-term market swings. Froot et al. (1992) show that large financial intermediaries in the U.S. are not typically long-run investors.

In summary, this section provides three explanations: trading style, trading volume and investment horizons, for the results of foreign investors' positive impact and domestic individual and financial investors' negative impact on stock return volatility. The literature has shown that momentum trading style increases stock return volatility while contrarian trading reduces return volatility; trading volume is positively related to return volatility; and investment horizons should have a negative correlation with return volatility. All the results shown in this section are consistent with the literature that foreign investors, who increase stock return volatility, are momentum traders, have the highest trading volume and the shortest investment horizons; individual investors, who have the strongest negative impact on return volatility, are contrarian traders, have the lowest trading volume and the longest investment horizons; and financial investors with a weaker negative impact on return volatility, which is between that of individual investors and foreign investors, have trading behavior in the middle ground.

## 2.7 Conclusion

This paper enhances our understanding of how and why domestic individual investors, financial investors and foreign investors affect stock return volatility at the stock level, by using a unique Norwegian holding data set with detailed information on investor types. The extant studies, which focus on the impact of one type of investor on volatility due to data limitation, find that institutional investors exacerbate stock return volatility, which implies that individual investors decrease stock return volatility (Sias (1996), and Malkiel and Xu (2003)). The availability of detailed information on investor categories enables us to provide more accurate and detailed evidence on investors' heterogenous trading behavior and their different impacts on return volatility.

Our surprising and interesting results show that, although both foreign investors and domestic financial investors are institutional investors, they have opposite impacts on stock return volatility. While the former increase return volatility, the latter decrease volatility. This indicates that institutional investors, from different geographical regions, could have different behavior and impacts on stock return volatility. This paper also finds that both domestic individual investors and domestic financial investors reduce stock return volatility, though the former have a stronger negative impact on volatility than the latter. This is striking because financial investors and individual investors are supposed to be counter parties that would have different rather than similar impact on stock return volatility. We provide three explanations: trading style, trading volume and investment horizons, for the results of different types of investors' impacts on stock return volatility. The results show that foreign investors, who exacerbate stock return volatility, are momentum traders, trade the most and have the shortest investment horizons; individual investors, who have the strongest negative impact on return volatility, are contrarian traders, trade the least and have the longest investment horizons; and financial investors fall somewhere in-between.

The negative impact of domestic individual investors on return volatility is especially striking and seems to contradict the theory of noise trading, although it is in line with the implication in Sias (1996) and Malkiel and Xu (2003). De Long et al. (1990b) model how noise affects stock return volatility and show that noise traders make stocks more volatile. However, our result is not necessary contradicting the model of De Long et al. (1990b). It is very likely that the Norwegian individual investors are noise traders and their noise trading increases stock return volatility. What we argue is that investors' trading behavior, in addition to information, also affects stock return volatility. We document that individual investors' contrarian trading strategy, low trading volume and long investment horizons induce negative impact on stock return volatility. It looks like that individual investors' negative impact on return volatility, a result of their trading behavior, is stronger than their positive impact on return volatility from their noise trading. Consequently, the aggregate impact of individual investors on return volatility is negative.

This paper provides interesting implications for future theoretical research on investors' impact on stock return volatility. The existing models consider only one determinant of return volatility, investors' information or trading behavior. For example, De Long et al. (1990b) focus on information while De Long et al. (1990a) concentrate on positive feedback trading behavior. Since many factors affect stock return volatility simultaneously, such as information, trading style and trading volume, it is important to take into account many variables at the same time in order to get a more complete understanding. Hence, it would be very interesting to see how, for example, individual investors, who are noise traders and follow contrarian trading strategy, affect stock return volatility in a theoretical setting.

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## 2.8 Tables

Table 2.1: Holding ownership of all types of investors

This table presents equal- and value- weighted holding ownership for investors on the Norwegian stock market over a period of 178 months from December 1992 to September 2007. All the investors are categorized into 5 main groups: foreign investors, domestic individual investors, financial investors, non-financial corporate investors, and state investors. We calculate holding ownership for domestic individual investors, financial investors and foreign investors as follows:

$$H_{i,t}^{j} = \frac{\sum_{k=1}^{K^j} S_{i,t}^{k}}{FreeFloat_{i,t}},$$

where $H_{i,t}^{j}$ measures the fraction of holding ownership of stock i held by investor type j in month t. $S_{i,t}^{k}$ is the number of shares of stock i in month t held by investor k that belongs to investor type j. In month t, stock i has $K^j$ investors in investor type j. $\sum_{k=1}^{K^j} S_{i,t}^{j}$ measures the aggregate number of shares of stock i held by investor type j in month t. The investors' holding ownership is adjusted by free float. The definition of free float is following that of MSCI return index. We exclude the holding fraction of state investors, corporate investors, and large block holders with minimum holding of X among individual investors, financial investors and foreign investors, where X=10%, 20%, 30%, 50% and 70%. The results in which holding is adjusted by free floats are reported in the first 5 columns. We also measure the holding using total number of shares outstanding, and report investors' holding ownership by this measure in the last column. Panel A reports the equal-weighted average of holding ownership for individual investors, financial investors and foreign investors, while Panel B presents the value weighted average of holding ownership.

| | Free float adjusted holding | | | | | |
|---|---|---|---|---|---|---|
| Type | Ex min. 10% blockholders | Ex min. 20% blockholders | Ex min. 30% blockholders | Ex min. 50% blockholders | Ex min. 70% blockholders | All Shares |
| **Panel A. Equally weighted holding ownership** | | | | | | |
| Ind | 0.395 | 0.387 | 0.383 | 0.377 | 0.380 | 0.197 |
| Fin | 0.329 | 0.323 | 0.320 | 0.316 | 0.309 | 0.238 |
| For | 0.276 | 0.289 | 0.297 | 0.307 | 0.312 | 0.199 |
| Free float | 0.478 | 0.524 | 0.543 | 0.571 | 0.591 | 1.000 |
| **Panel B. Value weighted holding ownership** | | | | | | |
| Ind | 0.150 | 0.146 | 0.147 | 0.144 | 0.147 | 0.081 |
| Fin | 0.310 | 0.296 | 0.290 | 0.283 | 0.277 | 0.149 |
| For | 0.540 | 0.559 | 0.564 | 0.573 | 0.576 | 0.315 |
| Free float | 0.539 | 0.584 | 0.602 | 0.623 | 0.639 | 1.000 |

Table 2.2: Stock characteristics sorted on holdings

This table reports the time series average of equal-weighted average of stock characteristics: market capitalization, price, volatility, turnover and stock return in the Norwegian stock market over a sample of 178 months from December 1992 to September 2007. We exclude small stocks in the lowest 10% percentile and illiquid stocks with zero monthly trading volume. The first row in panel A reports the equal-weighted average of the above mentioned variables. Panels B, C and D report holdings and stock characteristics for portfolios sorted on individual investor ownership, domestic financial investor ownership, and foreign investor ownership respectively. In each month t, all the stocks are sorted into quintile by ownership holdings of one type of investors at t-1. We then calculate, for each portfolio in month t, the equal-weighted cross-sectional average of stock characteristics and report the time series average for each portfolio. Panel E reports the correlation among investors' holdings and the stock characteristics.

| rank | ownership | mktcap mNOK | price | volatility | turnover | return | NumSec |
|---|---|---|---|---|---|---|---|
| **Panel A. Average across all the stocks** | | | | | | | |
| Mean | | 3520 | 95 | 0.178 | 0.076 | 0.022 | 193.5 |
| Median | | 679 | 59 | 0.136 | 0.035 | 0.009 | 193.5 |
| **Panel B. Sorted on Individual investors' ownership** | | | | | | | |
| High | 0.797 | 390 | 104 | 0.217 | 0.066 | 0.028 | 39.1 |
| 2 | 0.527 | 691 | 84 | 0.193 | 0.079 | 0.022 | 38.9 |
| 3 | 0.314 | 1531 | 78 | 0.180 | 0.081 | 0.023 | 38.7 |
| 4 | 0.161 | 4203 | 91 | 0.158 | 0.072 | 0.019 | 38.5 |
| Low | 0.055 | 10908 | 118 | 0.142 | 0.081 | 0.018 | 38.3 |
| **Panel C. Sorted on Financial investors' ownership** | | | | | | | |
| High | 0.662 | 2335 | 112 | 0.158 | 0.049 | 0.017 | 39.1 |
| 2 | 0.427 | 1952 | 101 | 0.158 | 0.068 | 0.021 | 38.9 |
| 3 | 0.281 | 4129 | 91 | 0.165 | 0.087 | 0.022 | 38.7 |
| 4 | 0.164 | 7099 | 90 | 0.176 | 0.098 | 0.025 | 38.5 |
| Low | 0.052 | 2097 | 80 | 0.235 | 0.078 | 0.026 | 38.3 |
| **Panel D. Sorted on Foreign investors' ownership** | | | | | | | |
| High | 0.732 | 11259 | 100 | 0.163 | 0.093 | 0.024 | 39.1 |
| 2 | 0.442 | 2802 | 79 | 0.174 | 0.090 | 0.020 | 38.9 |
| 3 | 0.237 | 1672 | 81 | 0.175 | 0.085 | 0.020 | 38.7 |
| 4 | 0.102 | 1122 | 75 | 0.193 | 0.068 | 0.023 | 38.5 |
| Low | 0.020 | 640 | 140 | 0.187 | 0.042 | 0.023 | 38.3 |

**Panel E. Correlations**

| vari | Fin. Hld. | For. Hld. | vola | ret | TO | size | price |
|---|---|---|---|---|---|---|---|
| Ind. Hld | -0.467 | -0.654 | 0.167 | 0.022 | -0.037 | -0.626 | -0.210 |
| Fin. Hld. | | -0.351 | -0.173 | -0.024 | -0.049 | 0.223 | 0.240 |
| For. Hld. | | | -0.022 | -0.002 | 0.077 | 0.465 | 0.013 |
| vola | | | | 0.104 | 0.111 | -0.402 | -0.389 |
| ret | | | | | 0.179 | 0.039 | 0.068 |
| TO | | | | | | 0.091 | -0.151 |
| size | | | | | | | 0.424 |

Table 2.3: Investors' holdings and stock characteristics sorted on stock characteristics

This table sorts stocks on stock characteristics and report the equal-weighted average of investors' holdings and other stock characteristics. The stock characteristics are monthly stock market capitalization, price, volatility, turnover and stock return, using the Norwegian data over a sample of 178 months from December 1992 to September 2007. There are three types of investors: domestic individual investors, financial investors and foreign investors. In each month t, we sort stocks on one stock characteristic at t-1 into quintiles and calculate the equal-weighted average of investors' holdings and all the other stock characteristics for each portfolio. We report the time series average of investors' holdings and stock characteristics for each portfolio. Panel A sorts stocks on size. Panels B, C, D and E sort stocks on price, volatility, turnover and return, respectively.

| rank | mktcap mNOK | price | volatility | turnover | return | Ind. hld | Fin hld | For hld | NumSec |
|---|---|---|---|---|---|---|---|---|---|
| | | | | **Panel A. Sort on size** | | | | | |
| Large | 14659 | 147 | 0.109 | 0.080 | 0.024 | 0.141 | 0.345 | 0.514 | 39.1 |
| 2 | 1698 | 107 | 0.131 | 0.077 | 0.026 | 0.249 | 0.397 | 0.355 | 38.9 |
| 3 | 695 | 81 | 0.170 | 0.076 | 0.026 | 0.373 | 0.344 | 0.282 | 38.7 |
| 4 | 303 | 64 | 0.200 | 0.083 | 0.023 | 0.482 | 0.285 | 0.233 | 38.5 |
| Small | 102 | 75 | 0.285 | 0.063 | 0.012 | 0.625 | 0.221 | 0.153 | 38.3 |
| | | | | **Panel B. Sort on price** | | | | | |
| High | 7793 | 268 | 0.125 | 0.055 | 0.030 | 0.377 | 0.351 | 0.272 | 39.1 |
| 2 | 5122 | 109 | 0.132 | 0.062 | 0.024 | 0.297 | 0.364 | 0.340 | 38.9 |
| 3 | 3051 | 60 | 0.156 | 0.076 | 0.023 | 0.286 | 0.360 | 0.354 | 38.7 |
| 4 | 966 | 27 | 0.209 | 0.082 | 0.022 | 0.379 | 0.302 | 0.319 | 38.5 |
| Low | 583 | 7 | 0.272 | 0.105 | 0.011 | 0.527 | 0.216 | 0.257 | 38.3 |
| | | | | **Panel C. Sort on volatility** | | | | | |
| High | 767 | 75 | 0.397 | 0.102 | 0.055 | 0.488 | 0.247 | 0.266 | 39.1 |
| 2 | 1528 | 75 | 0.190 | 0.089 | 0.022 | 0.404 | 0.290 | 0.305 | 38.9 |
| 3 | 2995 | 85 | 0.136 | 0.078 | 0.015 | 0.339 | 0.336 | 0.325 | 38.7 |
| 4 | 5058 | 103 | 0.101 | 0.060 | 0.009 | 0.283 | 0.377 | 0.341 | 38.5 |
| Low | 7338 | 137 | 0.064 | 0.049 | 0.009 | 0.347 | 0.347 | 0.306 | 38.3 |
| | | | | **Panel D. Sort on turnover** | | | | | |
| High | 3557 | 68 | 0.183 | 0.250 | 0.063 | 0.347 | 0.280 | 0.372 | 39.1 |
| 2 | 6557 | 83 | 0.147 | 0.074 | 0.022 | 0.308 | 0.314 | 0.378 | 38.9 |
| 3 | 4009 | 85 | 0.146 | 0.035 | 0.010 | 0.339 | 0.340 | 0.321 | 38.7 |
| 4 | 2328 | 95 | 0.164 | 0.014 | 0.006 | 0.401 | 0.345 | 0.254 | 38.5 |
| Low | 1119 | 144 | 0.252 | 0.003 | 0.008 | 0.470 | 0.316 | 0.214 | 38.3 |
| | | | | **Panel E. Sort on return** | | | | | |
| High | 3130 | 95 | 0.229 | 0.126 | 0.218 | 0.381 | 0.301 | 0.318 | 39.1 |
| 2 | 4548 | 110 | 0.149 | 0.071 | 0.060 | 0.358 | 0.333 | 0.309 | 38.9 |
| 3 | 4282 | 107 | 0.136 | 0.056 | 0.008 | 0.370 | 0.335 | 0.295 | 38.7 |
| 4 | 3519 | 96 | 0.151 | 0.054 | -0.039 | 0.367 | 0.331 | 0.302 | 38.5 |
| Low | 2111 | 67 | 0.227 | 0.073 | -0.140 | 0.387 | 0.294 | 0.319 | 38.3 |

Table 2.4: Impacts of lagged holdings on volatility

This table presents results of Fama Macbeth (1973) regression of monthly stock return volatility on one month lagged holding ownership, controlling for one month lagged natural logarithm of volatility and stock characteristics (monthly return, turnover, natural logarithm of market capitalization, log value of price, free float, book to market ratio and a dummy variable for the presence of state investors).

$$Vol_{i,t} = \beta_j H^j_{i,t-1} + \gamma_{vol} vol_{i,t-1} + controls + \epsilon_{i,t}$$

Both the dependent variable and independent variables are standardized to have the same mean (0) and standard deviation (1) to make the coefficient estimates comparable across investor types. We follow Brandt et al. (2010) to correct the standard errors for potential higher order serial correlation by using the Pontiff (1996) method. The Pontiff (1996) adjusted t values are reported in the parentheses in the row below the coefficients. Panel A reports the coefficients and the Pontiff (1996) adjusted t statistics on all the independent variables. The first 3 columns use total return volatility as dependent variable, while the last 3 columns use idiosyncratic volatility as dependent variable. In Panel B, we regress investors' holding levels and changes in holdings on one monthly lagged natural logarithm of volatility, control for other variables, respectively. The first 2 rows in Panel B report the coefficients and t statistics on lagged volatility when investors' holding levels are used as dependent variables. The last 2 rows present the results when changes in holdings are used as dependent variables. The first 3 columns are the results for individual investors ("Ind"), financial investors ("Fin"), and foreign investors ("For") when we use total volatility as the explanatory variable. The last 3 columns are the results when using idiosyncratic volatility as the explanatory variable.

Panel A: Impact of investors' holdings on volatility

| Indep. var. | Dep. var: Total volatility | | | Dep. var: Idiosyncratic volatility | | |
|---|---|---|---|---|---|---|
| Ind hld | -0.060 | | | -0.054 | | |
| | ( -5.3 ) | | | ( -4.4 ) | | |
| Fin hld | | -0.038 | | | -0.035 | |
| | | ( -5.3 ) | | | ( -5.0 ) | |
| For hld | | | 0.100 | | | 0.090 |
| | | | ( 12.8 ) | | | ( 8.9 ) |
| Vol | 0.551 | 0.556 | 0.541 | 0.520 | 0.525 | 0.514 |
| | ( 57.7 ) | ( 56.9 ) | ( 60.2 ) | ( 52.3 ) | ( 50.7 ) | ( 53.9 ) |
| Ret | -0.059 | -0.062 | -0.060 | -0.061 | -0.064 | -0.061 |
| | ( -10.8 ) | ( -10.9 ) | ( -10.4 ) | ( -9.0 ) | ( -9.1 ) | ( -8.7 ) |
| Turnover | -0.036 | -0.038 | -0.036 | -0.044 | -0.046 | -0.044 |
| | ( -4.2 ) | ( -4.8 ) | ( -4.2 ) | ( -5.2 ) | ( -5.6 ) | ( -5.2 ) |
| mcap | -0.185 | -0.139 | -0.213 | -0.200 | -0.163 | -0.222 |
| | ( -19.2 ) | ( -14.0 ) | ( -21.6 ) | ( -23.1 ) | ( -16.5 ) | ( -26.7 ) |
| mprc | -0.087 | -0.084 | -0.070 | -0.078 | -0.076 | -0.065 |
| | ( -9.0 ) | ( -7.5 ) | ( -7.3 ) | ( -7.5 ) | ( -6.5 ) | ( -6.6 ) |
| float | -0.054 | -0.060 | -0.081 | -0.048 | -0.055 | -0.074 |
| | ( -8.1 ) | ( -9.5 ) | ( -10.5 ) | ( -8.0 ) | ( -9.0 ) | ( -9.9 ) |
| B/M | -0.068 | -0.070 | -0.071 | -0.077 | -0.078 | -0.080 |
| | ( -8.3 ) | ( -7.9 ) | ( -8.7 ) | ( -9.0 ) | ( -8.4 ) | ( -9.6 ) |
| DummyState | -0.030 | -0.022 | -0.017 | -0.037 | -0.029 | -0.023 |
| | ( -4.0 ) | ( -2.7 ) | ( -2.3 ) | ( -5.8 ) | ( -4.1 ) | ( -3.9 ) |
| AdjR2 | 0.521 | 0.518 | 0.523 | 0.492 | 0.489 | 0.495 |

Panel B: Causality from volatility to holdings

| | On total volatility | | | On Idiosyncratic volatility | | |
|---|---|---|---|---|---|---|
| Dep. var. | Ind | Fin | For | Ind | Fin | For |
| Hold level | 0.001 | -0.003 | 0.001 | 0.003 | -0.003 | -0.001 |
| | ( 0.540 ) | ( -1.223 ) | ( 0.672 ) | ( 1.573 ) | ( -1.074 ) | ( -0.335 ) |
| Hold Changes | 0.020 | -0.001 | -0.015 | 0.029 | 0.000 | -0.023 |
| | ( 2.173 ) | ( -0.094 ) | ( -1.617 ) | ( 2.759 ) | ( -0.006 ) | ( -2.295 ) |

Table 2.5: Effects of lagged holdings on future volatility in sub-samples

This table presents, for different sub-samples, the coefficient and its t statistics on the lagged investors' holdings, by using the Fama and MacBeth (1973) regression of stock monthly volatility on one month lagged holdings, natural logarithm of volatility and one month lagged stock characteristics (monthly return, turnover, natural logarithm of market capitalization, natural logarithm of price, free float, book to market ratio and a dummy variable for the presence of state investos).

$$Vol_{i,t} = \beta_j H^j_{i,t-1} + \gamma_{vol} vol_{i,t-1} + controls + \epsilon_{i,t}$$

We do the same analysis for individual investors ("ind"), financial investors ("fin"), and foreign investors ("for"), respectively. Both the dependent variable and independent variables are standardized to have the same mean (0) and standard deviation (1) to make the coefficient estimates comparable across investor types. We follow Brandt et al. (2010) to correct the standard errors for potential higher order serial correlation by using the Pontiff (1996) method. The Pontiff (1996) adjusted t values are reported in the parentheses in the rows below the coefficients.

In panel A, we divide the whole sample from December 1992 to September 2007 into two sub-samples based on two events, respectively. The first event is the abolition of restrictions on foreign holding in January 1995. We divide the whole period into pre 199501 and after 199501 two sub-periods. The second event is the lift of short sales constraints in January 1997. We therefore divide the whole period into pre 199701 and after 199701. In panel B, we divide the whole sample into two sub-samples based on stock market capitalization and price, respectively. The "Small size" is for the 50% stocks below the median stock market capitalization and the "Large size" is for the 50% stocks above the median market capitalization. Similarly, the "Low price" is for the 50% stocks below the median price and the "High price" is for stocks with price above the median price.

**Panel A. Period subsamples**

| | Foreign holding constraint | | Short sales constraint | |
|---|---|---|---|---|
| type | pre 199501 | after 199501 | pre 199701 | after 199701 |
| Ind | -0.0101 | -0.0678 | -0.0149 | -0.0767 |
| | ( -0.8145 ) | ( -5.7239 ) | ( -1.6339 ) | ( -6.0018 ) |
| Fin | -0.0460 | -0.0361 | -0.0613 | -0.0285 |
| | ( -3.3908 ) | ( -4.6458 ) | ( -6.7433 ) | ( -3.6671 ) |
| For | 0.0487 | 0.1087 | 0.0755 | 0.1096 |
| | ( 4.0494 ) | ( 13.9110 ) | ( 6.3280 ) | ( 12.0584 ) |

**Panel B. Size and price portfolios**

| | Price portfolios | | Size portfolios | |
|---|---|---|---|---|
| type | Low price | High price | Small size | Large size |
| Ind | -0.0484 | -0.0853 | -0.0705 | -0.0509 |
| | ( -3.4124 ) | ( -7.7433 ) | ( -6.1797 ) | ( -5.4133 ) |
| Fin | -0.0480 | -0.0385 | -0.0235 | -0.0484 |
| | ( -3.9847 ) | ( -5.7468 ) | ( -2.8900 ) | ( -3.3210 ) |
| For | 0.0920 | 0.1387 | 0.0953 | 0.0883 |
| | ( 8.8916 ) | ( 11.8188 ) | ( 10.1076 ) | ( 6.6060 ) |

Table 2.6: Impacts of holdings on volatility using other data frequency and volatility measures

This table presents the impacts of lagged holding on stock return volatility using quarterly and annual data frequency (Panel A), different volatility measurements (Panel B), and changes in holding (Panel C) over the sample period from December 1992 to September 2007 on the Norwegian stock market. We do the following Fama and MacBeth (1973) regression of stock monthly volatility on one period lagged holdings, volatility and stock characteristics (monthly return, turnover, log value of market capitalization, log value of price, free float, book to market ratio and a dummy variable for the presence of state investors).

$$Vol_{i,t} = \beta_j H^j_{i,t-1} + \gamma_{vol} vol_{i,t-1} + controls + \epsilon_{i,t}$$

We do the same analysis for individual investors (ind), financial investors (fin), and foreign investors (for), respectively. Both the dependent variable and independent variables are standardized to have the same mean (0) and standard deviation (1) to make the coefficient estimates comparable across investor types. We follow Brandt et al. (2010) to correct the standard errors for potential higher order serial correlation by using the Pontiff (1996) method. The Pontiff (1996) adjusted t values are reported in the parentheses in the rows below the coefficients. Panel A reports the coefficients and t-statistics on the lagged holding using data at quarterly and annual frequency, respectively. Panel B presents the coefficients and t-statistics using the other three measures of volatility. The first column in panel B ("Measure 2") uses the square root of sum of squared daily returns in one month to measure the monthly return volatility. The second column in panel B ("Measure 3") uses the sum of absolute daily returns in one month to measure the monthly return volatility. The last column in panel B ("Measure 4") uses the standard deviation of the daily difference between its return and the market return in one month to measure the monthly idiosyncratic volatility. Panel C reports the results using changes in holding to predict future return volatility. We use monthly, quarterly and annual changes in holding, respectively.

**Panel A. Quarterly and annual frequency**

| | Quarterly | Annual |
|---|---|---|
| Ind | -0.0683 | -0.0872 |
| | ( -3.6889 ) | ( -3.8251 ) |
| Fin | -0.0472 | -0.0388 |
| | ( -2.9180 ) | ( -2.0340 ) |
| For | 0.1178 | 0.1187 |
| | ( 10.1428 ) | ( 7.3153 ) |

**Panel B. Use other 3 volatility measures**

| | Measure 2 | Measure 3 | Measure 4 |
|---|---|---|---|
| Ind | -0.0497 | -0.0514 | -0.0460 |
| | ( -4.4721 ) | ( -4.5260 ) | ( -4.3064 ) |
| Fin | -0.0452 | -0.0370 | -0.0463 |
| | ( -5.6406 ) | ( -4.3870 ) | ( -6.6020 ) |
| For | 0.0945 | 0.0906 | 0.0907 |
| | ( 11.0357 ) | ( 10.1957 ) | ( 9.3923 ) |

**Panel C. Use changes in holding**

| Type | Monthly | Quarterly | Annual |
|---|---|---|---|
| Ind | -0.0016 | -0.0119 | -0.0188 |
| | ( -0.3374 ) | ( -2.3768 ) | ( -2.4651 ) |
| Fin | -0.0041 | -0.0050 | -0.0112 |
| | ( -0.8217 ) | ( -1.1404 ) | ( -1.5032 ) |
| For | 0.0035 | 0.0125 | 0.0205 |
| | ( 0.6611 ) | ( 2.4469 ) | ( 3.4969 ) |

Table 2.7: Oil price, investors' holdings and the impact on return volatility

Panel A presents the results for how investors' equal-weighted (column 1) and value-weighted (column 2) holdings are affected by 1 month lagged oil prices, controlling for lagged market returns, over the whole sample period from December 1992 to September 2007. In Panel B, we conduct the Fama and MacBeth (1973) analysis of regressing stock return volatility on lagged investors' holdings, a dummy variable for stocks with different oil sensitivity (1 for the 50% stocks above the median oil sensitivity, and 0 otherwise), and the interaction term between investors' holdings and the dummy variable, in addition to other variables. The results present the coefficient and t-statistics on investors' holdings (column 1), the interaction term (column 2), and the dummy variable (column 3). Panel C reports the coefficients and the Pontiff (1996) adjusted t-statistics on investors' holdings by conducting the Fama and MacBeth (1973) analysis of regressing stock return volatility on lagged investors' holding and other variables, for stocks with high oil sensitivity and low oil sensitivity, respectively. We measure how one stock is sensitive to oil shocks by regressing stock returns on contemporaneous and 2 lagged oil returns. In Panel D, we repeat the procedure in Panel A for the two sub-periods before and after January 2004. In Panel E, we redo the analysis in Panel B for the two sub-periods before and after January 2004.

**Panel A. Correlation of holdings and lagged oil prices**

| Type | EW holding | VW holding |
|---|---|---|
| Ind | -0.0537 | -0.0213 |
| | ( -10.2486 ) | ( -3.7116 ) |
| Fin | -0.0174 | -0.0285 |
| | ( -2.8336 ) | ( -5.2569 ) |
| For | 0.0649 | 0.0453 |
| | ( 13.5683 ) | ( 8.7765 ) |

**Panel B: Coefficients on holdings, the dummy variable and interaction term**

| Type | Holding | Holding*Dummy | OilDummy |
|---|---|---|---|
| Ind | -0.0520 | -0.0481 | 0.0130 |
| | ( -5.1431 ) | ( -4.8897 ) | ( 2.0677 ) |
| Fin | -0.0518 | 0.0308 | 0.0125 |
| | ( -5.1273 ) | ( 2.9951 ) | ( 1.9397 ) |
| For | 0.1065 | 0.0240 | 0.0113 |
| | ( 14.5262 ) | ( 3.8417 ) | ( 1.8176 ) |

**Panel C: The impact of holdings on volatility conditional on oil sensitivity**

| Type | High oil sensitivity | Low oil sensitivity |
|---|---|---|

| | | |
|---|---|---|
| Ind | -0.0804 | -0.0258 |
| | ( -7.7981 ) | ( -2.3435 ) |
| Fin | -0.0044 | -0.0259 |
| | ( -0.6373 ) | ( -3.4594 ) |
| For | 0.0738 | 0.0481 |
| | ( 9.3967 ) | ( 5.9659 ) |

**Panel D: Correlation of holdings and lagged oil prices in sub periods**

| | Before Jan. 2004 | | After Jan. 2004 | |
|---|---|---|---|---|
| Type | EW holding | VW holding | EW holding | VW holding |
| Ind | 0.0913 | -0.0157 | -0.1998 | -0.0706 |
| | ( 11.0642 ) | ( -2.0748 ) | ( -12.4152 ) | ( -14.8897 ) |
| Fin | -0.0758 | -0.0520 | -0.0155 | -0.1365 |
| | ( -10.0767 ) | ( -4.6786 ) | ( -5.2659 ) | ( -15.3637 ) |
| For | -0.0156 | 0.0677 | 0.2153 | 0.2071 |
| | ( -2.1407 ) | ( 6.3719 ) | ( 13.9842 ) | ( 17.8147 ) |

**Panel E: The impact of holdings on volatility conditional on oil sensitivity**

| | Before Jan. 2004 | | After Jan. 2004 | |
|---|---|---|---|---|
| Type | High oil sensitivity | Low oil sensitivity | High oil sensitivity | Low oil sensitivity |
| Ind | -0.0854 | -0.0253 | -0.0660 | -0.0272 |
| | ( -7.1099 ) | ( -2.2685 ) | ( -3.6249 ) | ( -1.0025 ) |
| Fin | 0.0070 | -0.0202 | -0.0372 | -0.0420 |
| | ( 1.0994 ) | ( -2.4229 ) | ( -3.5365 ) | ( -2.6863 ) |
| For | 0.0678 | 0.0440 | 0.0911 | 0.0598 |
| | ( 7.8923 ) | ( 5.0519 ) | ( 5.4274 ) | ( 3.3415 ) |

Table 2.8: Sub-types of foreign investors and individual investors

This table presents the results for the Fama and MacBeth (1973) analysis of regressing stock return volatility on lagged holdings of sub sets of foreign and individual investors, controlling for other variables. Panel A reports the coefficients and the Pontiff (1996) adjusted t-statistics on holdings of foreign investors that have known identities ("Non-nominee" in column 1), have nominee accounts ("Nominee" in column 2), are Norwegian ("Norwegian" in column 3) and are from other countries ("Non-norwegian" in column 4). Panel B reports the results for large and small foreign investors, requiring a minimum average portfolio value of K million NOK for large foreign investors, where K=50, 100, 500, and 1000. Panel C presents the results for large and small individual investors, in which large individual investors have to have a minimum average portfolio value of X million NOK, where X=0.5, 1, 5 and 10.

**Panel A. Subsets of foreign investors**

| | Non-nominee | Nominee | Norwegian | Non-norwegian |
|---|---|---|---|---|
| For | 0.0349 | 0.0309 | 0.0072 | 0.0418 |
| | ( 5.9033 ) | ( 5.7963 ) | ( 1.1940 ) | ( 7.0577 ) |

**Panel B. Large and small foreign investors**

| | min 50M NOK | min 100M NOK | min 500M NOK | min 1000M NOK |
|---|---|---|---|---|
| Large For | 0.0914 | 0.0850 | 0.0593 | 0.0512 |
| | ( 12.3356 ) | ( 12.3977 ) | ( 10.8565 ) | ( 9.8238 ) |
| Small For | 0.0433 | 0.0508 | 0.0753 | 0.0820 |
| | ( 7.3613 ) | ( 8.2385 ) | ( 10.9503 ) | ( 12.5607 ) |

**Panel C. Large and small individual investors**

| | min 0.5M NOK | min 1M NOK | min 5M NOK | min 10M NOK |
|---|---|---|---|---|
| Large Ind | -0.0339 | -0.0229 | -0.0003 | 0.0096 |
| | ( -7.7868 ) | ( -5.1817 ) | ( -0.0656 ) | ( 2.4326 ) |
| Small Ind | -0.0490 | -0.0542 | -0.0569 | -0.0577 |
| | ( -10.2468 ) | ( -11.4314 ) | ( -13.3560 ) | ( -14.3040 ) |

Table 2.9: Volatility of portfolios sorted on market capitalization and holdings

In each month t, we first sort stocks into size quintile based on stock market capitalizations at t-1, and within each size quintile, further sort stocks into holding quintile based on the fraction of shares held by one type of investors at t-1. We calculate equal-weighted portfolio return, using stock monthly return at t, for each of the 25 portfolios in each month, and then calculate, for each portfolio, the monthly standard deviation of the time series portfolio returns. We report portfolio volatility in the first 5 columns and ownership holdings in the last 5 columns. Panel A reports volatility and holdings of portfolios sorted on size and holdings of individual investors. Panels B, and C report volatility and holdings of portfolios sorted on size and holdings of Norwegian financial investors, and on size and holdings of foreign investors, respectively.

| Holding | **Volatility** | | | | | **Holdings** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Panel A. Portfolios sorted on size and individual holdings** | | | | | | | | | |
| | Large | 2 | 3 | 4 | Small | Large | 2 | 3 | 4 | Small |
| High | 0.075 | 0.068 | 0.067 | 0.077 | 0.076 | 0.346 | 0.568 | 0.725 | 0.828 | 0.923 |
| 2 | 0.068 | 0.070 | 0.074 | 0.093 | 0.089 | 0.160 | 0.310 | 0.504 | 0.626 | 0.778 |
| 3 | 0.095 | 0.076 | 0.083 | 0.093 | 0.095 | 0.099 | 0.194 | 0.347 | 0.463 | 0.649 |
| 4 | 0.063 | 0.072 | 0.087 | 0.095 | 0.089 | 0.062 | 0.114 | 0.199 | 0.302 | 0.488 |
| Low | 0.068 | 0.073 | 0.077 | 0.090 | 0.147 | 0.030 | 0.044 | 0.077 | 0.147 | 0.266 |
| | **Panel B. Portfolios sorted on size and Financial holdings** | | | | | | | | | |
| | Large | 2 | 3 | 4 | Small | Large | 2 | 3 | 4 | Small |
| High | 0.081 | 0.061 | 0.066 | 0.083 | 0.092 | 0.688 | 0.708 | 0.675 | 0.584 | 0.524 |
| 2 | 0.146 | 0.071 | 0.073 | 0.078 | 0.100 | 0.429 | 0.518 | 0.440 | 0.370 | 0.294 |
| 3 | 0.065 | 0.067 | 0.080 | 0.087 | 0.096 | 0.289 | 0.378 | 0.297 | 0.239 | 0.168 |
| 4 | 0.063 | 0.082 | 0.089 | 0.096 | 0.111 | 0.197 | 0.233 | 0.180 | 0.137 | 0.073 |
| Low | 0.072 | 0.077 | 0.080 | 0.096 | 0.103 | 0.103 | 0.085 | 0.063 | 0.046 | 0.013 |
| | **Panel C. Portfolios sorted on size and foreign holdings** | | | | | | | | | |
| | Large | 2 | 3 | 4 | Small | Large | 2 | 3 | 4 | Small |
| High | 0.062 | 0.078 | 0.089 | 0.096 | 0.140 | 0.826 | 0.743 | 0.663 | 0.601 | 0.450 |
| 2 | 0.070 | 0.082 | 0.093 | 0.108 | 0.105 | 0.676 | 0.477 | 0.377 | 0.301 | 0.170 |
| 3 | 0.061 | 0.070 | 0.074 | 0.095 | 0.097 | 0.529 | 0.296 | 0.210 | 0.157 | 0.070 |
| 4 | 0.142 | 0.060 | 0.072 | 0.081 | 0.072 | 0.341 | 0.166 | 0.099 | 0.066 | 0.025 |
| Low | 0.084 | 0.060 | 0.053 | 0.068 | 0.054 | 0.135 | 0.058 | 0.026 | 0.017 | 0.004 |

Table 2.10: Trading behavior based on lagged returns

This table presents the coefficients and t statistics (in the parentheses) on lagged returns from the Fama Macbeth (1973) regression of changes in monthly ownership holdings (in Panel A) and holding levels (in Panel B) on lagged stock returns up to month k, controlling for one month lagged stock return volatility and stock characteristics (monthly turnover, log value of market capitalization, log value of price, free float, book to market ratio, and dummy for state investors).

$$\Delta H^j_{i,t} = \beta ret_{i,t-k,t-1} + controls + \epsilon_{i,t},$$

$$H^j_{i,t} = \beta ret_{i,t-k,t-1} + controls + \epsilon_{i,t},$$

where $\Delta H^j_{i,t}$ measures the change in ownership holdings of stock i by investor type j from month t-1 to month t, and $H^j_{i,t}$ measures the holding level of stock i at t for investor type j. $ret_{i,t-k,t-1}$ measures the cumulative stock return from month t-k to month t-1, where k=1, 2, 3 and 6 and corresponds to the horizons in Grinblatt and Keloharju (2000). Both the dependent variable and independent variables are standardized to have the same mean (0) and standard deviation (1) to make the coefficient estimates comparable across investor types. We follow Brandt et al. (2010) to correct the standard errors for potential higher order serial correlation by using the Pontiff (1996) method. The Pontiff (1996) adjusted t values are reported in the parentheses in the rows below the coefficients. The column (-m,-n) presents the coefficients on lagged returns which is the cumulative return from month t-m to month t-n, (-m, -1), where m=1, 2, 3 and 6. In panel C, we report the results similar to the above analysis, but separate positive and negative lagged returns in the regression in which the change in holdings is the dependent variable.

| | | | | | |
|---|---|---|---|---|---|
| | | Panel A: Regress ΔHolding on lagged return | | | |
| Type | | -1,-1 | -2,-1 | -3,-1 | -6,-1 |
| Ind | tot ret | -0.0409 | -0.0465 | -0.0553 | -0.0652 |
| | | ( -3.8622 ) | ( -4.6019 ) | ( -5.5331 ) | ( -6.0540 ) |
| Fin | tot ret | -0.0032 | 0.0026 | 0.0058 | 0.0157 |
| | | ( -0.2894 ) | ( 0.2644 ) | ( 0.6792 ) | ( 1.9529 ) |
| For | tot ret | 0.0382 | 0.0400 | 0.0430 | 0.0441 |
| | | ( 3.2755 ) | ( 3.3736 ) | ( 3.9176 ) | ( 4.5578 ) |
| | | Panel B: Regress Holding Level on lagged return | | | |
| Type | | -1,-1 | -2,-1 | -3,-1 | -6,-1 |
| Ind | tot ret | -0.0049 | -0.0046 | -0.0058 | -0.0069 |
| | | ( -2.6158 ) | ( -2.8180 ) | ( -4.0099 ) | ( -4.4264 ) |
| Fin | tot ret | -0.0003 | -0.0013 | -0.0012 | -0.0003 |
| | | ( -0.1000 ) | ( -0.6133 ) | ( -0.6911 ) | ( -0.1639 ) |
| For | tot ret | 0.0052 | 0.0056 | 0.0066 | 0.0068 |
| | | ( 2.2928 ) | ( 2.7674 ) | ( 3.7330 ) | ( 3.8548 ) |
| | | Panel C: Regress ΔHolding on lagged Positive and Negative returns | | | |
| Type | | -1,-1 | -2,-1 | -3,-1 | -6,-1 |
| Ind | Posi. ret | -0.0112 | -0.0052 | -0.0102 | -0.0347 |
| | | ( -0.9881 ) | ( -0.4060 ) | ( -0.8482 ) | ( -3.2033 ) |
| | Nega. Ret | -0.0374 | -0.0513 | -0.0595 | -0.0428 |
| | | ( -3.7401 ) | ( -5.1983 ) | ( -5.4445 ) | ( -4.0816 ) |
| Fin | Posi. ret | -0.0105 | -0.0180 | -0.0164 | -0.0007 |
| | | ( -1.0437 ) | ( -1.6707 ) | ( -1.9279 ) | ( -0.0765 ) |
| | Nega. Ret | 0.0061 | 0.0198 | 0.0255 | 0.0194 |
| | | ( 0.6009 ) | ( 2.0937 ) | ( 2.5582 ) | ( 2.1458 ) |
| For | Posi. ret | 0.0152 | 0.0238 | 0.0271 | 0.0339 |
| | | ( 1.1972 ) | ( 1.8900 ) | ( 2.3929 ) | ( 3.5020 ) |
| | Nega. Ret | 0.0315 | 0.0272 | 0.0257 | 0.0194 |
| | | ( 3.9313 ) | ( 4.0838 ) | ( 3.5113 ) | ( 2.2515 ) |

Table 2.11: Additional analysis of investors' trading style

Panel A reports the trading style of large and small individual investors, using both changes in holdings (in the first 4 columns), and levels of holdings (in the last 4 columns). We require large individual investors to have a minimum average portfolio value of X million NOK, where X=0.5, 1, 5, and 10. Panel B reports the measure of investment styles related to past returns for individual investors, financial investors and foreign investors, using the method in Grinblatt and Keloharju (2000). For each stock in each month, we calculate, for each type of investors, the buy ratio – the number of shares bought divided by the sum of the number of shares bought and the number of shares sold. In each month t, we sort stocks on past returns into quartiles and calculate the equal-weighted cross-sectional average of buy ratio for each portfolio. The difference between the average buy ratio in the top quartile (with the highest past return) and the average buy ratio in the bottom quartile (with the lowest past returns) is the measure of investment style in month t. If the difference for investor type j in month t is positive, then investor type j is considered as momentum trader in month t, since the buy ratio for past winning stocks is higher than the buy ratio for past losing stocks. On the other hand, investor type j with a negative value of the difference between buy ratio in the top and bottom quartile, is considered as contrarian. In the first 4 columns, we present the fraction of months for which the buy ratio is positive. We measure trading style conditional on returns up to 6 months in the past, as Grinblatt and Keloharju (2000) have done. The past return for month t is the cumulative return of monthly return from month t-m to t-1, (-m,-1), where m=1, 2, 3 and 6. The last 4 columns report the binomial test p-values.

**Panel A: Trading style of large and small individual investors**

| | Changes in Holding | | | | Levels of holding | | | |
|---|---|---|---|---|---|---|---|---|
| | min 0.5M | min 1M | min 5M | min 10M | min 0.5M | min 1M | min 5M | min 10M |
| Small ind | -0.0898 | -0.0815 | -0.0765 | -0.0770 | -0.0078 | -0.0071 | -0.0072 | -0.0071 |
| | ( -7.574 ) | ( -6.643 ) | ( -6.330 ) | ( -6.583 ) | ( -4.206 ) | ( -4.111 ) | ( -4.652 ) | ( -4.644 ) |
| Large ind | -0.0305 | -0.0255 | -0.0056 | 0.0035 | -0.0039 | -0.0030 | -0.0007 | -0.0001 |
| | ( -2.910 ) | ( -2.506 ) | ( -0.552 ) | ( 0.364 ) | ( -2.564 ) | ( -1.827 ) | ( -0.440 ) | ( -0.038 ) |

**Panel B: Proportion of positive buy ratio difference (Grinblatt and Keloharju(2000))**

| | Past return from month t-m to t-1 (-m,-1) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **P{ buy ratio diff>0}** | | | | **Binomial test p-value** | | | |
| Investor type | -1,-1 | -2,-1 | -3,-1 | -6,-1 | -1,-1 | -2,-1 | -3,-1 | -6,-1 |
| Individual | 0.1977 | 0.1695 | 0.1130 | 0.1582 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Financial | 0.4802 | 0.4859 | 0.5085 | 0.5819 | 0.0522 | 0.0558 | 0.0584 | 0.0056 |
| Foreign | 0.7401 | 0.7175 | 0.6893 | 0.7627 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Table 2.12: Trading volume

This table reports the total trading volume and the total trading volume adjusted for holding for the three types of investors: individual, financial and foreign investors, in the Norwegian stock market over the sample period December 1992 to September 2007. The total trading of stock i in month t by investor type j is:

$$TotTrade_{i,t}^{j} = \frac{\sum_{k=1}^{K^j} |\Delta S_{i,t}^{k}|}{SHS_{i,t-1}},$$

where $\Delta S_{i,t}^{k}$ is the change in holding shares of stock i from month t-1 to month t by investor k who belongs to investor type j, and j denotes individual investors, financial investors and foreign investors. $\sum_{k=1}^{K^j} |\Delta S_{i,t}^{k}|$ measures the aggregate number of shares net traded by all the investors in type j. There are $K^j$ investors in type j. $SHS_{i,t-1}$ measures free float or the number of shares outstanding of stock i in month t-1.
In each month t, we sort stocks on size into quintiles and calculate the equal-weighted average of total trading (in the first 3 columns) and of total trading adjusted for holdings (in the last 3 columns) for each type of investor. Panel A reports the results where trading is adjusted by free float. Panel B reports the results where trading is adjusted by the total number of shares outstanding.

**Panel A. Trading adjusted by free float**

| | **Total trading** | | | **Total trading/Holding** | | |
|---|---|---|---|---|---|---|
| Rank | Individual | Financial | Foreign | Individual | Financial | Foreign |
| Small | 0.084 | 0.043 | 0.069 | 0.145 | 0.176 | 0.389 |
| 2 | 0.050 | 0.100 | 0.069 | 0.135 | 0.298 | 0.236 |
| Large | 0.054 | 0.176 | 0.294 | 0.301 | 0.476 | 0.653 |
| Average | 0.063 | 0.106 | 0.144 | 0.194 | 0.317 | 0.426 |

**Panel B. Trading adjusted by shares outstanding**

| | **Total trading** | | | **Total trading/Holding** | | |
|---|---|---|---|---|---|---|
| Rank | Individual | Financial | Foreign | Individual | Financial | Foreign |
| Low | 0.044 | 0.022 | 0.037 | 0.138 | 0.165 | 0.314 |
| 2 | 0.027 | 0.035 | 0.038 | 0.131 | 0.185 | 0.178 |
| High | 0.019 | 0.053 | 0.091 | 0.186 | 0.272 | 0.283 |
| Avgerage | 0.030 | 0.036 | 0.055 | 0.152 | 0.207 | 0.258 |

Table 2.13: Investment horizon

This table presents the number and percentage of investors in each type that have stock holdings for different investment horizons on the Norwegian stock market from December 1992 to September 2007. There are three types of investors: (domestic) individual investors ("ind"), financial investors ("fin"), and foreign investors ("for"). Panel A and Panel B, using all the investors in the data, report the number and percentage of investors that have invested in the Norwegian stock for a period between m and n months, (m, n]. For example, the Column "(0,6]" reports the number and fraction of investors that had stock portfolio equal to or less than 6 months. Column "(6,12]" shows the number and fraction of investors that have invested in stocks for between 6 to 12 months, including 12 months. The last column reports the total number of investors in each sector. Panels C and D repeat the procedure in Panel A and Panel B, but require the investors have to be in the data between January 1995 to January 2000.

**Panel A1. Number of investors in the whole sample period**

| type | (0,6] | (6,12] | (12,24] | (24,36] | (36,48] | (48,60] | (60,84] | (84,120] | (120,144] | (144,178] | all |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ind | 71441 | 58636 | 68127 | 43365 | 42843 | 35841 | 160241 | 113739 | 52509 | 145836 | 792578 |
| fin | 123 | 96 | 110 | 106 | 93 | 84 | 144 | 145 | 57 | 240 | 1198 |
| for | 27621 | 14986 | 13541 | 9691 | 6763 | 5158 | 10326 | 8621 | 2071 | 3380 | 102158 |

**Panel A2. Percentage of investors in the whole sample period**

| type | (0,6] | (6,12] | (12,24] | (24,36] | (36,48] | (48,60] | (60,84] | (84,120] | (120,144] | (144,178] | $> 60$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ind | 9.01 | 7.40 | 8.60 | 5.47 | 5.41 | 4.52 | 20.22 | 14.35 | 6.63 | 18.40 | 59.59 |
| fin | 10.27 | 8.01 | 9.18 | 8.85 | 7.76 | 7.01 | 12.02 | 12.10 | 4.76 | 20.03 | 48.91 |
| for | 27.04 | 14.67 | 13.25 | 9.49 | 6.62 | 5.05 | 10.11 | 8.44 | 2.03 | 3.31 | 23.88 |

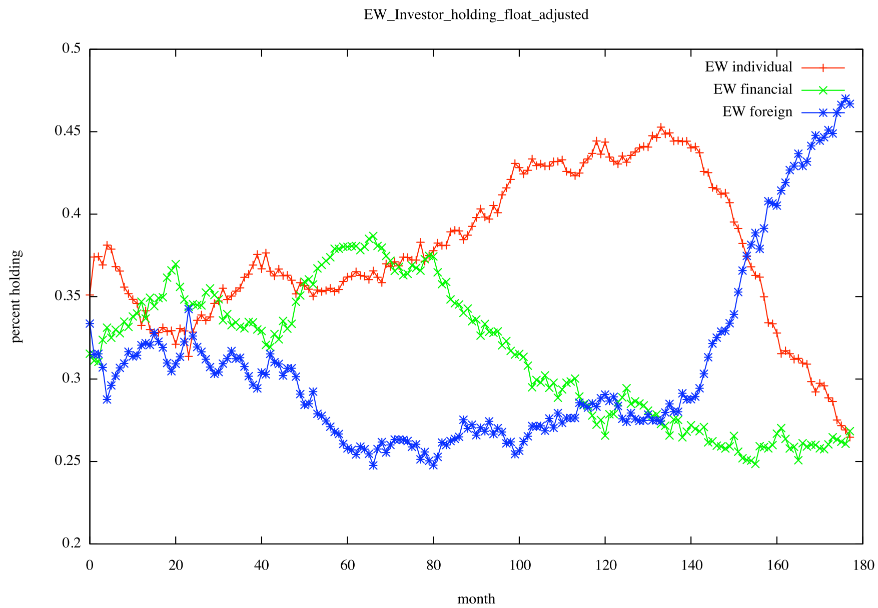
**Panel B1. Number of investors in the data between 1995 and 2000**

| type | (0,6] | (6,12] | (12,24] | (24,36] | (36,48] | (48,60] | (60,84] | (84,120] | (120,144] | (144,178] | all |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ind | 9614 | 6737 | 14168 | 21201 | 23082 | 20887 | 93017 | 99210 | 52509 | 145836 | 486261 |
| fin | 22 | 27 | 46 | 59 | 52 | 51 | 79 | 123 | 57 | 240 | 756 |
| for | 4514 | 2022 | 2933 | 6177 | 4054 | 2244 | 6832 | 7695 | 2071 | 3380 | 41922 |

**Panel B2. Percentage of investors in the data between 1995 and 2000**

| type | (0,6] | (6,12] | (12,24] | (24,36] | (36,48] | (48,60] | (60,84] | (84,120] | (120,144] | (144,178] | $> 60$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ind | 1.98 | 1.39 | 2.91 | 4.36 | 4.75 | 4.30 | 19.13 | 20.40 | 10.80 | 29.99 | 80.32 |
| fin | 2.91 | 3.57 | 6.08 | 7.80 | 6.88 | 6.75 | 10.45 | 16.27 | 7.54 | 31.75 | 66.01 |
| for | 10.77 | 4.82 | 7.00 | 14.73 | 9.67 | 5.35 | 16.30 | 18.36 | 4.94 | 8.06 | 47.66 |

**Panel A: Equal-weighted average of holdings**




**Panel B: Value-weighted average of holdings**


Figure 2.1: Holding ownership

Time series plots of monthly equal-weighted (Panel A) and value-weighted (Panel B) average of holding ownership of three types of investors in the Norwegian stock market from December 1992 to September 2007. The three types of investors are domestic individual investors, domestic financial institutions and foreign investors.

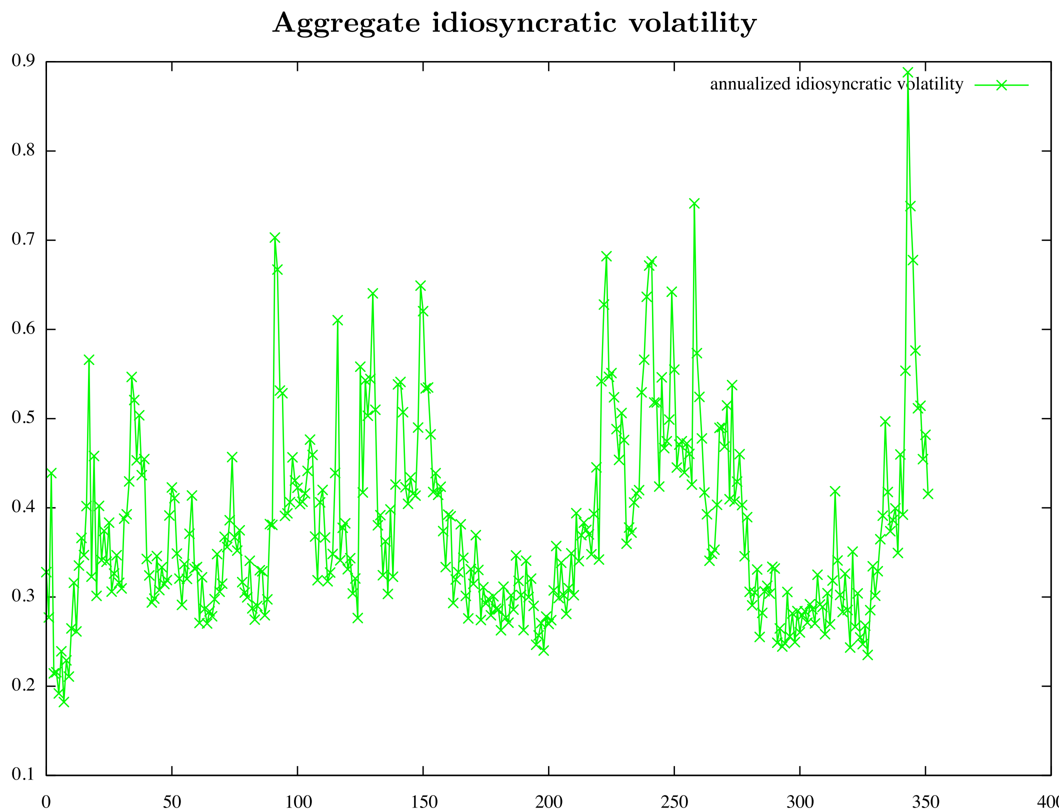
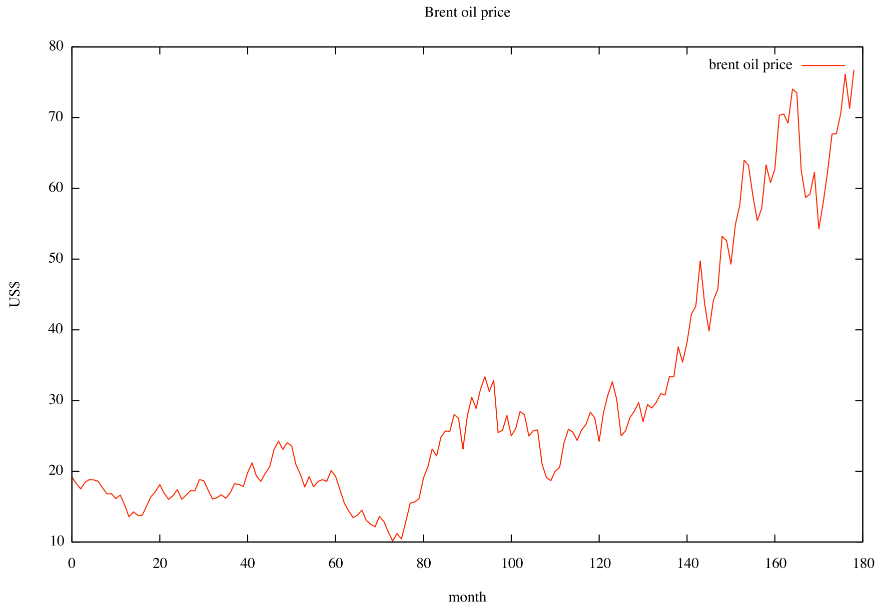



Figure 2.2: Aggregated Idiosyncratic volatility

This figure plots the time series of annualized value weighted aggregate stock idiosyncratic volatility for all the stocks on the Norwegian stocks market for a sample period of 352 months from March 1980 to June 2009. The measure of aggregated idiosyncratic volatility is similar to the method in Campbell et al. (2001).

**Panel A: Price of Brent Crude oil**




**Panel B: Brent oil return**

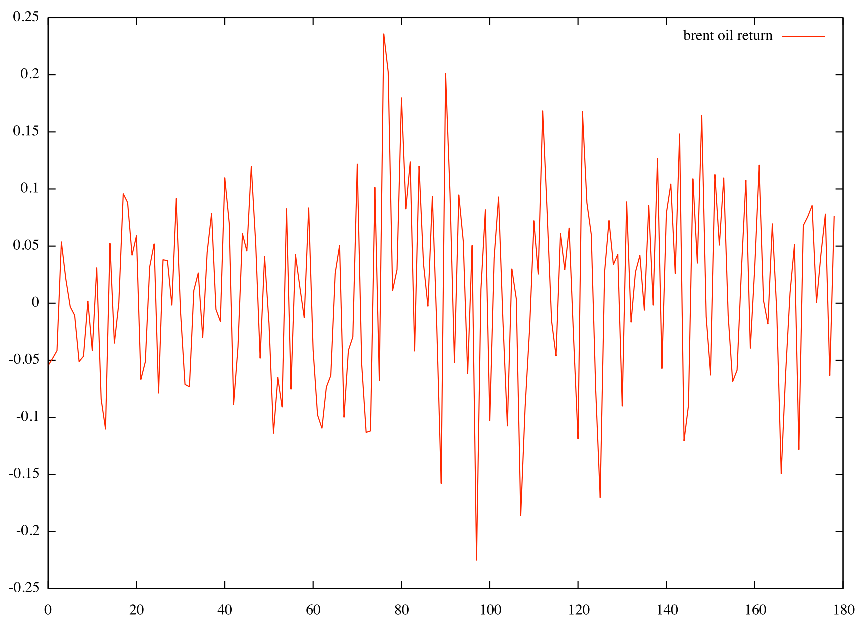



Figure 2.3: Price and return of Brent Crude oil

Panels A and B exhibit the time series of prices and returns of Brent Crude oil from December 1992 to September 2007, respectively.

# Chapter 3

# Investor Timing Ability Between Stock and Bond Markets

**Abstract** We examine the ability of Norwegian individual and financial investors to time the stock market by focusing on their dynamic asset allocation between equity and bond markets. Unlike the extant literature that investigates market timing by examining whether investors invest in higher beta stocks when markets are high, we ask the more natural question for a potential market timer of whether an investor increases their weight invested in equity markets, relative to bond markets, when equity markets are subsequently high. We are able to do this by using a unique monthly holding data set of both equities and bonds. We find evidence against the null hypothesis of no market timing for a substantial number of individual investors. An increase in the weight invested in equity markets for these investors predict high future stock market excess returns. We find marginal evidence for financial institutions. Individual investors who are identified as having timing ability have much higher portfolio performance than investors who have no timing ability.

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*JEL classification*: G11, D12, D14.
*Keywords*: timing ability, stocks, bonds, individual investors.

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## 3.1 Introduction

The performance of investors in terms of being able to time the stock market has generated substantial research interest. The general findings of the extant literature are that institutional investors are not able to time the market. Perhaps this is not a surprising result because, for fund managers, there are a number of impediments to orchestrating a successful market timing strategy. First, for a fund manager who is constrained to invest within a specific asset class, such as stocks, on the expectation of an increase in equity prices, fund investments should switch from low to high beta stocks. However, shifting large blocks of funds between stocks with different betas can be difficult and expensive. For example, high beta stocks tend to be small, volatile and often difficult to buy in large blocks. Second, mutual funds are often benchmarked to a specific index and moving into unbalanced positions of stocks that make up the benchmark, or moving into cash can be costly for the manager. Therefore, because institutional investors are often confined to invest within one single asset class, such as stocks, market timing is probably difficult to achieve. Moreover, most fund managers consider themselves stock pickers rather than market timers. Therefore, examining the population of mutual funds for market timing ability is likely to be futile from the start.

In contrast to institutional investors, individual investors do not face the constraints of fund managers regarding investing in a specific asset class or being tied to a benchmark. Moreover, if individual investors do have market timing ability, because they are relatively small investors, they can more easily execute a trading strategy. In this paper, we use a unique data set on the monthly holdings of all financial assets of all the investors in the Norwegian stock market to examine the ability of investors to time the market. Since the data allows us to observe the holdings of *all* financial assets held by an individual investor, we are able to devise a novel approach to assessing market timing.

Consider a hypothetical investor who has no constraints on his universe of investable assets and has perfect market timing ability. In this case the optimal timing strategy is not to shift from high to low beta stocks within the equity portfolio, but rather from 100% stocks to 100% bonds when the stock market is expected to perform worse than the bond market and from 100% bonds to 100% stocks when the stock market is expected to increase. Consequently, a more accurate measure of timing ability can be assessed by examining whether investors, who are unrestricted in their asset choices, are able to efficiently allocate their assets between the equity market and the bond market conditional on their forecast of future stock market performance.

Clearly, actual market timers do not have perfect market timing ability: in the data we do not see zero-one weights in the equity and bond markets. Rather, given the uncertainty regarding the signal of future market movements, it is likely that as investors' subjective probability of the stock market rising increases, they increase their relative weight in stocks versus bonds. As they receive more positive signals regarding the stock market's performance, their weight in the stock market should increase. In light of these arguments, it seems appropriate to examine the timing ability of individual investors using the time series of relative weights in each asset class to predict future performance. Our data allows us to do exactly this: we run time series regressions of the stock market excess returns on the weights invested in the equity market relative to total investment. If investors have timing ability an increase in the weight at time $t$ should forecast higher stock market excess returns in the subsequent n periods.

Employing this novel approach to assessing market timing, we present empirical evidence showing that a reasonable number of individual investors have market timing skill. The weight of an investor's portfolio in equity relative to her total portfolio forecasts higher subsequent stock market excess returns. Out of the sample of 11,390 individual investors who have a minimum holding period of 24 consecutive months, 1573 of them (14%) have positive timing ability when examining a one month forecasting horizon. This is considerable larger than the 285 (2.5%) investors that would be expected by chance under the null hypothesis of no timing ability. Moreover, the number of positive market timers rises to 20% when examining a three month horizon and focusing on investors who have at least 100 months of stock market holdings. It is worth noting that out of the sample of 11,390 investors we investigate, clearly not all of them are trying to time the market, so it is not surprising that the number of market timers is not large. Thus, our finding that 14% of investors can time the market at the one month horizon is likely to be a lower bound on the actual number of timers given the unobserved population of investors who are actually trying to time the market.

If the market timing that we have uncovered for some of the investors is true timing ability, and not driven by some form of biases in the way we measure timing ability, then this should translate into investors who have timing ability having higher performance than investors who can not time the market. We find that this is indeed the case. Individual market timers have higher portfolio returns, higher Sharpe ratios and higher alphas than individual investors who have no market ability. The differences in these performance metrics are economically large and statistically significant.

Our findings are in contrast to the large literature on market timing and to a large extent stem from two unique aspects of this study. First, this is the first paper to thoroughly examine individual investors who are likely to be more able to execute a market timing strategy, at the investor level. Second, the novel approach of using investment weights to assess timing ability is likely to be a more powerful method if investors' timing involves moving between asset classes.

In addition to examining the ability of investors to time the stock market using the relative weight in the equity market to total investment, we also use existing methodological techniques that look at whether investors time the market by increasing their investment in higher beta stocks. First, we use the portfolio beta approach which involves computing the correlation between investors' portfolio betas and stock market returns, following the model of Jiang et al. (2007). The reasoning underlying this model is that if one investor could successfully time the market, her portfolio beta would be high conditional on her forecast that the stock market performs well, and vice versa. Hence, there should be a positive correlation between portfolio beta and future stock market returns for positive market timers. We do find some evidence that investors do invest in higher beta stocks when they expect the stock market returns to increase. However, this evidence is not as strong as looking at the portfolio weights. Therefore, it seems that investors not only increase stocks in their portfolio in anticipation of stock market increases, for some of the investors the stocks they invest in tend to have higher risk than the stocks they currently invest in.

Second, we use the return based method of Treynor and Mazuy (1966), which also attempts to uncover whether investors increase their portfolio exposure to the market when market returns are higher in the future. We have the advantage of calculating portfolio returns using ex-ante portfolio holding, instead of using ex-post realized portfolio returns, to avoid the dynamic trading bias mentioned by Jagannathan and Korajczyk (1986). As is the case in the mutual fund literature, we find no evidence of market timing using this approach.

In sum, our findings that some individual investors can time the market are rather unique and stem from our ability to observe investors' holdings of stocks and bonds and to use this as a means of measuring timing ability. The extant methodologies of testing for timing ability, based on investing in higher beta stocks when markets are expected to increase, uncover less evidence, if any at all, regarding timing ability. Perhaps this is not surprising: given the uncertainty regarding the investor's signal, increasing the weight in the stock market and simultaneously increasing the risk of the stocks in the investor's portfolio is a risky strategy.

Whilst our main interest is in the timing ability of individual investors, we also examine the market timing ability of financial institutions in order to provide a benchmark relative to the results in the extant literature. We find marginal evidence that financial institutions have timing ability, consistent with the existing literature.

Our study is closely related to the extant literature on market timing. Most of the existing studies examine the timing ability of institutional investors (mutual funds, pension funds and hedge funds). Treynor and Mazuy (1966), develop a quadratic relation between portfolio return and contemporaneous market return based on the assumption that a successful market timer will increases portfolio risk exposure to the market when market is high and decreases risk exposure to the market when market is low. Therefore, for a positive market timer, the relationship between portfolio return and market return should be concave. Treynor and Mazuy (1966) document no evidence of timing skill. Henriksson (1984) evaluates the market timing performance of 116 open-ended mutual funds using the model in Henriksson and Merton (1981), and finds that only three funds have significantly positive estimates of market-timing ability for the whole sample period.

Similarly, Chang and Lewellen (1984) test the market timing ability on 67 mutual funds by employing the single factor market model and Henriksson and Merton (1981) model. They find that fund managers possess good selectivity skill but few fund managers display market timing skill. Graham and Harvey (1996) analyze investment newsletters' suggested allocations between equity and cash, thereby measuring explicitly the ex post performance of timing strategies. Using this methodology there is no evidence of timing ability. Goetzmann et al. (2000) study timing skills of daily timers and find no timing ability.

In contrast to the previous evidence, a few recent papers use higher frequency return data or quarterly holding data to assess market timing ability. Using both daily and monthly data on 230 US equity funds, Bollen and Busse (2001) find that mutual funds exhibit significant market timing ability in both monthly and daily data frequency, but more often in at the daily frequency (34.2%) than at the monthly frequency (11.9%).

Instead of using realized portfolio return data, as most papers have done, Jiang et al. (2007) employ quarterly holding data to investigate U.S. equity mutual fund managers' timing ability. They compute the portfolio beta which is the value weighted average of the beta estimates for stocks held by the fund. Jiang et al. (2007) test the correlation between the future stock market excess return and fund beta for 2294 U.S. mutual funds and document that on average mutual funds possess positive market timing ability over 3 and 6 month forecasting horizons. However, they find no evidence that fund managers have the ability to successfully time the return on the stock market over a 1 month horizon. Over a 12 month forecasting horizon, the average timing ability is positive but insignificant. They also conduct the Treynor and Mazuy (1966) timing model using realized portfolio return and find no evidence of skillful market timers. To check whether fund managers' volatility timing ability could impede their return timing ability, Chen and Liang (2007) study a sample of 221 self-described market timing hedge fund managers' return timing and volatility timing ability jointly. They find significant evidence of both return timing and volatility timing at both the aggregate and the fund levels. Even after controlling for volatility timing, hedge funds are still positive timers on market returns. Breon-Drish and Sagi (2009) also find some evidence of timing ability, by studying fund managers' asset allocation decisions.

In the literature there is scant evidence regarding the timing ability of individual investors. Barber et al. (2009) conduct a simple analysis of market timing ability of individual investors at the aggregate level instead of at the investor level. They first construct a long portfolio and a short portfolio for each day and then compound the daily returns for the long and short portfolios to yield a monthly time-series of returns for each portfolio. They regress the difference between the monthly return on the long portfolio and the short portfolio on the market risk premium. They find that individual investors, as a group, lose from market timing.

The rest of the paper is organized as follows. Data, sample selection and descriptive statistics are outlined in section 2. Our main analysis using the portfolio weight level based timing approach is presented in section 3. Section 4 considers alternative market timing tests. Section 5 examines the portfolio performance of individual investors who have market timing ability. Section 6 offers some concluding remarks.

## 3.2 Data, sample selection and descriptive statistics

### 3.2.1 Data

This paper employs high quality Norwegian data on month-end portfolio holdings from December 1992 to June 2003. At the end of June 2003, the Oslo Stock Exchange ranks 11th out of twenty-three European stock exchanges based on market capitalization and 12th based on the number of listed companies.[2] Thus, compared to other European exchanges, the Oslo Stock Exchange is close to the "median exchange" when it comes to market capitalization and number of shares listed. Stock market turnover data (measured as annualized electronic order book transactions) indicates the exchange has the eighth highest turnover. Bohren et al. (1997) show that the intensity of seasoned equity offerings is comparable to that of active markets like the New York Stock Exchange. In sum, the Oslo Stock Exchange is an established and mature market where liquidity and turnover are high enough to be an interesting laboratory to study investor behavior.

The main data set employed in this paper contains month-end share holdings on stocks, mutual funds (equity funds, bond funds, and money market funds) and bonds for all investors who have ever participated in the Oslo Stock Exchange over the period from December 1992 to June 2003. The holding data is provided by National Central Securities Depository (NCSD), which is authorized by the Norwegian government to register the portfolio holdings for taxation purpose, and is of high quality. Hence, our data is immune from sampling error and survivorship bias. We focus on the timing ability of individual investors and financial institutions.[3]

Stock market data are provided by OBI (Oslo Stock Exchange Information AS) and include monthly security returns, monthly security prices, and the number of shares outstanding for stocks, mutual funds and bonds, respectively. The stock market index is a value-weighted portfolio of all stocks traded (with a price above 5 NOK) on the Oslo Stock Exchange. Returns include dividends and are before expenses and transaction costs. The bond return index is provided by OBI. We use the 1 month Norwegian interbank interest rate (NIBOR) from DataStream as the monthly risk free rate. To reduce the bias of illiquid holdings and noise caused by small stocks, we require stocks to have a price higher than 5 NOK and non-zero monthly trading volume in order to be included in the sample.

[2] See www.fese.eu.
[3] Each investor has an ID code which indicates which type she belongs to.

### 3.2.2 Sample selection of investors

Since not all investors are pursuing a timing strategy, we consider different criteria to exclude investors that are unlikely to time the market. First, we require investors to hold a minimum of 5 stocks in their portfolios. Secondly, the holding period might matter for the possibility of an investor being a market timer. For example, investors who have been active on the Oslo Stock Exchange for 100 months would be more likely to be trying to time the market than an investor who has been investing in the market for only 12 months. Therefore, we require that investors have been on the Norwegian financial market for a minimum period of T months (T=24, 60, or 100) to check whether holding periods matter for detecting investors' timing ability. Thirdly, to time the market, an investor has to both buy and sell a reasonable fraction of her total portfolio from time to time. If an investor does not trade, or only buys or sells a tiny fraction of their portfolio, it might be difficult to conceive that the investor is pursuing a timing strategy. Hence, we require that investors have to buy a minimum number of X times and sell a minimum number of Y times of at least M% of her total portfolio, where X=3, 5 and 10, Y=3, 5 and 10, and M=5, 10 and 20. Fourthly, we assume a potential market timer would have been active in the past months. To be considered as an active investor or a potential market timer, we require investors to trade N times in the previous M consecutive months. We set N = 4, 5, or 6, and M = 6. We try various tests either by combining some of the requirements or using one specific requirement separately.

### 3.2.3 Portfolio construction

For each qualified investor included in our timing analysis, we record their holdings of all Norwegian stocks, Norwegian equity mutual funds, bond mutual funds, money market funds, and Norwegian bonds in each month. We construct a time series of equity portfolios and bond portfolios at the investor level. The monthly equity portfolio consists of Norwegian stocks and Norwegian equity funds and the monthly bond portfolio includes Norwegian bond mutual funds, money market funds, Norwegian bonds, and cash balance.[4] For investor $i$ in month $t$, the equity portfolio weight is the fraction of equity portfolio value divided by the sum of equity portfolio value and bond portfolio value.

$$w_{i,t} = \frac{\sum_{j=1}^{J_t} N_{j,t} P_{j,t}}{\sum_{j=1}^{J_t} N_{j,t} P_{j,t} + \sum_{k=1}^{K_t} N_{k,t} P_{k,t}}, \tag{3.1}$$

[4] We record the cash balance from security selling as part of the bond portfolio which is assumed to earn the risk free rate as measured by the one month NIBOR. When investors buy securities, we deduct the investment from the cash balance. The cash balance is always non-negative.

where $w_{i,t}$ represents investor $i$'s equity portfolio weight in month $t$, and $1 - w_{i,t}$ is the bond portfolio weight; $N_{j,t}$ and $P_{j,t}$ denote the number of shares and price of equity security $j$ in month $t$; $N_{k,t}$ and $P_{k,t}$ denote the number of shares and price of bond security $k$ in month $t$;

### 3.2.4 Descriptive statistics

Table 3.1 reports, for each type of investors, the number (Panel A) and fraction (Panel B) of investors that hold stocks over various holding periods. The last column of Panel A shows that there are total 989 institutional investors and 636,501 individual investors who have ever participated in the Oslo Stock Exchange over the 127 months period from December 1992 to June 2003. Panel A presents the number of investors who have been on the market for more than $m$ months but no longer than $n$ months (column (m,n]). For example, there are 106 financial investors and 28,319 individual investors that were on the market for less than 6 months.

Panel B reports the fraction of investors with different holding periods. The second column shows that 10.72% of financial investors and 4.45% of individual investors have existed for less than 6 months on the Oslo Stock Market. The next to the last column shows that 14.46% of institutional investors and 17.25% of individual investors hold a position in equities for the whole sample period of 127 months. The sum of the fractions in the four columns preceding the final column in Panel B shows the fraction of investors who have participated in the Norwegian stock market for longer than 60 months. While 50.33% (=17.97%+6.87%+8.24%+17.25%) of individual investors have been investing in the Oslo Stock Market for more than 60 months, about 40% of institutional investors have a holding period greater than 60 months.

Table 3.2 reports portfolio characteristics of the financial and individual investors that have, on average, a minimum of 5 stocks in their portfolio. Panel A reports the portfolio characteristics of investors that have at least a 24 month holding period, in addition to the minimum of 5 stocks requirement. The column "No. of owners" shows that there are 400 financial investors and 11,390 individual investors that satisfy the filtering criteria. There are considerably less individual investors comparing to the total number of individual investors in the market since most individual investors have only a few (less than 5) stocks in their portfolios. This might imply that the 11,390 individual investors who are left in the sample are likely to be more sophisticated individuals. The next 4 columns report the number of stocks, equity mutual funds, bond mutual funds and bonds in investors' portfolios. Financial institutions have on average 24.5 stocks, 0.36 equity mutual funds, 0.27 bond funds and 5.27 bonds in their portfolios. The individual investors have 8 stocks, 0.67 equity mutual funds, 0.11 bond funds and 0.49 bonds on average in their portfolios. The average portfolio value of individual investors is much smaller than that of the financial investors, 1.02 million NOK vs. 180 million NOK, as indicated in the column "Value(mNOK)".

The three columns next to the final column present equity portfolio weights, the time series standard deviation of equity weights, and the persistence in the level of the weights. Financial investors have an average equity weight of 0.34, lower than that of individual investors, 0.65. The standard deviation of the average equity weight is 0.39 for financial investors and 0.29 for individual investors, which means that financial investors change their equity portfolio weight more than individual investors do. The weight persistence is similar for both groups of investors, at about 0.8. The last column, "Fraction trading", reports the decimal fraction of the number of months in which investors have traded out of the total number of holding months. On average, financial investors have traded 87%, while individual investors have traded 50% of the months they have been participating in the Norwegian stock exchange.

In summary, the goal of these sample selection criteria is to reduce the number of investors who have no aim at all in orchestrating an market timing strategy.

## 3.3 Market timing analysis

This section investigates the relationship between one investor's equity weight relative to the total portfolio and the subsequent stock market excess return over bond market return. The intuition of the portfolio weight approach, which is in spirit similar to the portfolio weight measure in Grinblatt and Titman (1993), is that a skillful market timer would increase her equity portfolio weight by investing more in equity and less in bonds conditional on her forecast that the equity market will outperform the bond market in the next periods, and vice versa. Therefore, there should be a positive relationship between the equity portfolio weight and future stock market return in excess of the bond return for a positive market timer.

Using monthly portfolio holdings, we first investigate the timing ability over a one month forecasting horizon. However, it is possible that investors might be able to predict the market better over longer horizons, for example, investors could be forecasting short term business cycle conditions. We therefore check investors' timing ability over 3-month, 6-month and 12-month forecasting horizons as well.

Stock market returns are positively autocorrelated in our sample. An increase in the return on the stock market will lead to an increase in the weight invested in the stock market without any active investment from an investor. Positive autocorrelation means that returns will be higher in the next period, which is not due to active timing. To control for the potential biased results from stock market return autocorrelation, we regress future stock market excess returns on equity portfolio weights and the lagged market excess returns, at the investor level:

$$r_{m,t+k} = \alpha + \gamma w_t + \delta r_{m,t-k} + \epsilon_{t+k}, \tag{3.2}$$

where $r_{m,t+k}$ is compounded stock market excess returns over bond index returns from month $t+1$ to month $t+k$, and $r_{m,t-k}$ is compounded market excess returns $k$ months prior to month

$t$, where $k$=1, 3, 6, and 12. $w_t$ is the equity relative to total portfolio weight in month $t$; the coefficient $\gamma$ measures the timing ability.

We use the Newey and West (1987) autocorrelation- and heteroskedasticity-consistent covariance matrix to calculate standard errors. However, standard OLS analysis with Newey and West (1987) adjusted standard errors might not provide reliable statistical results due to the well documented non-normality of market return, small sample problems and persistence in the weight levels. We therefore apply the bootstrap statistical technique in Kosowski et al. (2006) instead of using the standard OLS $t$-statistics to draw our statistical inference.

For each investor, we first conduct the regression (3.2) and record the coefficient $\gamma$ and $\delta$, the t-statistics of $\gamma$ and the error terms. In the bootstrap procedure, for each time t, we randomly draw one error term with replacement and calculate the market excess return under the null hypothesis of no market timing ability. We construct a time series market excess returns and regress them on the investors' equity weight levels and the lagged market excess returns. We record the hypothetical estimate of coefficient estimate $\gamma$ and its $t$-statistic for each simulation. We repeat this procedure 1000 times.[5] We then compare the investor's actual $t$-statistic of the the coefficient estimate to the distribution of the 1000 simulated $t$-statistics. We examine the $t$-statistics of the coefficient estimates instead of coefficient estimates because the $t$-statistic, as a pivotal statistic, provides better sampling properties, while coefficient estimates are affected by the variance of standard errors (Kosowski et al. (2006)). We define the bootstrapped $p$-value as follows:

$$p = \frac{1}{N}\sum_{n=1}^{N} I_{t^*_{\gamma,n} > t_\gamma},$$

where $I_{t^*_{\gamma,n} > t_\gamma}$ equals 1 if $t^*_{\gamma,n} > t_\gamma$ and 0 otherwise. $t^*_{\gamma,n}$ is the nth bootstrapped t value of the coefficient estimate of $\gamma$ under no timing ability, and $t_\gamma$ is the actual t statistics of the coefficient estimate of $\gamma$. N is the number of simulations and is set to 1000. A low bootstrapped $p$-value demonstrates that the actual timing measure is consistently larger than its bootstrapped values, and a high bootstrapped $p$-value indicates that the actual timing measure is consistently smaller than its bootstrapped values. When one investor has a bootstrapped $p$-value smaller than 2.5%, the investor is considered to have significantly positive timing ability at the 5% significance level. On the other hand, one investor with a bootstrapped $p$-value larger than 97.5% will have significant and negative timing ability at the 5% significance level.

[5] Generally speaking, 1000 times simulations should provide reliable results. Bollen and Busse (2001) also bootstrap 1000 times in their study of mutual funds' timing ability. In addition, we have tried 5000 simulations and the results are consistent with the ones with 1000 simulations.

### 3.3.1 Empirical Results

Table 3.3 reports the number and fraction of investors who have significant timing ability in each investor category, based on the OLS t-statistics and the bootstrapped p-values.[6]

Panel A presents the number and fraction of investors with significant timing ability over a 1-month forecasting horizon. The column "Min. holding" indicates a minimum number of X holding months, where X=24, 60 and 100. The column "No. of owners" reports that there are 400, 276 and 161 institutional investors who have at least 5 stocks and are present in the market for at least 24 months, 60 months and 100 months, respectively. There are 11,390, 9,666 and 7,411 individual investors who remain after the filtering procedure for the minimum 24-month, 60-month, and 100-month holding periods. We first focus on the last 4 columns, which report the number and percentage of investors with significantly negative and significantly positive results based on the bootstrapped results. The columns "$\#BS--$" and "$\#BS++$" report the number of investors with significant negative and significant positive estimates of timing coefficients, at the 5% level. Under the null hypothesis of no market timing ability, there should be 2.5% of the sample size in each tail. In the case of the individual investors, under the null hypothesis, we would expect to find 285 investors have positive timing ability and 285 have negative timing ability, when requiring a minimum holding of 24 months. Similarly, we would expect 10 financial investors should by chance have positive timing ability and 10 should have negative timing ability. The last 2 columns ("$\%BS--$" and "$\%BS++$") present the decimal fraction of investors with significant negative and positive timing ability based on the bootstrapped $p$-values.

The results reported in Panel A clearly reject the null hypothesis of no timing ability for individual investors at the one month forecasting horizon. There are 1,573 individual investors, 14% of the total, who have positive timing ability. The percentages of significant and positive timers are 16% and 16.5% for minimum holding periods of 60 months and 100 months, respectively. Whilst these numbers are not large, they are nonetheless statistically significant and it is also worth bearing in mind that it is unlikely that a large proportion of the 11,390 investors in the sample are actually trying to time the market. Therefore, the actual number of successful market timers out of the population of individual investors that are actually trying to time the market is likely to be somewhat higher. Hence, the number of market timers that we observe can be thought of as a lower bound on the actual number of market timers who are trying to time the market.

In the case of institutional investors, we find that, when we restrict the minimum holding period to be 24 months, 4.25% of institutional investors have positive timing ability, slightly

[6]We conduct timing analysis for the potential timers who have at least 5 stocks in their portfolios and have a minimum of X holding months, where X=24, 60 and 100. The results of timing analysis using other investor filtering criteria are not quantitatively different.

higher than under the null. The percentage is marginally higher when requiring the minimum holding periods are 60 months and 100 months. This finding is in line with previous studies of institutional investors which generally finds little evidence of positive market timing. However, when looking at the other tail of the distribution, we find that about 12% of institutional investors have negative timing ability, substantially more than under the null of no negative timing ability.

We also report the results of investors' timing ability based on the Newey and West (1987) adjusted OLS t values. The 2 columns, "$\#OLS--$" and "$\#OLS++$", report, for each investor type, the number of investors who have significant negative and positive timing ability at the significance level of 5% based on the OLS t-statistics. The columns, "$\%OLS--$" and "$\%OLS++$", report the decimal fraction of investors who have significant negative and positive timing ability at the significance level of 5%, based on the OLS t-statistics. There are more significant and positive market timers based on the Newey and West (1987) adjusted OLS t-statistics, comparing to the bootstrapped results, for both individual investors and for financial investors.

Panel B of Table 3.3 reports the same results as panel A but looking at a 3 month forecasting horizon. Recall that our rationale for looking at longer horizon is motivated by the possibility that investors may base their forecast on business cycle conditions. Based on the bootstrapped results in the last 4 columns, we find that 1,822, which corresponds to 16%, of individual investors with a minimum 24 months holding period have positive market timing ability. The percentages of significant market timers increase to 18% and 20% when requiring the minimum holding periods to be 60 months and 100 months. The numbers of negative market timers at the 3 month horizon are very similar to those at the 1 month horizon, around 6%. For institutional investors, we find that there is some evidence of positive market timing where over 6% have positive timing ability. A similar number of institutional investors at the 3 month horizon have negative timing ability as at the 1 month horizon. Looking at the results based on the OLS t values, the percentages of positive timers are 8% more than the bootstrapped results for financial investors, and are about 5% more than the bootstrapped results for individual investors.

It is evident that increasing the required holding period of individual investors leads to a larger percentage of investors having positive timing ability. The reason for this might be that investors with shorter holding periods are less likely to time the market. Therefore, omitting them leads to more evidence of positive timing ability. That is, by omitting investors with shorter horizons we come closer to the population of investors who are actually trying to time the market.

Examining the 6 month horizon results in Panel C, the percentages of individual investors with positive timing ability fall to around 7%, whereas the percentages of negative timers are also around 7%. The results at the 6 month horizon for institutional investors show that there are slightly less significant positive timers and slightly more significant negative timers, comparing to the numbers at the 3 month horizon. Panel D reports results at the 12 month forecasting horizon. In this case, the timing ability of individual investors largely disappears with about 4% of individual investors recorded as having significant positive timing ability. However, while the number of positive timers falls, the number of negative timers remains the same. Institutional investors also show no evidence of positive timing ability at the 12 month horizon, but the number of negative timers remains largely unchanged.

In sum, there is evidence that individual investors can time the market at 1 to 6 month horizons with the strongest results at the quarterly horizon. The evidence suggests that investors' weights are adjusted for short term changes in stock market movements. With regard to negative timers, they seem to stay the same, irrespective of holding period.

An interesting aspect of the results is that the negative timing ability is largely consistent across the horizons for both individual and institutional investors. It might be difficult to conceive why some investors could systematically time the market in the wrong direction. However, Bollen and Busse (2001) find that, using daily and monthly returns, while 34.2% and 11.9% of funds have positive timing ability, 33.3% and 8.8% of funds have significant negative timing coefficient estimates using the Treynor and Mazuy (1966) model. Similarly, in the performance persistence literature, Carhart (1997) finds significant persistence in under-performance by the worst-return mutual funds. Che et al. (2009) also show that both good and poor performance of individual individuals persists.

There are a number of potential explanations regarding the significant negative timing ability. First, when some skillful timers systematically trade conditional on their forecasts of future market returns, it is likely that the counterparties trade in the opposite direction and hence there are some negative timers as well, which is similar to the logic that when there are winners there should be losers to make the total aggregate gain zero. Second, some investors might have behavioral biases. For example, they enter the stock market when the market is at peak and about to decline, and exit the stock market when the market is at its bottom and just before it recovers.

In summary, the novel evidence presented in Table 3 indicates that a good number of individual investors have the ability to time the stock market, especially at the one and three month forecasting horizons. The bootstrapped standard errors we use in order to judge whether there is statistically significant evidence of market timing should go a long way to assure us that the results are not due to biases in our testing methodology.

## 3.4 Alternative timing methodologies

In this section of the paper, we assess whether there is any evidence of market timing ability employing equity weight change method and techniques that have been used in the extant literature: the portfolio beta model in Jiang et al. (2007) and the Treynor and Mazuy (1966) timing model, which we refer to as the return based approach.

The main difference between the portfolio weight approach and the portfolio beta and return based techniques, is that the former method allows for investors to shift more of their wealth into stocks relative to bonds when they forecast higher future stock market returns. In contrast, the latter two methods assume that when an investor forecasts higher future stock returns they buy riskier stocks and sell less risky stocks. In these latter two cases there is no role for switching between bonds and stocks. Whilst this may be interesting for equity mutual funds who are constrained to invest in a single asset class, for individual investors, it seems more natural that they would shift from bonds to stocks if they forecast higher stock market returns. In this section, we first present the results using equity weight change approach and then the portfolio beta and return based timing techniques.

### 3.4.1 Timing ability using equity weight change approach

Grinblatt and Titman (1993), Daniel et al. (1997) and Eckbo and Smith (1998) all have employed weight changes to check investors' performance. One advantage of using weight changes rather than weight levels is that the changes are not persistent. The main dissadvantage of using weight changes is that we have to assume a measurement period which may or may not coincide with the period over which investors make their investment decisions. Using the wrong measurement period will reduce our chances of detecting timing ability. To see this, consider an example where investors with timing ability typically time the market six months ahead and start adjusting their portfolio accordingly. In such a setting, regressing one-month weight changes on one-month market returns would have little power to detect the timing-ability.

Similar to the main analysis in the previous section, we focus on individual investors and financial investors that have at least 5 stocks on average in their portfolios, and also require investors to have a minimum number of X holding months, where X=24, 60 and 100. We conduct, for each investor, a time series regression of future stock market excess returns over bond returns on the investor's equity portfolio weight changes and the lagged stock market excess return.

$$r_{m,t+k} = \alpha + \gamma \Delta w_t + \delta r_{m,t-k} + \epsilon_{t+k}, \tag{3.3}$$

where $r_{m,t+k}$ is the cumulative stock market excess returns over bond index returns from month $t+1$ to month $t+k$, and $r_{m,t-k}$ is the cumulative market excess returns $k$ months prior to month $t$, where $k$=1, 3, 6, and 12. $\Delta w_t$ is the change in equity portfolio weight from month $t-1$ to month $t$; the coefficient $\gamma$ measures the timing ability. A statistically significant and positive $\gamma$ means that the investor is a successful timer by allocating more into equity when forecasting higher future returns, and vice versa. We use the Newey and West (1987) autocorrelation- and heteroskedasticity-consistent covariance matrix to calculate standard errors, and follow the bootstrap statistical technique in Kosowski et al. (2006) instead of using the standard OLS $t$-statistics to draw our statistical inference.

The results of timing ability based on the bootstrapped procedure are reported in Table 3.4. Panels A, B, C and D present the results for investors' timing ability over future 1-month, 3-month, 6-month and 12-month forecasting horizons, respectively. For each panel, we report the results for investors with a minimum of 24 months, 60 months and 100 months holding data. The column "No. of owners" reports the total number of qualified financial and individual investors that are included in the timing analysis. The next 2 columns report, for each investor type, the number of investors who have significant negative and positive timing ability at the significance level of 5%. The last two columns report the decimal fractions of investors who have significant negative and positive timing ability at the significance level of 5%. The last column in Panel A shows that about 8% of financial and about 12% of individual investors have significant and positive timing ability over the 1-month forecasting horizon. The results are weaker for individual investors, but stronger for financial investors comparing to the results over the 1-month forecasting horizon using the equity weight level approach. When we forecast investors' timing ability over a 3-month forecasting horizon, with the results presented in Panel B, the percentages of investors with significant and positive timing ability drop dramatically, from about 8% to about 3% for financial investors and from about 12% to about 7% for individual investors. The results of investors' timing over even longer horizons, 6-month horizon in Panel C and 12-month horizon in Panel D, show that there is no evidence of positive timing ability at all, both for financial investors and individual investors. The next to last column in all the panels present no evidence of significant and negative timing ability.

In short, the results of timing ability using equity weight change approach provides some evidence of timing ability over the 1 month forecasting horizon, but the results are much weaker than those using the equity weight level approach.

### 3.4.2 Timing ability using portfolio beta approach

Due to the inability to observe the stock and bond holdings of institutional investors, or due to the fact that institutional investors only hold stocks, the approach to assessing timing ability of institutional investors involves examining whether investors increase the riskiness of the assets they invest in at time $t$ when they forecast higher returns at time $t$+1. In particular, an investor who can successfully forecast stock market returns in the subsequent period, would increase her portfolio beta when there is a positive signal and decrease her portfolio beta when she receives a negative signal. Hence, the correlation between the portfolio beta and future stock market excess returns should be positive for investors who can successfully time the market.

We follow the portfolio beta approach in Jiang et al. (2007) and regress portfolio betas on future stock market excess returns at the investor level:

$$\beta_{p,t} = \beta_{p,0} + \gamma r_{m,t+k} + \epsilon_{t+k} \tag{3.4}$$

$$\beta_{p,t} = \sum_{i=1}^{I} w_{i,t}\beta_{i,t}$$

$$\sum_{i=1}^{I} w_{i,t} = 1$$

where $\beta_{p,t}$ is the portfolio beta of investor $p$ at time $t$, which is value weighted average of beta estimates ($\beta_{i,t}$) of securities in the portfolio. The coefficient $\gamma$ measures the timing ability, $\beta_{i,t}$ is the beta estimate of security $i$ in month $t$, $w_{i,t}$ is the portfolio weight of security $i$ in month $t$ and $r_{m,t+k}$ is the cumulative stock market excess returns from $t+1$ to $t+k$, where $k$=1, 3, 6 and 12.

We calculate monthly betas for each security $\beta_{i,t}$ using up to 60 months prior return data and setting a minimum of 36 months of returns, prior to month $t$. For stocks where there is less than 36 months of return data in the estimation period, we follow Jiang et al. (2007) and assume the stock beta is 1. We use the following regression as in Jiang et al. (2007) to calculate security beta. The one month lagged market excess return accounts for the effect of nonsynchronous trading:

$$r_{i,\tau} = a_i + b_{i1} r_{m,\tau} + b_{i2} r_{m,\tau-1} + \epsilon_{i,\tau}, \tag{3.5}$$

where the security beta estimate is $\hat{\beta}_i = \hat{b}_{i1} + \hat{b}_{i2}$.

Table 3.5 reports the bootstrapped results based on equation (3.4). Panels A, B, C and D report the numbers and percentages of investors that have significant timing ability, at the 5% significance level, over 1, 3, 6, and 12 months forecasting horizons, respectively. The columns, "#negative timer" and "#positive timer", present the numbers of investors with significant negative and positive timing coefficient estimates, and the last two columns report the percentages of investors with significant negative and positive timing coefficient estimates.

In Panel A, we observe that, for investors with a minimum holding period of 24 months, 8.7% of individual investors, that is nearly 1,000 individual investors, have positive timing ability, as opposed to 3.7% who have negative timing ability, much closer to the null hypothesis of no timing ability. Institutional investors have little positive timing ability, 3.2%, whilst 6.3% have negative timing ability. Consistent with the portfolio weight approach, there are higher percentage of individual investors, around 11%, with significant positive timing ability when increasing the minimum holding period from 24 months to 60 months and 100 months.

The percentage of individual investors with positive timing ability at the 3 month horizon, reported in Panel B, remains similar to that in panel A. This is the case whether we consider investors who have a minimum holding period of 24, 60, or 100 months. Financial institutions have no positive timing ability over a 3-month forecasting horizon. As in the case when forecasting future market returns with portfolio weights, the number of positive timers falls at the 6 and 12 month horizons to about 5.5% and 2.2% for individual investors. The findings for institutional investors mirror those at the 3 month forecasting horizon that no positive timing ability exists for institutional investors. There remains some evidence of negative timing for both types of investors at these longer horizons.

The results using the portfolio beta method are, by and large, consistent with the results using the portfolio weight approach. The only difference is that there are about half the number of market timers uncovered with the portfolio beta approach relative to the portfolio weight approach. About 10% of individual investors have positive timing ability at 1 month and 3 months forecasting horizons using the portfolio beta approach as compared with around 14% to 20% using the portfolio weight level approach. Similar to the case when using portfolio weight levels to forecast future returns, there are a larger number of positive timers when increasing the number of months the investors are required in the sample whilst the number of negative timers declines marginally.

### 3.4.3 Return based approach

As an additional robustness test, we employ the traditional return based timing approach to test investors' timing ability. Treynor and Mazuy (1966) develop a quadratic relationship between portfolio return and contemporaneous market return, based on the intuition that an investor with timing ability would have higher exposure to the market when the stock market returns are high and vice versa.

Following the Treynor and Mazuy (1966) model, we conduct the following time series regression at the investor level:

$$r_{p,t} = \alpha_p + \beta_p r_{m,t} + \gamma_p r_{m,t}^2 + \varepsilon_{p,t}, \tag{3.6}$$

where $r_{p,t}$ is the portfolio excess return in month t, $r_{m,t}$ is the stock market excess return in month t, and $\gamma_p$ measures the timing ability. The sign of $\gamma_p$ indicates the direction of timing ability.[7]

Most studies using the Treynor and Mazuy (1966) model, employ realized portfolio return data. This might induce a dynamic trading effect (interim trading bias) when trading activities

[7] We also use an extension of equation (4) that controls for the Fama-French (1993) size and book-to-market factors and the momentum factor of Carhart (1997). The results are similar to the results report using the standard one factor Treynor and Mazuy (1966) model.

take place at a higher frequency than the measured frequency of portfolio returns (Jagannathan and Korajczyk (1986)). We use ex-ante portfolio holdings to calculate portfolio returns, which are value-weighted averages of returns on securities in the portfolio, instead of using ex-post realized portfolio returns, and therefore eliminate the dynamic trading bias.

In Table 3.6, panels A, B, C and D present the bootstrapped results for financial institutions and individual investors' timing ability over future 1 month, 3 months, 6 months and 12 months forecasting horizons, respectively. The column "Minimum holding" indicates a minimum number of X holding months, where X=24, 60 and 100. The column "No. of owners" denotes the number of investors in each investor group that have at least 5 stocks on average in their portfolios and satisfy the minimum holding requirement. The columns ("#negative timers" and "#positive timer") show the number of investors with significant negative and positive timing ability at the 5% significance level using bootstrapped standard errors. The last two columns present the percentages of investors with significant negative and positive timing skill.

The return based timing approach shows very little evidence of positive timing ability for both individual investors and financial investors over future 1 month, 3 months, and 6 months forecasting horizons. When forecasting stock returns over a 12-month horizon, there is some evidence of positive and negative timing ability for individual investors, about 7%. Overall, we find results that are consistent with the extant literature that employs the Treynor and Mazuy (1966) method. In particular, the quadratic formulation uncovers no major evidence regarding timing ability.

## 3.5 Analysis of positive timers' portfolio performance

If investors have genuine ability to time the stock market, they should have a higher portfolio performance than investors that have no timing ability or negative timing ability. To check whether the evidence that some individual investors can time the market is spurious, we examine the portfolio performance for individual investors with positive timing ability, for individual investors with no timing ability, and for individual investors with negative timing ability.

### 3.5.1 Portfolio performance of individual investors

We report three measures of portfolio performance: (1) total portfolio return, (2) Sharpe ratio and (3) Jensen's alpha. For each investor in each month t , we compute the value weighted average of returns across all the assets in the investor's portfolio. The total portfolio return is the time series average of the monthly portfolio returns. The Sharpe ratio is the total portfolio excess return divided by the standard deviation of the monthly portfolio returns. The Jensen's alpha is obtained using the Fama and French (1993) 3-factor model.[8] The reported 3 measures of performance are the equal weighted cross sectional average across all the investors in each group: investors with significant and positive timing ability, significant and negative timing ability and insignificant timing ability.[9]

Table 3.7 reports the results of the three measures of portfolio performance for each group of individual investors. We also conduct t-tests to check whether the differences between the performance of individual investors who have timing ability and the performance of individual investors who can not time the market is significant. The first column "Timer" denotes the three groups: negative timers, non-timers and positive timers, who are marked as "Neg.", "Ins." and "Pos.", respectively. The next 3 columns report the three performance measures for individual investors with a minimum of 24 holding months. The middle 3 columns and the last 3 columns present portfolio performance for individual investors with minimum holding periods of 60 and 100 months, respectively. Panels A, B, C and D report portfolio performance for different groups of individual investors based on their timing ability over future 1-month, 3-month, 6-month and 12-month forecasting horizons.

The results show that the portfolio performance of positive timers is always higher than non-timers and negative timers, regardless of the performance measure employed, the minimum holding period required, or the length of forecasting horizon. For example, in Panel A, we focus on the one month forecasting horizon and report results for investors who have minimum holdings periods of 24, 60 and 100 months. The portfolio return for negative market timers is 0.33% per month, for investors with no timing ability 0.82% per month and for investors with timing ability 1.07% per month. There is a clear difference in the portfolio returns of negative timers and the non-timers and timers. The difference between the portfolio returns of the non-timers and timers is 0.25% per month. However, examining the Sharpe ratios, the difference between the non-timers and timers is much more pronounced. For the non-timers the Sharpe ratio is 0.068, for the timers it is 0.11, about 50% higher.

The differences in portfolio performance amongst non-timers and timers is even more extenuated when looking at the Jensen's alpha of the investors' portfolios. In this case, the non-timers have an alpha of 0.08% per month. In sharp contrast, the alpha of the market timers is 0.33% per month, or 4% per annum. Similar findings are reported in Panel A for investors who have minimum holding periods of 60 and 100 months. The last 2 rows in Panel A report the t value of the difference between positive timers' performance and non-timers' performance, in column "t(Pos-Ins)", and the t value of the difference between positive timers' performance and negative

[8] We also compute Jensen's alpha using the 1 risk factor model and the 4 risk factors model including the momentum factor used in Carhart (1997) The results are consistent with the ones with the 3 risk factor model.

[9] We check portfolio performance of individual investors with different timing skills using the results of portfolio weight level approach. The portfolio performance of the three types of individual investors with different timing ability from the portfolio beta approach are very similar.

timers' performance, in column "t(Pos-Neg)". The differences between the average performance measures of the positive timers and the two non-timing groups (no timing and negative timing) are always statistically significant.

In Panel B of Table 4, we report the performance measures for investors based on their timing ability over the three month forecasting horizon. For the investors with a minimum holding period of 24 months, the total portfolio returns are 0.31, 0.81 and 1.13 per cent per month for the negative timers, non-timers and positive timers, respectively. These are pretty much the same as those reported in Panel A. The Sharpe ratio, however, shows a much larger difference between the non-timers (0.063) and the timers (0.13), indicating more than double the performance. The difference in the estimate of Jensen's alpha, which is statistically significant, is also economically substantial at this horizon, 0.08 and 0.35 per cent per month for non-timers and timers, respectively. These results are also similar for the remaining cases reported in Panel B where we impose the restriction that investors have minimum holding periods of 60 and 100 months, respectively.

Panels C and D present results regarding the performance of investors' portfolios when considering a six and a twelve month forecasting horizons. Recall from Table 3 that the number of positive timers fell when considering these two forecasting horizons. However, even though there are a smaller number of positive timers, their performance, as measured by the three metrics that we are considering, is still much better than the non-timers, and the differences are similar to those reported in Panels A and B, being both statistically different from one another and economically large.

All the results reported in Table 3.7 show that the individual investors with significant and positive timing ability have higher performance than the other types of timers. This lends supports to our finding that there are a sizable number of individual investors who have the ability to time the stock market. The findings that the investors identified as having timing ability also have better performance than those that are not identified as positive timers should also allay any fears that the timing results reported in Table 3 are spurious.

### 3.5.2 Distribution of Jensen's alpha of positive timers

To avoid the possibility that the higher performance of individual investors with significant and positive timing ability is driven by some extreme outliers, we check the cross sectional distribution of these investors' Jensen's alphas. We plot the Jensen's alphas based on the Fama and French (1993) 3-factor model for all the individual investors that have a minimum holding of 24, 60 and 100 months and have significant and positive timing ability. We use the results of timing ability from the equity weight level approach over a 3-month forecasting horizon. Figure 1 plots the histogram distribution of Jensen's alphas for the positive timers with a minimum of 24, 60 and 100 holding months in panels A, B and C, respectively. Most of the individual investors with significant positive timing ability have positive alpha and it is clearly shown that the positive average alphas of positive timers are not driven by extreme outliers.

### 3.5.3 Performance of aggregate individual investors

We have shown that individual investors with positive timing ability have higher performance. The representative investor, who aggregates the holdings of all the positive timers, should also have higher performance than the aggregation of other investors who can not time the market. For each security in each month t, we aggregate the shareholdings of all the individual investors who have significant and positive timing ability. We then calculate the value weighted average of portfolio return for each month. We repeat this procedure for investors with insignificant timing ability and for investors with significant and negative timing ability. Table 3.8 presents the results of different measures of performance for the 3 aggregated investors: significant and positive timers ("SigPosi"), insignificant timers ("Insig"), and significant and negative timers ("SigNega"). For the positive timers over different forecasting horizons in all the panels, the aggregated significant and positive timers always have higher total portfolio returns and Sharpe ratio. The 3 measures of alphas for aggregated positive timers are always significant at 5% or 10% levels and higher than those of the other investors. This provides support for our previous results.

### 3.5.4 Persistence of timing ability

The performance results reported in the previous section may be caused by the way we select investors with timing-ability. To identify investors with positive timing ability, we select those investors that tend to have a high weight in the stock market prior to months where the stock market did well. Since individual portfolio performance should be positively related to market performance, it seems reasonable to expect that the portfolio performance of these investors, when using all available data to measure performance, would be better than average. In this section, we overcome this "hard-wiring" of performance by using different sets of sample-months to examine investors' timing ability and to measure their portfolio performance. If one investor has genuine timing ability, then this investor should have higher performance not only for the period used to examine their timing ability, but also for her other holding periods.

We split each investor's time-series of portfolio holdings in two. One set of months is used to estimate timing ability. The other set of months is used to estimate performance. Specifically, we require individual investors to have a minimum of 100 months of data and to hold at least 5 stocks. For each individual investor who satisfies the selection criteria, we start by randomly drawing 70 months from the time-series of portfolio holdings and the corresponding market excess returns. We then employ the equity weight level approach to conduct the timing analysis using these 70 months, adjusted by Newey and West (1987) and the bootstrap procedure as done previously. The remainder of the investor's time-series of portfolio holdings is used to estimate performance. Given the overall sample period and the 100-months minimum time series length, we use between 30 and 57 months to measure performance.

Table 3.9 reports the results. Panel A presents the results of timing ability over a 1-month forecasting horizon using the 70 months data and the performance measures using the rest of holding months. The first 3 rows report the results for individual investors with significant and positive timing ability, (SigPosi), insignificant timing ability (inSig), and significant and negative timing ability (SigNega). Columns "#OLS" and "%OLS" present the number and percentage of investors who have significant and positive, insignificant, and significant and negative timing ability, based on the OLS t-statistics. There are 7.84% individual investors have significant and positive timing ability and 5.48% individual investors with significant and negative timing ability. The next 2 columns "#BS", and "%BS" report the results based on the bootstrapped p values. The bootstrapped percentage of positive timers decreases from 7.84%, based on the OLS t-statistics, to 4.79%. The bootstrapped percentage of negative timers is 4.05%. The results in this panel are weaker comparing to the results using the whole sample, which is reasonable since we have less observations for most of the investors.

The last 5 columns report the performance measures, using the rest of months which are not used for timing analysis. Column "TotRet" reports the equal weighted cross sectional average of total portfolio return for each group. Column "SR" denotes the equal weighted cross sectional average of Sharpe ratio for each group. The last 3 columns, "alpha1", "alpha3", and "alpha4", present the one, three and four risk factors adjusted Jensen's alpha, respectively. All the performance results show that individual investors with significant and positive timing ability have higher performance.[10] For example, the Jensen's alpha based on the Fama and French (1993) model is 0.002 for positive timers, 0.0013 for insignificant timers and -0.0002 for negative timers. Since the data used to calculate performance is different from the data for measuring timing ability, these performance results provide strong support to the evidence that the timing ability we have detected are not spurious results or by chance.

Panel B reports the results of market timing ability and portfolio performance over a 3-month forecasting horizon. There are a higher percentage of individual investors with significant and positive timing ability, comparing to the results over the 1-month forecasting horizon in Panel A, which is in accordance with the previous evidence that investors have stronger timing ability over a 3-month horizon. There are 15.24% individual investors with significant and positive timing ability based on the the OLS t- statistics, and the percentage of positive timers based on the bootstrapped results is 9%. The next 5 columns, which present portfolio performance of the

[10] We have also tried to use 50 and 30 months to check the timing ability and the rest for computing performance. There are slightly lower percentage of individual investors with significant and positive timing ability. But the results are qualitatively similar.

three groups of individual investors, provide consistent evidence as in Panel A that individual investors with significant and positive timing ability have higher performance. Panels C and D report the results of timing and performance over 6- and 12-month forecasting horizons. In line with the evidence using investors' entire holding data, investors have less timing ability over these two forecasting horizons. Although there is marginal evidence of positive timing ability, the performance of positive timers is always higher than the other investors, regardless of which performance measure is used.

In summary, this analysis in which we randomly draw 70 months of one investor's data to evaluate her timing ability and use the rest of data to measure her performance provides consistent evidence of timing ability as the results using investors' entire holding data. The evidence that positive timers have higher performance than other investors when using different data from the data for examining timing ability provides even stronger supports to the results that these investors' timing skills are not spurious or only by chance.

## 3.6 Conclusion

This paper is the first to examine the timing ability of individual investors at the investor level. With the availability of a unique monthly holding data set on stocks, mutual funds and bonds in the Norwegian stock market from December 1992 to June 2003, we are well positioned to use both new timing technique and existing methods to investigate investors' timing ability. We first check the correlation between investors' equity portfolio weight and future stock market excess returns to investigate whether investors are able to time the stock market by shifting their assets between equity and bonds. This is a novel and more natural way to check investors' timing ability, since a market timer would shift her portfolio from equity to bond when forecasting stock market outperforms bond market and vice versa. We find a sizable individual investors have the ability to successfully time the stock market over 1 month, 3 months and 6 months forecasting horizons. The timing ability is strongest over the 3 month forecasting horizon. The results using the portfolio beta method developed in Jiang et al. (2007) are consistent with, but weaker than, the evidence from portfolio weight level approach. There is little evidence of timing ability using Treynor and Mazuy (1966), consistent with evidence from previous studies.

If the result that some individual investors have timing ability is not spurious, then the portfolio performance of these investors should be higher than other investors who have no or even negative timing ability. Our performance analysis shows that individual investors who can successfully time the stock market do have higher portfolio performance, which supports the results that these investors can successfully time the stock market.

Since the timing literature has been focusing on financial institutions, we also examine the timing ability of Norwegian financial investors. There is marginal evidence that some financial investors are able to time the stock market. It might seem surprising that more individual investors than financial investors can time the market. We argue that individual investors might be better positioned for timing activity because they do not face the different constraints as institutional investors do, and individual investors can conduct their asset allocation more easily due to their relative smaller portfolio size.

It is worth noting that we have tried different filtering criteria to select the potential timers who are likely to pursue a timing strategy. We do not believe that the whole population of individual investors can time the market and gain from doing so. Barber et al. (2009) provide evidence on this. By examining the timing ability of the aggregate individual investors in the Taiwan stock market, they find that, as a group, individual investors lose from timing ability.

Similar to the evidence in this paper, some recent studies have shown interesting evidence that some individual investors have superior skills. Barber et al. (2004) analyze performance of individual day traders in Taiwan and find strong evidence of persistent ability for a relatively small group of day traders. Grinblatt et al. (2010), using the Finnish data, find that high IQ investors exhibit superior investment performance. Che et al. (2009) also show that a sizable individual investors in the Norwegian market exhibit significant performance persistence.

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## 3.7 Tables

Table 3.1: Investment duration

This table presents the length of Norwegian investors' stock portfolio holding period in a data sample from December 1992 to June 2003. Panel A and Panel B report the number and fraction of financial (institutional) investors and individual investors that have stock holdings for different investment horizons, respectively. The columns "(m,n]" report the number (fraction) of investors that held stock portfolio for more than m months but less than or equal to n months. For example, column "(6,12]" shows the number (fraction) of investors that have invested in Norwegian stocks for longer than 6 months but less than or equal to 12 months. The next to the last column "[127]" reports the number (fraction) of investors that have held Norwegian stocks for 127 months, from the beginning of the data period December 1992 to the end of the data period June 2003. The last column reports the total number of investors in each sector.

| Sector | (0 , 6] | (6 , 12] | (12 , 24] | (24 , 36] | (36 , 48] | (48 , 60] | (60 , 84] | (84 , 108] | (108, 126] | [127] | All |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | **Panel A. Number of investors** | | | | | | |
| Financial | 106 | 94 | 120 | 124 | 81 | 57 | 94 | 107 | 63 | 143 | 989 |
| Individual | 28319 | 56332 | 59898 | 92116 | 45219 | 34048 | 114297 | 43706 | 52401 | 109715 | 636051 |
| | | | | | **Panel B. Percentage (%)** | | | | | | |
| Financial | 10.72 | 9.50 | 12.13 | 12.54 | 8.19 | 5.76 | 9.50 | 10.82 | 6.37 | 14.46 | 100 |
| Individual | 4.45 | 8.86 | 9.42 | 14.48 | 7.11 | 5.35 | 17.97 | 6.87 | 8.24 | 17.25 | 100 |

Table 3.2: Portfolio characteristics of potential market timers

This table describes portfolio characteristics of Norwegian financial and individual investors that have at least 5 stocks on average in their portfolios. The monthly holding data set consists of all the stocks, equity mutual funds, bond mutual funds and bonds each investor has invested in the Norwegian stock exchange from December 1992 to June 2003. The portfolio characteristics of investors with at least 24 months, 60 months and 100 months holding periods are reported in panels A, B and C, respectively. The column "No. of owners" denotes the number of investors that are qualified for the selection criteria. The next four columns report the average number of stocks, equity mutual funds, bond mutual funds and bonds in investors' portfolios. The column "Value(mNOK)" presents the cross sectional average of investors' total portfolio values. The 3 columns next to the last column report the average of equity weight, time series standard deviation of equity weight, and weight persistence. The last column "Fraction trading" reports the decimal fraction of investors trading (the number of months with trading/the total number of months in the market).

| Sector | No. of owners | No. of stocks | No. of E. MF | No. of B. MF | No. of bonds | Value (mNOK) | Equity weight | STDEV Eweight | Weight persistence | Fraction trading |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A. Minimum holding period of 24 months** | | | | | | | | | | |
| Financial | 400 | 24.55 | 0.36 | 0.27 | 5.27 | 179.75 | 0.34 | 0.39 | 0.80 | 0.87 |
| Individual | 11390 | 7.95 | 0.67 | 0.11 | 0.49 | 1.02 | 0.65 | 0.29 | 0.83 | 0.50 |
| **Panel B. Minimum holding period of 60 months** | | | | | | | | | | |
| Financial | 276 | 25.11 | 0.43 | 0.32 | 5.79 | 220.93 | 0.26 | 0.36 | 0.83 | 0.85 |
| Individual | 9666 | 8.09 | 0.70 | 0.12 | 0.53 | 1.11 | 0.63 | 0.29 | 0.85 | 0.50 |
| **Panel C. Minimum holding period of 100 months** | | | | | | | | | | |
| Financial | 161 | 27.45 | 0.50 | 0.36 | 6.42 | 293.17 | 0.21 | 0.34 | 0.84 | 0.84 |
| Individual | 7411 | 8.32 | 0.73 | 0.13 | 0.59 | 1.18 | 0.61 | 0.30 | 0.86 | 0.49 |

Table 3.3: Timing ability using portfolio weight level approach

This table reports the results of investors' timing ability based on both the OLS regression and the bootstrap technique. The monthly holding data set consists of the number of shares of stocks, mutual funds and bonds that each investor has held in the Norwegian stock market from December 1992 to June 2003. We focus on individual investors and financial investors that have at least 5 stocks on average in their portfolios. We also require investors have a minimum number of X holding months, where X=24, 60 and 100. We do a time series regression of future stock market excess return over bond return on one investor's equity portfolio weight level and lagged stock market excess return, at the investor level.

$$r_{m,t+k} = \alpha + \gamma w_t + \delta r_{m,t-k} + \epsilon_{t+k},$$

where $r_{m,t+k}$ is the cumulative stock market excess return over bond index return from month *t+1* to month *t+k*, and $r_{m,t-k}$ is the cumulative market excess return $k$ months prior to month $t$, where $k$=1, 3, 6, and 12. $w_t$ is the equity portfolio weight relative to the total portfolio in month $t$; the coefficient $\gamma$ measures the timing ability.

We use the NeweWest87 autocorrelation- and heteroskedasticity-consistent covariance matrix to calculate standard errors, and follow the bootstrap statistical technique in Kosowski et al. (2006) to draw our statistical inference. We report the results based on both the standard OLS $t$-statistics and the bootstrap procedure. Panels A, B, C and D present the results for investors' timing ability over future 1-month, 3-month, 6-month and 12-month forecasting horizons, respectively. For each panel, we report the results for investors with a minimum of 24, 60 and 100 months holding data. The column "No. of owners" reports the total number of qualified financial and individual investors that are included in the analysis. The next 2 columns, "$\#OLS--$" and "$\#OLS++$", report, for each investor type, the number of investors who have significant negative and positive timing ability at the significance level of 5% based on the OLS t-statistics. The columns, "$\%OLS--$" and "$\%OLS++$", report the decimal fraction of investors who have significant negative and positive timing ability at the significance level of 5%, based on the OLS t-statistics. The last 4 columns report the number and percentage of investors with significantly negative and significantly positive results based on the bootstrapped results.

| | Min. holding | No. of owners | #OLS −− | #OLS ++ | %OLS −− | %OLS ++ | #BS −− | #BS ++ | %BS −− | %BS ++ |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A. 1 month forecasting horizon** | | | | | | | | | | |
| Financial | 24 | 400 | 59 | 32 | 0.1475 | 0.0800 | 47 | 17 | 0.1175 | 0.0425 |
| Financial | 60 | 276 | 35 | 30 | 0.1268 | 0.1087 | 29 | 16 | 0.1051 | 0.0580 |
| Financial | 100 | 161 | 23 | 16 | 0.1429 | 0.0994 | 20 | 8 | 0.1242 | 0.0497 |
| Individual | 24 | 11390 | 647 | 1964 | 0.0568 | 0.1724 | 497 | 1573 | 0.0436 | 0.1381 |
| Individual | 60 | 9666 | 471 | 1828 | 0.0487 | 0.1891 | 395 | 1545 | 0.0409 | 0.1598 |
| Individual | 100 | 7411 | 398 | 1441 | 0.0537 | 0.1944 | 354 | 1226 | 0.0478 | 0.1654 |
| **Panel B. 3 month forecasting horizon** | | | | | | | | | | |
| Financial | 24 | 400 | 76 | 59 | 0.1900 | 0.1475 | 56 | 27 | 0.1400 | 0.0675 |
| Financial | 60 | 276 | 45 | 49 | 0.1630 | 0.1775 | 36 | 23 | 0.1304 | 0.0833 |
| Financial | 100 | 161 | 34 | 27 | 0.2112 | 0.1677 | 27 | 13 | 0.1677 | 0.0807 |
| Individual | 24 | 11390 | 893 | 2487 | 0.0784 | 0.2183 | 661 | 1822 | 0.0580 | 0.1600 |
| Individual | 60 | 9666 | 673 | 2248 | 0.0696 | 0.2326 | 543 | 1743 | 0.0562 | 0.1803 |
| Individual | 100 | 7411 | 582 | 1880 | 0.0785 | 0.2537 | 500 | 1499 | 0.0675 | 0.2023 |
| **Panel C. 6 month forecasting horizon** | | | | | | | | | | |
| Financial | 24 | 400 | 100 | 50 | 0.2500 | 0.1250 | 62 | 21 | 0.1550 | 0.0525 |
| Financial | 60 | 276 | 63 | 39 | 0.2283 | 0.1413 | 42 | 17 | 0.1522 | 0.0616 |
| Financial | 100 | 161 | 41 | 22 | 0.2547 | 0.1366 | 32 | 11 | 0.1988 | 0.0683 |

| | Min. holding | No. of owners | #OLS −− | #OLS ++ | %OLS −− | %OLS ++ | #BS −− | #BS ++ | %BS −− | %BS ++ |
|---|---|---|---|---|---|---|---|---|---|---|
| Individual | 24 | 11390 | 1177 | 1401 | 0.1033 | 0.1230 | 763 | 820 | 0.0670 | 0.0720 |
| Individual | 60 | 9666 | 847 | 1220 | 0.0876 | 0.1262 | 595 | 742 | 0.0616 | 0.0768 |
| Individual | 100 | 7411 | 693 | 949 | 0.0935 | 0.1281 | 504 | 601 | 0.0680 | 0.0811 |
| **Panel D. 12 month forecasting horizon** | | | | | | | | | | |
| Financial | 24 | 400 | 113 | 47 | 0.2825 | 0.1175 | 73 | 12 | 0.1825 | 0.0300 |
| Financial | 60 | 276 | 66 | 35 | 0.2391 | 0.1268 | 44 | 7 | 0.1594 | 0.0254 |
| Financial | 100 | 161 | 44 | 19 | 0.2733 | 0.1180 | 33 | 6 | 0.2050 | 0.0373 |
| Individual | 24 | 11390 | 1517 | 1148 | 0.1332 | 0.1008 | 822 | 473 | 0.0722 | 0.0415 |
| Individual | 60 | 9666 | 1023 | 965 | 0.1058 | 0.0998 | 588 | 413 | 0.0608 | 0.0427 |
| Individual | 100 | 7411 | 768 | 697 | 0.1036 | 0.0940 | 471 | 299 | 0.0636 | 0.0403 |

Table 3.4: Timing ability using portfolio weight change approach

This table reports the bootstrapped results of investors' timing ability, using equity portfolio weight changes. The monthly holding data set consists of the number of shares of stocks, mutual funds and bonds that each investor has held in the Norwegian stock market from December 1992 to June 2003. We focus on individual investors and financial investors that have at least 5 stocks on average in their portfolios. We also require investors have a minimum number of X holding months, where X=24, 60 and 100. We do, for each investor, a time series regression of future stock market excess return over bond return on the investor's equity portfolio weight changes and the lagged stock market excess return.

$$r_{m,t+k} = \alpha + \gamma \Delta w_t + \delta r_{m,t-k} + \epsilon_{t+k},$$

where $r_{m,t+k}$ is the cumulative stock market excess return over bond index return from month *t+1* to month *t+k*, and $r_{m,t-k}$ is the cumulative market excess return $k$ months prior to month $t$, where $k$=1, 3, 6, and 12. $\Delta w_t$ is the change in equity portfolio weight in month $t$; the coefficient $\gamma$ measures the timing ability. We use the Newey and West (1987) autocorrelation- and heteroskedasticity-consistent covariance matrix to calculate standard errors, and follow the bootstrap statistical technique in Kosowski et al. (2006) instead of using the standard OLS $t$-statistics to draw our statistical inference.

Panels A, B, C and D present the results for investors' timing ability over future 1-month, 3-month, 6-month and 12-month forecasting horizons, respectively. For each panel, we report the results for investors with minimum 24 months, 60 months and 100 months holding data. The column "No. of owners" reports the total number of qualified financial and individual investors that are included in the analysis. The next 2 columns report, for each investor type, the number of investors who have significant negative and positive timing ability at the significance level of 5%. The last two columns report the decimal fraction of investors who have significant negative and positive timing ability at the significance level of 5%.

| sector | Minimim holding | No. of owners | #negative timer | #positive timer | %negative timer | %positive timer |
|---|---|---|---|---|---|---|
| **Panel A. 1 month forecasting horizon** | | | | | | |
| Financial | 24 | 400 | 13 | 24 | 0.0325 | 0.0600 |
| Financial | 60 | 276 | 5 | 23 | 0.0181 | 0.0833 |
| Financial | 100 | 161 | 3 | 14 | 0.0186 | 0.0870 |
| Individual | 24 | 11390 | 205 | 1258 | 0.0181 | 0.1113 |
| Individual | 60 | 9666 | 172 | 1216 | 0.0178 | 0.1258 |
| Individual | 100 | 7411 | 143 | 911 | 0.0193 | 0.1229 |
| **Panel B. 3 month forecasting horizon** | | | | | | |
| Financial | 24 | 400 | 12 | 10 | 0.0300 | 0.0250 |
| Financial | 60 | 276 | 6 | 9 | 0.0217 | 0.0326 |
| Financial | 100 | 161 | 3 | 6 | 0.0186 | 0.0373 |
| Individual | 24 | 11390 | 173 | 681 | 0.0153 | 0.0603 |
| Individual | 60 | 9666 | 143 | 667 | 0.0148 | 0.0690 |
| Individual | 100 | 7411 | 122 | 531 | 0.0165 | 0.0717 |
| **Panel C. 6 month forecasting horizon** | | | | | | |
| Financial | 24 | 400 | 10 | 8 | 0.0250 | 0.0200 |
| Financial | 60 | 276 | 8 | 7 | 0.0290 | 0.0254 |
| Financial | 100 | 161 | 3 | 6 | 0.0186 | 0.0373 |
| Individual | 24 | 11390 | 124 | 202 | 0.0119 | 0.0179 |
| Individual | 60 | 9666 | 109 | 191 | 0.0113 | 0.0198 |

| sector | Minimim holding | No. of owners | #negative timer | #positive timer | %negative timer | %positive timer |
|---|---|---|---|---|---|---|
| Individual | 100 | 7411 | 91 | 157 | 0.0123 | 0.0212 |
| **Panel D. 12 month forecasting horizon** | | | | | | |
| Financial | 24 | 400 | 10 | 1 | 0.0250 | 0.0025 |
| Financial | 60 | 276 | 9 | 1 | 0.0326 | 0.0036 |
| Financial | 100 | 161 | 5 | 0 | 0.0311 | 0.0000 |
| Individual | 24 | 11390 | 103 | 189 | 0.0092 | 0.0169 |
| Individual | 60 | 9666 | 87 | 179 | 0.0090 | 0.0185 |
| Individual | 100 | 7411 | 74 | 145 | 0.0100 | 0.0196 |

Table 3.5: Timing ability using portfolio beta approach

This table reports the bootstrapped results of the number and fraction of investors that have significant timing ability. We focus on financial investors and individual investors, and require that investors have a minimum number of 5 stocks in their equity portfolio and hold their stock portfolio for at least X months, where X=24, 60 and 100, in the sample period from December 1992 to June 2003. For each investor, we regress her portfolio beta at t on stock market excess returns from month t+1 to t+k, where k=1, 3, 6 and 12, as Jiang et al. (2007) have done.

$$\beta_{p,t} = \beta_{p,0} + \gamma r_{m,t+k} + \epsilon_{t+k},$$

where $\beta_{p,t}$ is the portfolio beta of investor $p$ at time $t$, which is the value weighted average of beta estimates of the securities in the portfolio. The coefficient $\gamma$ measures the timing ability. We use the Newey and West (1987) autocorrelation- and heteroskedasticity-consistent covariance matrix to calculate standard errors, and follow the bootstrap statistical technique in Kosowski et al. (2006) instead of using the standard OLS $t$-statistics to draw our statistical inference.

Panels A, B, C and D present the results of timing ability over 1-month, 3-month, 6-month and 12-month forecasting horizons, respectively. The column, "No. of owners", reports the total number of investors in each investor sector that meet the requirements above. The next two columns report the number of investors with significant negative and positive timing ability, while the last two columns present the decimal fraction of investors with significant negative and positive timing ability based on bootstrapped p value.

| sector | Minimim holding | No. of owners | #negative timer | #positive timer | %negative timer | %positive timer |
|---|---|---|---|---|---|---|
| **Panel A. 1 month forecasting horizon** | | | | | | |
| Financial | 24 | 400 | 25 | 13 | 0.0625 | 0.0325 |
| Financial | 60 | 276 | 10 | 12 | 0.0362 | 0.0435 |
| Financial | 100 | 161 | 6 | 8 | 0.0373 | 0.0497 |
| Individual | 24 | 11390 | 423 | 989 | 0.0371 | 0.0868 |
| Individual | 60 | 9666 | 288 | 957 | 0.0298 | 0.0990 |
| Individual | 100 | 7411 | 217 | 854 | 0.0293 | 0.1152 |
| **Panel B. 3 month forecasting horizon** | | | | | | |
| Financial | 24 | 400 | 22 | 11 | 0.0550 | 0.0275 |
| Financial | 60 | 276 | 13 | 7 | 0.0471 | 0.0254 |
| Financial | 100 | 161 | 7 | 5 | 0.0435 | 0.0311 |
| Individual | 24 | 11390 | 627 | 1025 | 0.0550 | 0.0900 |
| Individual | 60 | 9666 | 398 | 950 | 0.0412 | 0.0983 |
| Individual | 100 | 7411 | 288 | 820 | 0.0389 | 0.1106 |
| **Panel C. 6 month forecasting horizon** | | | | | | |
| Financial | 24 | 400 | 32 | 13 | 0.0800 | 0.0325 |
| Financial | 60 | 276 | 20 | 6 | 0.0725 | 0.0217 |
| Financial | 100 | 161 | 10 | 4 | 0.0621 | 0.0248 |
| Individual | 24 | 11390 | 665 | 614 | 0.0584 | 0.0539 |
| Individual | 60 | 9666 | 399 | 547 | 0.0413 | 0.0566 |
| Individual | 100 | 7411 | 262 | 443 | 0.0354 | 0.0598 |
| **Panel D. 12 month forecasting horizon** | | | | | | |
| Financial | 24 | 400 | 29 | 6 | 0.0725 | 0.0150 |

| sector | Minimim holding | No. of owners | #negative timer | #positive timer | %negative timer | %positive timer |
|---|---|---|---|---|---|---|
| Financial | 60 | 276 | 13 | 2 | 0.0471 | 0.0072 |
| Financial | 100 | 161 | 6 | 1 | 0.0373 | 0.0062 |
| | | | | | | |
| Individual | 24 | 11390 | 719 | 273 | 0.0631 | 0.0240 |
| Individual | 60 | 9666 | 404 | 217 | 0.0418 | 0.0225 |
| Individual | 100 | 7411 | 225 | 161 | 0.0304 | 0.0217 |

Table 3.6: Timing ability using Treynor and Mazuy (1966) return based timing approach

This table reports the bootstrapped results of investors' timing ability, using Treynor and Mazuy (1966) return based timing approach. The monthly holding data set consists of the number of shares of stocks, mutual funds and bonds that each investor has held in the Norwegian stock market from December 1992 to June 2003. We focus on individual investors and financial investors that have at least 5 stocks on average in their portfolios. We also require investors have a minimum number of X holding months, where X=24, 60 and 100. For each investor included in the analysis, we do the following time series regression.

$$r_{p,t+k} = \alpha_p + \beta_p r_{m,t+k} + \gamma_p r_{m,t+k}^2 + \varepsilon_{p,t},$$

where $r_{p,t}$ is the cumulative portfolio excess return from month t+1 to month t+k, $r_{m,t+k}$ is the cumulative stock market excess return from month t+1 to month t+k, and $\gamma_p$ measures investors' timing ability. The sign of $\gamma_p$ indicates the direction of timing ability. We use the Newey and West (1987) autocorrelation- and heteroskedasticity-consistent covariance matrix to calculate standard errors, and follow the bootstrap statistical technique in Kosowski et al. (2006) instead of using the standard OLS $t$-statistics to draw our statistical inference.

Panels A, B, C and D present the results for investors' timing ability over future 1-month, 3-month, 6-month and 12-month forecasting horizons, respectively. For each panel, we report the results for investors with a minimum of 24 months, 60 months and 100 months holding data. The column "No. of owners" reports the total number of financial and individual investors that are included in the analysis. The next 2 columns report, for each investor type, the number of investors who have significant negative and positive timing ability at the significance level of 5%. The last two columns report the decimal fraction of investors who have significant negative and positive timing ability at the significance level of 5%.

| sector | Minimim holding | No. of owners | #negative timer | #positive timer | %negative timer | %positive timer |
|---|---|---|---|---|---|---|
| | | | **Panel A. 1 month forecasting horizon** | | | |
| Financial | 24 | 400 | 14 | 6 | 0.0350 | 0.015 |
| Financial | 60 | 276 | 13 | 3 | 0.0471 | 0.0109 |
| Financial | 100 | 161 | 9 | 1 | 0.0559 | 0.0062 |
| Individual | 24 | 11390 | 303 | 496 | 0.0266 | 0.0435 |
| Individual | 60 | 9666 | 274 | 424 | 0.0283 | 0.0439 |
| Individual | 100 | 7411 | 236 | 318 | 0.0318 | 0.0429 |
| | | | **Panel B. 3 month forecasting horizon** | | | |
| Financial | 24 | 400 | 10 | 6 | 0.0250 | 0.015 |
| Financial | 60 | 276 | 7 | 5 | 0.0254 | 0.0181 |
| Financial | 100 | 161 | 4 | 3 | 0.0248 | 0.0186 |
| Individual | 24 | 11390 | 545 | 347 | 0.0478 | 0.0305 |
| Individual | 60 | 9666 | 474 | 273 | 0.0490 | 0.0282 |
| Individual | 100 | 7411 | 383 | 175 | 0.0517 | 0.0236 |
| | | | **Panel C. 6 month forecasting horizon** | | | |
| Financial | 24 | 400 | 10 | 19 | 0.0250 | 0.0475 |
| Financial | 60 | 276 | 9 | 12 | 0.0326 | 0.0435 |
| Financial | 100 | 161 | 4 | 4 | 0.0248 | 0.0248 |
| Individual | 24 | 11390 | 517 | 526 | 0.0454 | 0.0462 |
| Individual | 60 | 9666 | 425 | 418 | 0.0440 | 0.0432 |
| Individual | 100 | 7411 | 350 | 303 | 0.0472 | 0.0409 |

| sector | Minimim holding | No. of owners | #negative timer | #positive timer | %negative timer | %positive timer |
|---|---|---|---|---|---|---|
| **Panel D. 12 month forecasting horizon** | | | | | | |
| Financial | 24 | 400 | 10 | 22 | 0.0250 | 0.055 |
| Financial | 60 | 276 | 9 | 9 | 0.0326 | 0.0326 |
| Financial | 100 | 161 | 8 | 3 | 0.0497 | 0.0186 |
| Individual | 24 | 11390 | 765 | 858 | 0.0672 | 0.0753 |
| Individual | 60 | 9666 | 733 | 636 | 0.0758 | 0.0658 |
| Individual | 100 | 7411 | 635 | 427 | 0.0857 | 0.0576 |

Table 3.7: Individual investors' portfolio performance

This table reports three different measures of portfolio performance for individual investors with different timing abilities based on the portfolio weight level approach. The three performance measures are (1) total portfolio return, (2) Sharpe ratio, and (3) alpha using the Fama and French (1993) model. We calculate the portfolio performance for each investor, and then compute the cross-sectional average for the investors in each group. The first column "Timer" indicates the three timing groups: negative timers, who are investors with significant and negative timing ability and are marked as "Neg."; non-timers, who are investors with insignificant timing ability and are marked as "Ins."; and positive timers, who are investors with significant and positive timing ability and are marked as "Pos.". The next three columns report the three portfolio performances for individual investors with a minimum of 24 months holding horizon requirement. The middle 3 columns and the last 3 columns present performance for individual investors with a minimum of 60 months and 100 months holding requirement. Panels A, B, C and D report performance for different timing groups using portfolio weight level approach over future 1-month, 3-month, 6-month and 12-month forecasting horizons, respectively. The last two rows in each panel present the t values of the differences of the portfolio performance between investors with significantly positive timing ability and investors with insignificant timing ability, "t(Pos-Ins)", and between investors with significantly positive timing ability and investors with significantly negative timing ability, "t(Pos-Neg)".

| | Min 24 month holding | | | Min 60 month holding | | | Min 100 month holding | | |
|---|---|---|---|---|---|---|---|---|---|
| Timer | portf ret | SR | alpha | portf ret | SR | alpha | portf ret | SR | alpha |
| **Panel A. portfolio wlevel over 1 month forecasting horizon** | | | | | | | | | |
| Neg. | 0.0033 | -0.0017 | -0.0046 | 0.0066 | 0.0343 | -0.0018 | 0.0069 | 0.0380 | -0.0016 |
| Ins. | 0.0082 | 0.0684 | 0.0008 | 0.0092 | 0.0799 | 0.0014 | 0.0099 | 0.0907 | 0.0019 |
| Pos. | 0.0107 | 0.1055 | 0.0033 | 0.0106 | 0.1037 | 0.0032 | 0.0113 | 0.1159 | 0.0038 |
| t(Pos-Ins) | 10.46 | 11.80 | 14.70 | 9.33 | 10.54 | 11.67 | 10.31 | 12.39 | 12.89 |
| t(Pos-Neg) | 103.11 | 158.32 | 16.62 | 16.50 | 17.75 | 18.36 | 19.99 | 22.04 | 20.68 |
| **Panel B. portfolio wlevel over 3 month forecasting horizon** | | | | | | | | | |
| Neg. | 0.0031 | -0.0040 | -0.0052 | 0.0059 | 0.0268 | -0.0028 | 0.0062 | 0.0296 | -0.0026 |
| Ins. | 0.0081 | 0.0633 | 0.0008 | 0.0091 | 0.0747 | 0.0015 | 0.0100 | 0.0872 | 0.0021 |
| Pos. | 0.0113 | 0.1322 | 0.0035 | 0.0112 | 0.1289 | 0.0034 | 0.0114 | 0.1318 | 0.0035 |
| t(Pos-Ins) | 13.12 | 14.31 | 17.04 | 16.00 | 26.79 | 13.38 | 11.62 | 23.35 | 10.23 |
| t(Pos-Neg) | 98.45 | 151.20 | 22.92 | 28.96 | 31.37 | 30.33 | 31.80 | 33.58 | 31.68 |
| **Panel C. portfolio wlevel over 6 month forecasting horizon** | | | | | | | | | |
| Neg. | 0.0021 | -0.0169 | -0.0057 | 0.0056 | 0.0198 | -0.0029 | 0.0061 | 0.0273 | -0.0027 |
| Ins. | 0.0086 | 0.0715 | 0.0012 | 0.0094 | 0.0815 | 0.0018 | 0.0102 | 0.0932 | 0.0024 |
| Pos. | 0.0112 | 0.1392 | 0.0030 | 0.0111 | 0.1348 | 0.0028 | 0.0112 | 0.1383 | 0.0029 |
| t(Pos-Ins) | 15.90 | 18.31 | 7.47 | 8.48 | 17.54 | 4.69 | 5.38 | 16.00 | 2.26 |
| t(Pos-Neg) | 115.40 | 172.05 | 19.78 | 20.16 | 27.05 | 18.95 | 21.86 | 29.07 | 19.62 |
| **Panel D. portfolio wlevel over 12 month forecasting horizon** | | | | | | | | | |
| Neg. | 0.0007 | -0.0337 | -0.0068 | 0.0055 | 0.0184 | -0.0030 | 0.0064 | 0.0318 | -0.0023 |
| Ins. | 0.0088 | 0.0759 | 0.0014 | 0.0095 | 0.0838 | 0.0017 | 0.0102 | 0.0949 | 0.0023 |
| Pos. | 0.0118 | 0.1351 | 0.0043 | 0.0119 | 0.1305 | 0.0044 | 0.0121 | 0.1314 | 0.0044 |

| | Min 24 month holding | | | Min 60 month holding | | | Min 100 month holding | | |
|---|---|---|---|---|---|---|---|---|---|
| Timer | portf ret | SR | alpha | portf ret | SR | alpha | portf ret | SR | alpha |
| t(Pos-Ins) | 19.09 | 22.48 | 9.28 | 9.03 | 11.37 | 8.47 | 7.01 | 9.50 | 6.44 |
| t(Pos-Neg) | 124.63 | 182.39 | 22.37 | 18.44 | 21.58 | 18.91 | 17.96 | 21.21 | 17.84 |

Table 3.8: Portfolio performance of aggregated investors.

This table presents different measures of portfolio performance: total portfolio return, Sharpe ratio and Jensen's alphas of the aggregated investors. For all the individual investors who have significant and positive timing ability using the equity weight level approach, we aggregate their shareholdings into one representative investor's holding. We do the same for all the investors with insignificant timing coefficients and for all the investors with significant and negative timing ability, respectively. We then calculate the performance of the aggregated investors. Columns "Portf. Ret" and "ShareRatio" report the total return and Sharpe ratio of the aggregated portfolios. The next two columns, "alpha1" and "t alpha1", report the 1 risk factor adjusted Jensen's alpha and its t statistics in parenthesis. The last four columns report the Fama and French (1993) 3 factors and the 4 risk factors, including the momentum factor in Carhart (1997), adjusted Jensen's alphas and their t statistics (in parentheses). Panels A, B, C and D present the performance measures for the aggregated investors with significant and positive timing ability over 1, 3, 6 and 12-month forecasting horizons, respectively. In each panel, the three rows present the portfolio performance of the aggregated investor that represents for all the individual investors with significant negative timing ability, "NegaSig" in the 1st row, with insignificant timing coefficients, "InSig" in the 2nd row, and with significant and positive timing ability, "PosiSig" in the 3rd row.

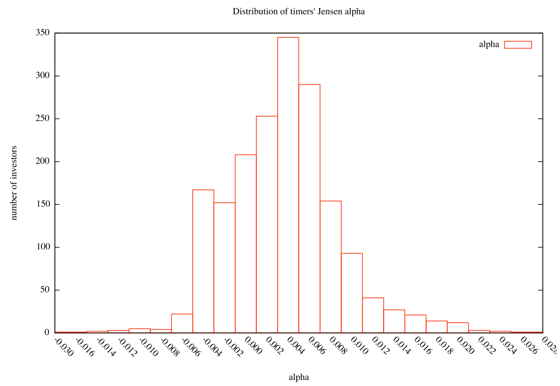
| Timing | Portf. Ret | SharpeRatio | alpha1 | t alpha1 | alpha3 | t alpha3 | alpha4 | t alpha4 |
|---|---|---|---|---|---|---|---|---|
| **Panel A. 1 month forecasting horizon** | | | | | | | | |
| NegaSig | 0.0061 | 0.0265 | -0.0034 | ( -1.97 ) | -0.0030 | ( -1.86 ) | -0.0018 | ( -1.18 ) |
| InSig | 0.0098 | 0.1360 | 0.0010 | ( 0.82 ) | 0.0009 | ( 0.69 ) | 0.0008 | ( 0.66 ) |
| PosiSig | 0.0125 | 0.2188 | 0.0040 | ( 2.64 ) | 0.0035 | ( 2.24 ) | 0.0029 | ( 1.85 ) |
| **Panel B. 3 month forecasting horizon** | | | | | | | | |
| NegaSig | 0.0066 | 0.0361 | -0.0031 | ( -1.71 ) | -0.0026 | ( -1.63 ) | -0.0016 | ( -1.02 ) |
| InSig | 0.0098 | 0.1377 | 0.0011 | ( 0.87 ) | 0.0009 | ( 0.73 ) | 0.0009 | ( 0.68 ) |
| PosiSig | 0.0129 | 0.2103 | 0.0041 | ( 2.49 ) | 0.0036 | ( 2.16 ) | 0.0031 | ( 1.81 ) |
| **Panel C. 6 month forecasting horizon** | | | | | | | | |
| NegaSig | 0.0068 | 0.0398 | -0.0029 | ( -1.56 ) | -0.0026 | ( -1.54 ) | -0.0017 | ( -1.01 ) |
| InSig | 0.0099 | 0.1425 | 0.0012 | ( 1.00 ) | 0.0010 | ( 0.83 ) | 0.0010 | ( 0.76 ) |
| PosiSig | 0.0130 | 0.1940 | 0.0037 | ( 2.19 ) | 0.0035 | ( 2.00 ) | 0.0031 | ( 1.75 ) |
| **Panel D. 12 month forecasting horizon** | | | | | | | | |
| NegaSig | 0.0077 | 0.0586 | -0.0021 | ( -1.08 ) | -0.0020 | ( -1.12 ) | -0.0012 | ( -0.70 ) |
| InSig | 0.0100 | 0.1441 | 0.0013 | ( 1.05 ) | 0.0011 | ( 0.88 ) | 0.0010 | ( 0.80 ) |
| PosiSig | 0.0126 | 0.1748 | 0.0030 | ( 1.79 ) | 0.0031 | ( 1.75 ) | 0.0033 | ( 1.83 ) |

Table 3.9: Persistence of timing ability

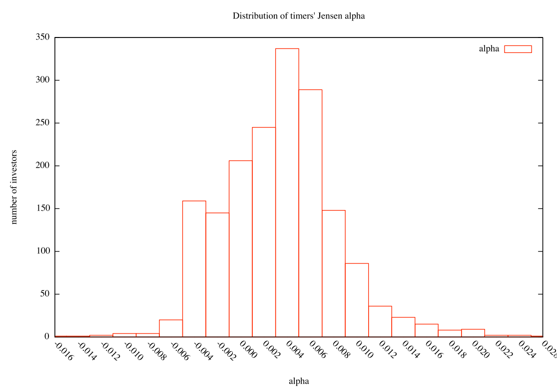
This table reports the number and percentage of individual investors who have significantly positive, significantly negative, and insignificant timing ability and their performance. For each individual investor who has at least 5 stocks and a minimum holding of 100 months, we randomly draw 70 months of equity weight level and the corresponding future and lagged market excess returns to check this investor's timing ability. We use the portfolio weight level approach, with the Newey and West (1987) adjusted standard errors, and the bootstrap technique for statistical references. The columns, "#OLS" and "%OLS", report the number and percentage of individual investors with significant and positive timing ability ("SigPosi", in the 1st row), with insignificant timing coefficients ("Insig", in the 2nd row), and with significant and negative timing ability ("SigNega", in the 3rd row). We then use the rest of this investor's holding months to compute this investor's performance. We calculate, for each individual investor, the total portfolio return, the Sharpe ratio, 1 risk factor adjusted Jensen's alpha, the Fama and French (1993) 3-factors model adjusted alpha, and the 4-factor model, including the momentum factor in Carhart (1997), adjusted alpha, reported in the last 5 columns. Finally, we report the cross sectional average of the performance for investors with significant and positive timing ability, with insignificant timing coefficients, and with significant and negative timing ability, respectively. Panels A, B, C and D report the results of timing ability over future 1, 3, 6 and 12 months forecasting horizons.

| Timing | #OLS | %OLS | #BS | %BS | TotRet | SR | alpha1 | alpha3 | alpha4 |
|---|---|---|---|---|---|---|---|---|---|
| **Panel A. 1 month forecasting horizon** | | | | | | | | | |
| SigPosi | 581 | 0.0784 | 355 | 0.0479 | 0.0098 | 0.1095 | 0.0027 | 0.0020 | 0.0013 |
| Insig | 6423 | 0.8668 | 6755 | 0.9116 | 0.0090 | 0.1019 | 0.0017 | 0.0013 | 0.0011 |
| SigNega | 406 | 0.0548 | 300 | 0.0405 | 0.0067 | 0.0758 | 0.0000 | -0.0002 | 0.0001 |
| t(posi-nega) | | | | | 4.34 | 3.81 | 6.09 | 5.19 | 2.99 |
| t(posi-ing) | | | | | 1.05 | 0.79 | 1.91 | 1.40 | 0.57 |
| **Panel B. 3 month forecasting horizon** | | | | | | | | | |
| SigPosi | 1129 | 0.1524 | 666 | 0.0899 | 0.0105 | 0.1352 | 0.0033 | 0.0026 | 0.0018 |
| Insig | 5644 | 0.7617 | 6339 | 0.8555 | 0.0091 | 0.1008 | 0.0017 | 0.0013 | 0.0010 |
| SigNega | 637 | 0.0860 | 405 | 0.0547 | 0.0040 | 0.0521 | -0.0008 | -0.0007 | -0.0002 |
| t(posi-nega) | | | | | 13.77 | 11.62 | 13.04 | 10.80 | 6.92 |
| t(posi-ing) | | | | | 2.48 | 4.46 | 3.86 | 3.17 | 2.08 |
| **Panel C. 6 month forecasting horizon** | | | | | | | | | |
| SigPosi | 916 | 0.1236 | 425 | 0.0574 | 0.0102 | 0.1391 | 0.0033 | 0.0025 | 0.0019 |
| Insig | 5710 | 0.7706 | 6568 | 0.8864 | 0.0091 | 0.1017 | 0.0017 | 0.0014 | 0.0011 |
| SigNega | 784 | 0.1058 | 417 | 0.0563 | 0.0047 | 0.0552 | -0.0006 | -0.0007 | -0.0003 |
| t(posi-nega) | | | | | 9.88 | 10.49 | 10.01 | 8.73 | 5.93 |
| t(posi-ing) | | | | | 1.75 | 4.47 | 3.45 | 2.78 | 1.92 |
| **Panel D. 12 month forecasting horizon** | | | | | | | | | |
| SigPosi | 858 | 0.1158 | 242 | 0.0327 | 0.0122 | 0.1407 | 0.0033 | 0.0032 | 0.0027 |
| Insig | 5699 | 0.7691 | 6815 | 0.9197 | 0.0090 | 0.1024 | 0.0018 | 0.0013 | 0.0010 |
| SigNega | 853 | 0.1151 | 353 | 0.0476 | 0.0046 | 0.0518 | -0.0005 | -0.0005 | -0.0001 |
| t(posi-nega) | | | | | 9.76 | 8.80 | 7.85 | 7.83 | 5.97 |
| t(posi-ing) | | | | | 3.86 | 3.70 | 2.79 | 3.53 | 3.27 |

**Panel A: Minimum holding of 24 months**




**Panel B: Minimum holding of 60 months**




**Panel C: Minimum holding of 100 months**

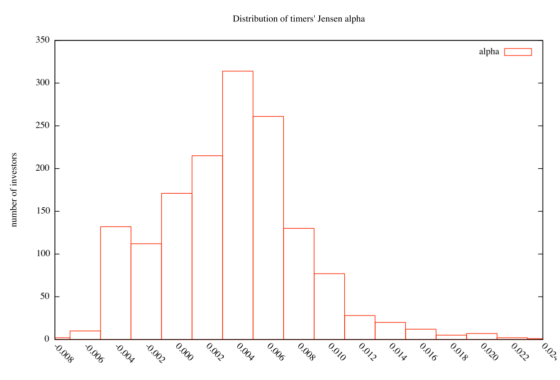



Figure 3.1: Histogram distribution of risk adjusted Jensen's alphas

We plot the histogram distribution of the Fama and French (1993) 3 risk factors adjusted Jensen's alphas for individual investors who have significant and positive timing ability. The results of timing ability are based on the portfolio weight level approach and over a 3-month forecasting horizon. Panels A, B and C exhibit the distribution for positive timers with least 24, 60 and 100 months holdings, respectively.

# Chapter 4

# Performance Persistence of Individual Investors

**Abstract**
Using unique data on month-end stock market portfolios of all individual investors over an eleven year period, we find that a substantial number of investors exhibit economically and statistically significant performance persistence. Furthermore, a portfolio that is long in stocks previously favored by top performing investors earns a substantial risk adjusted return. These findings are robust to how we measure past performance, how often investors trade, and to the size of investors' portfolios. Unlike the evidence from mutual and pension funds, the persistence in performance of individual investors is not concentrated in portfolios with poor prior performance.

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*JEL classification*: G11, D12, D14.
*Keywords*: Individual investors, performance, persistence. *Keywords*: Stock return volatility, investor type, holding ownership.

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## 4.1 Introduction

Most of the evidence on the stock market performance of individual investors suggests that they make poor investment decisions. Individuals show a tendency to sell stocks that subsequently do well and buy stocks that subsequently perform poorly. Those who trade the most underperform relative to the market, relative to more sophisticated investors, and relative to less active investors.[2] This paper documents that the dismal stock market performance of some individual investors does not apply to individuals in general. Although we confirm earlier findings that very active investors underperform, we find that a sizeable fraction of all individuals who invest in stocks are able to consistently outperform the market. This performance persistence is both economically and statistically significant.

In contrast to many studies that rely on trading data from a brokerage account to study individual investors, our research is based on the entire portfolio holdings of *all* individuals that are active in the market that we study. For the period December 1992 through June 2003 we observe the month-end stock market portfolio of all individual investors who owned stocks on the Oslo Stock Exchange. The monthly frequency, the long time-series, and the access to all Oslo Stock Exchange investments of any individual creates a unique opportunity to measure long-term performance persistence at the portfolio level. Our main finding is that individuals who have done well over the past two to five years outperform a passive benchmark for as long as the next three years. This result is robust to different ways of measuring past and future performance. For instance, we regress future performance, measured using an investment-style adjusted benchmark, on past abnormal performance measured using Jensen's alpha. These regressions, which are performed at the individual portfolio level, show a strong positive relationship between past abnormal performance and future performance. In a second set of results, we isolate stocks that are held primarily by individuals that rank in the top past-performance decile and stocks that are held primarily by individuals ranked in the bottom performance decile. Portfolios of stocks favored by top-performers generate statistically significant alphas of between 72 and 125 basis points per month, depending on the holding period. A portfolio of stocks favored by bottom performers has an alpha close to zero. Our results demonstrate that some individuals have the ability to consistently outperform a risk adjusted benchmark in a way that is economically significant.

Analyzing individual investor performance persistence is important for at least three reasons. First, individual investors work in a different regulatory environment than other investors such as mutual funds and pensions funds. In particular, fund managers are often constrained in their ability to short sell and borrow on margin. In addition, fund managers typically have a mandate to follow a certain "investment style"—which further constrains their investable universe. As

[2] See Odean (1998b, 1999), Barber and Odean (2000, 2001), Grinblatt and Keloharju (2000), Barber et al. (2009)

individuals are likely to be less constrained than institutional investors they may find it easier to execute profitable trading strategies.

Second, the behavioral finance literature has grown to become a significant provider of alternative ways of thinking about how assets are priced.[3] This literature largely understands asset pricing anomalies as rooted in behavioral biases held by individual investors. These behavioral biases are for the most part studied and documented in the cognitive psychology literature, often using laboratory experiments or relatively small samples. Our study is important since we are able to directly observe and investigate the portfolio choices made by the population, rather than a limited sample, of individual investors.

Third, professional fund managers who perform well often attract substantial inflows of new capital. Berk and Green (2004) point out that this process will lead to a lack of persistence in performance because managing more money drives costs up and returns down. If such a mechanism is at work in the mutual fund sector, uncovering anything other than very short run performance persistence using mutual fund data is unlikely (Bollen and Busse, 2005). Chevalier and Ellison (1999) offer an alternative explanation for why it is hard to find persistence in mutual fund performance. They find that well performing managers have a higher probability of surviving as managers and subsequently move to a bigger firm when compared to underperforming managers. If the best managers move around from fund to fund it will be difficult for a given fund to show persistence in performance. The strength of our paper is that we follow individuals, which first, guarantees that portfolio returns are linked to the same decision maker throughout and second, implies that returns are not influenced by fees and costs reacting to past performance. Since we show that a significant number of individual investors outperform the market consistently over time it would seem reasonable that a significant number of individuals hired as fund managers would possess some of the same ability. Thus, our findings can be interpreted as lending support to the view that some mutual fund managers have superior ability—but, that the rent from this ability is extracted by the mutual funds and not the investors in the funds. Berk and Green (2004) and Chevalier and Ellison (1999) suggest processes through which this rent extraction can happen.

This paper is related to a large literature on the stock market performance persistence of mutual fund managers. Early research documents significant performance persistence and interprets this evidence as being consistent with the view that fund managers have the ability to earn abnormal returns.[4] Carhart (1997) questions this interpretation and argues that performance persistence is driven by the momentum effect documented by Jegadeesh and Titman (1993).

[3]Hirshleifer (2001) surveys evidence and theories of the importance of investor psychology in security prices. Barberis and Thaler (2003) review the extensive evidence from cognitive psychology on behavioral biases. Baker et al. (2007) survey how behavioral biases impact managerial decision making.

[4]See Grinblatt and Titman (1992), Hendricks et al. (1993), Brown and Goetzmann (1995) and Elton et al. (1996).

Carhart (1997) points out that managers who have done well in the past will, by definition, have stocks in their portfolios that have experienced high returns. Jegadeesh and Titman (1993) show that such stocks will outperform the market in a period of up to twelve months following the ranking month. Controlling for the momentum-effect, Carhart (1997) finds that only the worst performing funds display persistence.

As discussed briefly above, Berk and Green (2004) develop a model showing that competition among investors will drive future costs up and future returns down to the point where investors get returns that are commensurate with the risk of the fund. Thus, in the long-run, we should not expect a fund to be able to maintain a positive alpha. Bollen and Busse (2005) argue that the information advantage of managers in the model of Berk and Green (2004) will be short lived and they use this to motivate an investigation of performance over a short horizon. They find that funds ranked in the top decile of past quarter performance generate an abnormal performance of 39 basis points per day over the quarter following the ranking period. The abnormal performance disappears if the holding period is extended beyond one quarter.

In a paper closely related to ours, Coval et al. (2005) study performance persistence using data from a large discount brokerage firm. They observe trades from a large number of accounts but focus much of their analysis on the trades from about 17,000 accounts that are active traders over their seven year sample period. While we focus on long horizon performance, their paper focuses the analysis on short performance horizons. Looking at the five-day performance of stocks after they have been bought by an account (ignoring sales) Coval et al. document strong performance persistence. Accounts that are classified as being in the top performance decile, based on past performance, obtain abnormal returns of between 12 and 15 basis points per day over the five-day holding period that follows the ranking period. They also document a similarly sized negative return for traders in the bottom performance decile. Coval et al. (2005) also investigate the portfolio-performance (i.e., both purchases and sales) of the accounts. Ranking each account on performance over the first four years of the sample period, they construct two portfolios consisting of top decile performers and bottom decile performers. Following these portfolios over the next three years, using daily returns, the authors find that a portfolio long in the top performers and short in the bottom performers yields an annual return of about eight percent per year.[5]

Given the performance persistence evidence in Coval et al. (2005) our results are interesting for several reasons. First, our investigation is based on access to the portfolio holdings of the population of Norwegian individuals that invest in stocks on the Oslo Stock Exchange. The portfolio holdings are observed monthly for a period of up to eleven years. This allows us to investigate the long-run performance persistence for individual investors in a way that previously

[5]The main findings of Coval et al. (2005) are reinforced by Bauer et al. (2007) using data from a Dutch online discount broker.

has only been possible for mutual fund managers. Second, Coval et al. use daily returns and focus their investigation on short horizon performance. Our study is based on monthly data, a longer time-series, and we focus on long horizon performance. Third, the use of discount brokerage data raises the concern that it is not representative of investors' trading in the stock market and, as a result, it is not possible to draw more general conclusions about investor performance. Given that we are using all stock holdings of the population of individuals that trade on the Oslo Stock Exchange, independent of what account that is used to trade the stocks, this is not a concern with our data. Thus, the fact that we are able to corroborate the findings in Coval et al. (2005) shows that the evidence from discount brokerage data may very well capture effects that generalize to the population of individual traders.

Our paper is also related to the literature on the investment decisions, trading behavior, and stock market performance of individual investors. A number of papers have found evidence consistent with a disposition effect, i.e., the tendency to sell winners too soon and hold on to losers too long, using trading records from a discount brokerage house.[6] Barber and Odean (2006) document that individual investors are net buyers of stocks that have caught their attention for exogenous reasons and Ivković and Weisbenner (2004) find that an investors' stock selections are correlated with the stock selections of investors that are geographically close. There is also evidence that individuals who trade excessively underperform other investors. For example, Grinblatt and Keloharju (2006) find that investors who trade the most frequently are overconfident and are prone to sensation seeking. Barber and Odean (2000) also present evidence that overconfidence plays a role in the poor performance of individual investors. Finally, Odean (1999) shows that individual investors trade excessively which results in them underperforming. Although we also document bad performance for very active investors, we are able to show that some individual investors display consistent superior ability.

The rest of the paper is organized as follows. Section 4.2 provides the details on the methodology used to measure stock market performance. In section 4.3 we discuss our data and the sample selection. Section 4.4 explains how we measure performance persistence, presents our main results, and provides robustness tests of our main findings. Section 4.5 concludes the paper.

## 4.2 Measures of Stock Market Performance

The column labeled "Jensen's alpha" reports abnormal portfolio returns using the time-series model:

$$r_{it} = \alpha_p + \beta(R_{mt} - R_{ft}) + sSMB_t + hHML_t + mMOM_t + \epsilon_{pt},$$

[6] See, for example, Odean (1998a) and Grinblatt and Keloharju (2001).

where $r_{it}$ is excess return on stock $i$ in month $t$, $R_{mt}$ is the return on a value-weighted portfolio of all stocks listed on the Oslo Stock Exchange (OSE) with a previous month market capitalization larger than the 10th percentile and with positive volume in the current month, $R_{ft}$ is the one-month NIBOR, $SMB_t$ is a size factor, $HML_t$ is a book-to-market factor, and $MOM_t$ is a momentum factor. The size (SMB) and book-to-market factors (HML) are constructed following the approach of Fama and French (1993). The momentum factor (MOM) is constructed as follows: Six value-weighted portfolios are constructed from the intersection of three portfolios formed using return momentum over months $t-12$ through month $t-2$ and two portfolios formed using market capitalization from month $t-1$. MOM is the average return on the two high momentum portfolios minus the average return on the two low momentum portfolios. To

This study relies heavily on various measures of stock market performance. We measure the performance of an individual investor's stock-market portfolio using (i) the Appraisal ratio, (ii) the Sharpe ratio, (iii) characteristic adjusted returns along the lines of Daniel et al. (1997), and (iv) a portfolio weight based measure similar to Grinblatt and Titman (1993).

**Appraisal ratio.** The Appraisal ratio of a portfolio is the Jensen's alpha (Jensen, 1968) of the portfolio normalized by the standard deviation of the error term from the regression used to estimate the alpha. We estimate the Jensen's alpha of portfolio $p$ over months $t = 1, \dots, T$ as the intercept $\alpha_p$ from the time-series regression:

$$r_{pt} = \alpha_p + \beta(R_{mt} - R_{ft}) + s\mathrm{SMB}_t + h\mathrm{HML}_t + m\mathrm{MOM}_t + \epsilon_{pt}, \tag{4.1}$$

where $r_{pt}$ is return on portfolio $p$ in month $t$ in excess of the risk-free return, $R_{mt}$ and $R_{ft}$ are returns on the proxy for the market portfolio and the risk-free rate, respectively. The three remaining variables capture returns related to market capitalization (size), book-to-market ratio, and stock return momentum. The size (SMB) and book-to-market factors (HML) are constructed following the approach of Fama and French (1993). The momentum factor (MOM) is constructed following the approach outlined on Ken French's web-site.[7] In particular, six value-weighted portfolios are constructed from the intersection of three portfolios formed using return momentum over months $t-12$ through month $t-2$ and two portfolios formed using market capitalization from month $t-1$. MOM is the average return on the two high momentum portfolios minus the average return on the two low momentum portfolios. The Appraisal ratio of portfolio $p$ is $\alpha_p$ normalized by the standard deviation of the error term $\epsilon_{pt}$.

Christopherson et al. (1998) point out that using the Appraisal ratio has several advantages. First, using $\alpha_p$ as a normalized explanatory variable, along with normalizing all other variables, results in a Weighted Least Squares (WLS) regression. This reduces the cross-sectional differ-

[7] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

ences related to variance which are likely to be important in our analysis because individual investors often hold stock-market portfolios that are not well diversified.

Second, Treynor and Black (1973) show that the Appraisal ratio is directly related to stock picking ability. In particular, they argue that when investors have stock-picking ability, the optimal portfolio choice can be thought of as a three-stage process (Treynor and Black, 1973, p. 74):

> ... the first stage is selection of an active portfolio to maximize the appraisal ratio, the second is blending the active portfolio with a suitable replica of the market portfolio to maximize the Sharpe ratio, and the third entails scaling positions in the combined portfolio up or down through lending or borrowing ...

Treynor and Black (1973) point out that Jensen's alpha is not invariant to the second stage. That is, Jensen's alpha varies with the balance between the active portfolio and the market portfolio. The implication for our study is important. The balance between the active portfolio and the market proxy is influenced by an investor's market expectations. Thus, Jensen's alpha is affected by market-timing ability while the Appraisal ratio is not. Thus, the Appraisal ratio is a better measure of ability related to picking individual securities.

**Sharpe ratio.** We measure the Sharpe ratio of portfolio $p$ at time $t$ as the average difference between the portfolio return and the risk-free return over the interval $t-T$ through $t-1$, divided by the standard deviation of the portfolio return over the same interval. This is a measure of ability that captures both stock picking skills and timing-ability.

**Characteristic adjusted returns.** We construct characteristic adjusted returns using an approach similar to Daniel et al. (1997). For a portfolio consisting of $J$ stocks at time $t$, we construct a size and momentum matched portfolio by matching each of the $J$ stocks in the portfolio with a stock of similar size and with similar stock return momentum. More specifically, for firm $j$ in the portfolio of investor $i$ at time $t$ with market capitalization $\mathrm{ME}_{jit}$, we identify all firms listed on the Oslo Stock Exchange with market capitalization in the interval $[0.7\mathrm{ME}_{jit}, 1.3\mathrm{ME}_{jit}]$. This set of firms is ranked according to stock return momentum measured over the six month period $t-6$ through $t-1$. The matching firm is the firm closest to firm $j$ in the momentum rank. The characteristic adjusted returns on portfolio $p$ is computed as the difference between the value-weighted return on portfolio $p$ and the value-weighted return on a portfolio of the size and momentum matched stocks.[8]

[8] The number of stocks listed on the Oslo Stock Exchange is insufficient to create a matching portfolio using three or more characteristics. Thus, we are prevented from matching on book-to-market ratio in addition to size and momentum.

## 4.3 Data and Sample Selection

This paper studies individual investors who held common shares traded on the Oslo Stock Exchange between December 1992 and June 2003. At the end of June 2003, the Oslo Stock Exchange ranks 11th out of twenty-three European stock exchanges based on market capitalization and 12th based on the number of listed companies.[9] Thus, compared to other European exchanges, the Oslo Stock Exchange is close to the "median exchange" when it comes to market capitalization and number of shares listed. Looking at stock market turnover (measured as annualized electronic order book transactions), the exchange has the eighth highest turnover. Bohren et al. (1997) show that the intensity of seasoned equity offerings is comparable to that of active markets like the New York Stock Exchange. In sum, the Oslo Stock Exchange is an established and mature market where liquidity and turnover are high enough to be an interesting laboratory to study investor behavior.

Our data source for the stock holdings of individual investors is the Norwegian Central Securities Depository (NCSD).[10] NCSD is a Norwegian company authorized to register rights to securities. Companies listed on the Oslo Stock Exchange are required by law to report to a security register. During our sample period, all listed companies registered their shares with NCSD. All investors that invest in stocks registered at NCSD must have a NCSD-account. Our main data is the month-end holdings of stocks of all NCSD-accounts between December 1992 and June 2003. When securities are traded, NCSD performs the settlement by transferring the security from the seller's NCSD-account to the buyer's NCSD-account. The Norwegian Central Bank subsequently performs the cash settlement. The NCSD-registry is used by the Norwegian government for taxation of investors. Thus, the quality of the data is a very high.

We study the stock holdings of all individuals and sole proprietorships. Since the latter entity is a business that is only owned by one person, we will refer to these investors jointly as individual investors. The number of individual investors that were registered at least once during the sample period is 718,185—around 17% of the Norwegian population. Many NCSD-accounts held by individual investors must be considered as "stale" in the sense that the owner of the account practically never trades. We will follow Coval et al. (2005), among others, and restrict our sample to accounts that are reasonably active. The next section describes the details of our sample selection procedure.

### 4.3.1 Sample Selection and Descriptive Statistics

Our sample selection procedure pertains to the inclusion of both stocks and investors. Regarding stocks, we restrict our sample by excluding the least liquid stocks on the Oslo Stock Exchange.

[9] See www.fese.eu.

[10] The Norwegian name for the Norwegian Central Securities Depository (NCSD) is VPS ASA—or better known as "Verdipapirsentralen." The below description of the activities of NCSD borrows from www.vps.no/english.

In particular, for a given stock and a given month, the stock is only included in the sample if it has traded during the month. In other words, we are not computing returns from bid and/or ask prices. For a given month $t$, we also exclude "penny-stocks"—defined as a stock with a price below NOK 5.0 at time $t-1$.[11]

Table 1 reports descriptive statistics for the Oslo Stock Exchange. The Table reports numbers year-on-year, for the entire sample (1993-2003), and for the estimation period (1995-2003). The second column reports the number of listed stocks that satisfy the selection criteria each year. From a low of 132 stocks in 1993, the number of listed stocks peaked at 222 in 1998, before steadily decreasing to 136 stocks in 2003. The averages over the sample and estimation period are 175 and 183, respectively. The third column reports the average market capitalization of the sample in NOK. The market capitalization is around three and a half times greater at the end of the sample than at the beginning of the sample, although there is not a monotonic increase in size over the sample period. In 1997, 1998 and 2003 the average market capitalization fell relative to the year before.

Analyzing performance persistence requires that we adjust portfolio performance for risk. This will, in part, be done using a four-factor model based on the three factors of Fama and French (1993) and the momentum factors of Carhart (1997). Using the stocks that satisfy our selection criteria, we construct a value-weighted market index, a size-factor, a book-to-market-factor, and a momentum factor for the Oslo Stock Exchange.[12]

The remaining columns of Table 1 report the factor premia on a monthly basis over the sample and estimation period. The market premium $(R_m - R_f)$ is 0.61 percent per month over the sample period (1993–2003), but falls to 0.30 per cent over the estimation period (1995–2003). This sharp fall is due to the omission of 1993's extraordinarily high return of 3.70 percent per month. The next three columns report a SMB premium of 0.66 per cent per month, a HML premium of 0.50 per cent per month, and a MOM premium of 0.71% per month. These premia are very similar to those reported for the US.[13]

Panel B of Table 1 reports a correlation matrix of the factor risk premia and shows that the market premium is negatively correlated with the other three factors. These patterns, and the extent of the correlations, are the same as those observed in the US stock market with the exception of the the SMB premia which is positively related to the market premium. The data on factor risk premia reported in Table 1 illustrates that the Oslo Stock Exchange has very similar aggregate risk premia to that of other stock markets.

Although we have shown that the factors studied in Table 1 have similar risk premia to those in other stock markets, we have not yet shown that they can price stocks listed in the Oslo Stock

[11] On April 23, 2007 NOK 5.0 is approximately USD 0.85.

[12] Section 4.2 provides the details on how the factors are constructed.

[13] The corresponding US premia are, in per cent per month, $(R_m - R_f) = 0.61$, SMB = 0.22, HML = 0.42, MOM = 0.96.

Exchange. This is essential because we want to avoid the possibility that estimated alphas in the empirical analysis of performance are a result of model misspecification, rather than investor ability.

To this end, Table 2 reports results from asset pricing tests. We consider portfolio sorts based on size, book-to-market, and momentum. Because of the relatively small number of stocks in the sample we do not attempt double or triple sorts on these three characteristics, but rather form quintile based portfolios on each individual characteristic. Panel A reports results from regressing the five size sorted portfolios on the four risk factors discussed in Table 1. If these factors are adequate at capturing the cross-section differences in the size portfolios then the intercepts (alphas) should be zero. The factor loadings are sensible in that, along with the market betas, the size betas are all statistically and economically significant and vary cross-sectionally in a sensible manner. Loadings on the other two factors are not important in the pricing of the size portfolios. The intercepts are all small and never statistically significant.

Panel B reports the same analysis as panel A but using the book-to-market portfolios. Similar findings are observed for these portfolios: the loadings on the book-to-market factor are sensible and the intercepts are small and not statistically significant. Finally, panel C considers the portfolios formed on momentum returns and only in the case of the portfolio that includes the worst performing stocks is the intercept statistically different from zero. In summary, the four factors seem to be able to price the stocks traded on the Oslo Stock Exchange, except for the extreme past losers. In light of these findings the four factors should provide a reasonable risk adjustment for stocks traded on the Oslo Stock Exchange.

With regard to investors, our sample is restricted to individuals that are active. To be considered as an active investor in month $t$, an individual investor's portfolio must contain at least two stocks at $t-1$, have at least twenty-four non-missing return observation between month $t-60$ and $t-1$, and finally must have traded $x$ times during the last twenty-four months. Table 3 reports average investor characteristics where each row corresponds to $x$ lying between 0 and 6, 7 and 12, 13 and 18, 19 and 24, and considering all investors. For most of the analysis in the results section, we restrict investors to have traded at least six times during the last twenty-four months.

Panel A of Table 3 reports summary statistics for all months in the sample. The first row reports investor characteristics when there is no restriction on the number of trades in the past. Without this restriction the sample contains 177,010 individual investors that satisfy the other sampling criteria at least once during the sample period. Notice that this is a significant drop from the population of 718,185 individual investors. This is a reflection of the fact that the majority of individual investors hold just one stock. Considering the second column of Panel A, the number of investors falls as the sample represents more and more active investors. If an investor is required to have traded more than six times during the last twenty-four months the sample size drops to 65,848 investors. If we require at least 19 trades during the last 24 months the sample contains 10,330 investors. Thus, the data contains a significant number of reasonable active investors, but a smaller number of very active investors.

All numbers in Table 3 other than the numbers in the first two columns are cross-sectional averages. Consider the last column, "VW Return," as an example. First, for a given investor that satisfies our selection criteria for month $t$, we determine the value-weighted return for this investor's portfolio at time $t$. Second, using the time-series of months for which the given investor satisfies the selection criteria we compute a time-series average. The table reports the cross-sectional average of these time-series averages. Appendix A describes the details of how we compute all variables described in this table.

Table 3 shows that investor's purchase and sales turnover increases as the number of trades increases, as we would expect. However, they do not increase symmetrically since purchase turnover is much higher than sales turnover. We also report the number of stocks held by investors, and consistent with the asymmetry between purchase and sales turnover, we find that the number of stocks held by investors increases as the number of trades increases, as does the value of the investor's portfolio. In the column "Avg. Stock Value" we report the average size of the firms in the investor's portfolio. Interestingly, this decreases as the number of trades increases, suggesting that the most active investors are investing in smaller stocks.

What is perhaps the most striking feature of Table 3 is reported in the final column where we record the value weighted return on the investor's portfolio. There is a dramatic drop in returns as investors become more active. Without any restrictions on the number of months an investor trades over the last two years, the average return for the 177,010 investors in the sample is 0.81 per cent per month. This is close to the average market return—as expected since in a large group of investors, their aggregate portfolio will mirror the market portfolio. However, the returns for individual investors are monotonically decreasing as the the number of trades increases. This finding is consistent with what is found using U.S. discount brokerage data (see, for example, Barber and Odean (2000), Odean (1999) and Barber and Odean (2001)).

Panels B and C of Table 3 explore the characteristics of investors' portfolios in months where the market returns are positive (Panel B) and negative (Panel C). All the investors' characteristics are basically the same in up and down markets except the return on the investors' portfolios. Here we see a dramatic difference in the average returns earned by investors depending on how much they trade. When considering months with positive returns in Panel B, investors who trade more earn higher return than investors who trade less. Panel C shows why the overall average return in Panel A falls as investor trade more: In down markets, investors who trade the most lose almost twice as much as investors who trade between 0 and 6 times. In sum, the most active investors seems to invest in small and risky stocks and their portfolio suffers big losses when the market drops. However, the large negative returns for active investors reported in Panel A are probably somewhat sample specific. From Table 1 we see that the average market return is less than $-1.49$ percent per month in three out of the eleven years. The tails of the return distribution have to be very fat for this to be a "normal" event during an eleven-year period.

## 4.4 Empirical Results

If some investors have the ability to consistently outperform the rest of the market, one would expect to find that these investors repeat as top performers over time. The literature has employed a variety of approaches to test this idea. One class of tests for performance persistence uses a cross-section of investors and regresses returns on measures of past performance. If performance persists, past performance should predict future performance. In a second class of tests, investors are first ranked based on some measure of past performance. Next, the future performance of the same investors are compared to a relevant benchmark. If performance persists, investors classified as top-performers in one period should outperform the benchmark in the following period. We present tests of the null hypothesis of no persistence in performance using both cross-sectional regressions and test based on performance-ranks. An alternative approach to assessing persistence is to examine the subsequent performance of stocks that are favored by the top performing invertors. If investors do have performance persistent then the subsequent return on a portfolio of stocks favored by the top performing investors should earn a statistically and economically significant abnormal return.

### 4.4.1 Cross Sectional Tests

The first approach that we use to measure performance persistence is a predictive cross-sectional regression where we examine if future benchmark adjusted returns can be predicted by a measure of past performance. This method lends from the Fama and MacBeth (1973) methodology of testing asset pricing models and has been used in assessing mutual and pension fund performance persistence in Hendricks et al. (1993) and Christopherson et al. (1998).

We follow the spirit of this idea and run the following cross-sectional regression:

$$R_p(t, t+\tau) - R_b(t, t+\tau) = \theta_{t,\tau} + \gamma_{t,\tau} X_{pt-2} + \epsilon_p(t, t+\tau) \tag{4.2}$$

where $R_p(t, t+\tau)$ is compounded return for investor portfolio $p$ for months $t$ through $t+\tau$, $R_b(t, t+\tau)$ is compounded return on a benchmark portfolio for months $t$ through $t+\tau$. The right-hand side variable, $X_{pt-2}$, is performance for portfolio $p$ measured over months $t-61$ through $t-2$, using a minimum of 24 observations. Variables that measure past performance are described in section 4.2. Note that we are skipping a month to avoid capturing autocorrelations not related to performance persistence.

The approach outlined above differs from the extant literature in an important way. In particular, Christopherson et al. (1998) use future excess returns as the dependent variable and Jensen's alpha as the predetermined variable. Hendricks et al. (1993) report results using a dependent variable that is adjusted using a constant-return benchmark as well as a CAPM based benchmark and define $X_{pt}$ as a vector of past excess returns over different horizons. The approach we adopt uses measures of abnormal performance both as the dependent and the predetermined variables. However, to avoid the potential problem that the regression captures persistence in model-misspecification, we use the Appraisal ratio and the Sharpe ratio to capture past performance (independent variables) and characteristic adjusted returns to measure future performance (dependent variable).

The regression in (4.2) is performed at every month $t = 26, \ldots T$.[14] Using the time-series of $\hat{\gamma}_{t,\tau}$, we test the null hypothesis of no performance persistence using the average:

$$\gamma_\tau = \frac{1}{T} \sum_{t=1}^{T} \hat{\gamma}_{t,\tau}.$$

We examine the predictability of future benchmark adjusted returns over horizons $\tau = 1$, 3, 6, 12, 18, 24, and 36 months. The null hypothesis that $\gamma_\tau = 0$ is tested using a $t$-statistic computed using Newey and West (1987) with $\tau - 1$ moving average terms. This accounts for the serial correlation induced by overlapping observations. When $X_{pt}$ is measured using the Appraisal ratio, we divide all right-hand side variables in equation (4.2) by the standard deviation of the error-term from equation (4.1), effectively running a Weighted Least Squares (WLS) regression. As pointed out in section 4.2, this reduces the cross-sectional differences related to variance. Taking the cross-sectional variance into account is important in our analysis because individual investors' stock-market portfolios are not well diversified.

Table 4 reports a summary of the results from the cross-sectional regressions using the three different measures of past performance. The table is split into three panels based on how often an investor trades. We follow Christopherson et al. (1998) and only report t-statistics for this test. Panel A reports the $t$-statistics for the estimates of $\gamma_\tau$ for all investors (around 20,000) who traded at least six out of the last twenty four months. At the one-month horizon there is marginal evidence of a positive relationship between past performance using the Appraisal ratio and future benchmark adjusted returns, $t = 1.82$. However, as the horizon increases to three months and subsequently for all other horizons, the $t$-statistics reveal that the null hypothesis of no relationship between past performance and future benchmark adjusted returns is rejected at the 1% level. The relationship between past performance and future returns is a little weaker

[14] Since we require at least 24 observations to compute $X_{pt}$ and since we skip a month, the first available date for running the cross-sectional regression is $t = 26$.

when the Sharpe ratio is employed as the past performance measure. A potential explanation for this finding is that the Sharpe ratio does not account for the systematic risk of a portfolio. Thus, an investor who holds high-beta stocks when the return on the market portfolio is high would tend to be classified as a top performer. If this investor has no ability to pick stocks that will outperform on a systematic risk-adjusted basis the Sharpe ratio should not predict future performance.

Panel B examines investors that have traded in at least twelve of the last twenty four months (around 7,000 investors) and finds results very similar to those in Panel A. In panel C we restrict the analysis to the investors who have traded in at least eighteen of the last twenty four months (around 2,500 investors). In this sample the results are weaker at the one month horizon, but otherwise confirm the results reported in panels A and B. Taken together, the results in Table 4 highlight a positive relationship between past performance and future benchmark adjusted returns which is robust to the choice of past performance measurement and to the extent of investor activity measured by frequency of trading. The relationship between past performance and future returns is stronger when we consider future returns at longer horizons. This result is consistent with the findings of Christopherson et al. (1998) who show that the persistence in performance of pension fund managers is stronger at longer horizons.

While there is clearly a robust link between past performance and future returns, it is not possible from Table 4 to know if this result is symmetric for investors whose past performance was poor and investors whose past performance was good. In particular, it is possible that the positive relationship between past performance and future returns is driven entirely by investors who in the past have performed poorly and in the future continue to perform poorly. Carhart (1997) and Christopherson et al. (1998) find that the positive relationship between past performance and future returns mainly is driven by the worst performing mutual fund and pension fund managers. To try and shed some light on this issue for individual investors, we split the sample of investors into quintiles based on past performance and examine the relationship between past performance and future abnormal returns for the top (best past performance) and bottom (worst past performance) quintiles.

Table 5 reports the findings from this exercise and shows, in Panel A, that the investors in the top past performance quintile have a statistically significant relationship between their past performance and future abnormal returns according to the Appraisal ratio and the Sharpe ratio. Panel B focuses on the bottom past performers and shows that there is also a strong positive relationship between past performance and future abnormal returns when measuring past performance with the Appraisal ratio. Using the Sharpe ratio, there is a negative relationship between past performance and future abnormal returns.

Overall, the results using the cross-sectional regression method show that there is a strong positive relationship between the past performance of individual investors and the returns on their portfolios in the future—especially when past performance is measured using the Appraisal ratio. The strong effect for the Appraisal ratio may be related to the fact that this is a measure that is related to stock picking ability (Treynor and Black (1973)). The relationship between past and future performance is positive both for investors with good performance in the past and for investors with bad performance in the past. Because earlier papers on the performance persistence of fund managers find that any evidence of persistence is typically driven by the worst performing managers, our finding of persistently good performance of individual investors is especially interesting.

### 4.4.2 Top and Bottom Performing Portfolios

In the previous section we identified a positive relationship between past performance and future abnormal portfolio returns. In order to consider the economic significance of this relationship we now turn to an alternative methodology that ranks individuals into decile portfolios based on their past performance. Subsequently, we compare the abnormal returns earned by investors in the top and bottom performance deciles. This approach is similar to that used by Hendricks et al. (1993) who rank mutual funds by returns (net of fees) over an evaluation period and examine the return on the portfolio one quarter ahead.

We adopt the following methodology. For each month $t$ all investors that have traded in at least six out of the last twenty-four months are ranked based on performance over the period $t-60$ through $t-1$. Top performing investors for month $t$ are the investors that rank above the 90th decile and bottom performing investors rank below the 10th decile. Investors are ranked based on their portfolio's Appraisal ratio and Sharpe ratio. For all investors ranked in month $t$, we compute average abnormal portfolio return as the difference between the average portfolio return over horizon $t+1$ through $t+\tau+1$ less the average return over the same horizon for a portfolio of size- and momentum matched stocks. Next, these abnormal retuns are averaged over all individuals ranked in month $t$. Using all available months, we obtain a time-series of abnormal returns for top- and bottom performing investors. We examine return horizons for $\tau = 1$, 3, 6, 12, 24, and 36 months.

Panel A of Table 6 reports average abnormal returns for the bottom and top performers when past performance is measured using the Appraisal ratio. At the one month horizon the top performers earn an abnormal return of 0.47% per month which falls to 0.26% at the thirty six month horizon. In sharp contrast, the bottom performers earn a negative abnormal return of $-0.13$% per month at the one month horizon which falls to $-0.02$% per month at the thirty six month horizon.

The row labeled "Top − Bottom" reports the time-series average of the differences between the abnormal returns for top performers and the abnormal return for bottom performers. This is always positive and is economically large, ranging from around 0.6% per month at horizons of up to six months and around 0.30% at the longest horizons. The row labeled "T-statistic" reports a Newey and West (1987) $t$-statistic which tests whether the difference between the abnormal returns on the top performing portfolio and the bottom portfolio are significantly different from zero. At the one month holding period we can reject the null hypothesis at the 10% level, while over all the remaining holding periods we can reject the null hypothesis at the 1% level.

Panel B presents the same analysis as in Panel A but using the Sharpe ratio as the measure of past performance. In this case the bottom performers earn a negative abnormal return at each horizon except at the twenty four and thirty six month horizons. The top performers always earn a positive abnormal return, irrespective of the horizon. The difference between the top and bottom performers is similar when using the Appraisal ratio to measure past performance at horizons up to twelve months, but is only statistically significant at the three and six month horizons.

It is often argued that mutual funds cannot outperform a given benchmark consistently because they are too large. We assess whether the size of an individual's portfolio affects the relationship between past performance and future abnormal return. Table 7 presents results of the difference in the abnormal returns between top and bottom portfolios for the quartile of investors with small portfolio and the quartile of investors with large portfolios. Panel A records the findings using the Appraisal ratio as a measure of past performance. The differences between the abnormal returns of top and bottom performers tends to be very small for investors with small and large portfolios up to and including a holding period of six months. For longer holding periods investors with larger portfolio do better. Irrespective of whether the investor's portfolio is large or small, the difference between the abnormal returns of top and bottom performers is always statistically different from zero at the three and six month horizons. For large investors, except at the one month horizon, the difference is always statistically significant.

Panel B reports findings using the Sharpe ratio as the measure of past performance. Recall from Table 6 that we found less evidence of a relationship between past performance using the Sharpe ratio and future abnormal returns. When we split investors by size there is a statistically and economically significant difference for large investors, but not for small investors.

The results in Tables 6 and 7 reinforce the findings from Table 4. Taken together, there exists a positive relationship between past performance and future returns for the individual investors observed in our data. This relationship tends to be stronger for investors that did well in the past and weaker for investors that were among the worst performers in the past. This relationship persists for both large and small investors, but is particulary strong for large investors.

### 4.4.3 Stocks Favored by the Best and the Worst Investors

In this section of the paper we form portfolios according to a trading strategy that attempts to exploit the ability of investors. We construct two portfolios, one that includes stocks favored in the past by investors whose past performance ranks them in the top performing decile, and another that includes stocks favored by investors whose past performance ranks them in the worst performing decile. If the top performing investors do well because they are able to include stocks that will do well in the future, we expect to observe that a portfolio of stocks favored by the top performing investors should outperform a passive benchmark.

We are not the first that try to exploit the stock-picking talent of successful investors. Cohen et al. (2005) develop a new mutual fund performance measure that evaluates a manager's skill based on the degree of overlap between a manager's stock holdings and the stock holdings of other managers who have been successful in the past. Their measure is constructed by first defining the quality of a stock as the average skill (measured using Jensen's alpha) of all managers that hold the stock. A manager's skill is next defined as being proportional to the number of high quality stocks held in the portfolio. While Cohen et al. (2005) use their measure to rank funds, Wermers, Yao and Zhao (2007) use a similar measure to pick stocks. They construct a portfolio of stocks held by managers that have been successful in the past, where weights in the portfolio are determined by the size of each funds investment in the stock. Thus, a stock heavily held by successful managers get a large weight in the portfolio.

We follow the basic idea of Cohen et al. (2005) and Wermers, Yao and Zhao (2007). However, to deal with overlapping returns and to increase the power of our test we apply the portfolio formation approach used by Jegadeesh and Titman (1993). More specifically, we form portfolios as follows: For each month $t$ all investors that have traded in at least six out of the last twenty-four months are ranked based on the performance of their portfolio over the period $t-60$ through $t-1$. Top performing investors for month $t$ are the investors that rank above the 90th decile and bottom performing investors rank below the 10th decile. Once we have classified investors, we identify which stocks are held by top performing investors and which stocks are held by bottom performing investors. A stock is said to be favored by top-performing investors if the stock is held by twice as many top-performers as bottom-performers. The opposite is true for stocks favored by bottom-performers. We then construct a portfolio with an $H$-month holding period from stocks favored by top-performers as follows. For month $t$, the portfolio contains stock favored by investors that was classified as top-performers in months $t - H$ through $t - 1$. Portfolio returns are computed as the weighted average of the returns on the stocks in the portfolio where the weight for stock $j$ is number of top-performers holding stock $j$ divided by total number of top-performing investors. Returns on a portfolio of stocks favored by bottom-performers are computed in a similar way.

Table 8 reports the average returns for the portfolios of stocks favored by top and bottom performers for monthly holding periods $H = 1$, 3, 6, 12, 18, 24, and 36 months. Using the Appraisal ratio to measure past performance we find that the portfolio of stocks favored by top performers earns 2.01% per month at the one month horizon while the return on the portfolio of stocks favored by bottom performers earns 0.29%. As the holding period increases the return difference between these two portfolios remains substantial. The remainder of Table 8 report results using the Sharpe ratio measure of past performance. Consistent with the results in Panel A, we find that there are substantial portfolio return differences between the top performers and bottom performers when using the Sharpe ratio.

Table 8 shows that a portfolio of stocks favored by top performing investors earns a substantially higher return than a portfolio of stocks favored by bottom performers. However, it is possible that these stocks have different risks and hence different returns. To assess this, Table 9 reports Jensen's alpha from a regression of the returns on the portfolios of stocks favored by individuals with the best past performance and individuals with the worst past performance on four risk factors. In Panel A we use the the Appraisal ratio to measure past performance. In this case, the portfolio of stocks favored by top performers has an economically and statistically significant alpha at all horizons. The statistical significance at the 24 and 36 month horizon is marginal, but, even here the economic significance is clear with a Jensen's alpha of 0.7% per month. The bottom performers have small alphas that are neither economically significant nor statistically different from zero.

Panels B of Table 9 repeats the analysis when the Sharpe ratio to assess past performance. Using the Sharpe ratio gives results that are similar to the findings in Panel A. In summary, it appears that by forming a portfolio of stocks that are favored by top performing investors it is possible to earn a statistically and economically significant risk adjusted return.

## 4.5 Conclusion

In this paper, we provide a novel analysis of stock market performance persistence for individual investors. We use a unique data set that includes all individual investors that at some point, during our eleven-year sample period, have owned stocks listed on the Oslo Stock Exchange. The monthly frequency of the data, the fact that we observe all the stock holdings of every individual investor, and the long time-series allow a unique opportunity to measure long-term performance persistence at the portfolio level. We analyze performance persistence using cross-sectional regressions and portfolio formation methods.

We find that a substantial number of investors exhibit economically and statistically significant performance persistence. This persistence is evident both for investors who did well in the past and for investors who did poorly in the past. The results that we report are robust to how persistence is measured. In addition, the findings are unaffected by how often investors trade and whether investors are small or large. We also show that forming a portfolio that is long in stocks previously favored by top performing investors earns a substantial risk adjusted return in the future.

One potential explanation for the finding that past performance is persistent, a finding that is absent in the mutual fund and pension funds literature, is that it is difficult to track successful professional fund managers over time. Chevalier and Ellison (1999) find that managers that perform well have a higher probability of surviving as managers and subsequently move to a bigger firm when compared to underperforming managers. An alternative explanation is offered by Berk and Green (2004). They develop a model showing that competition among investors to invest in the best performing funds will drive future costs up and future returns down to the point where investors get returns that are commensurate with the risk of the fund. Our data does not allow us to separate between these two explanations for the lack of performance persistence among mutual fund managers. We do, however, offer new insights into the performance of individual investors, a group of investors that generally have been viewed as one that makes poor investment decisions.

# Appendix A

This appendix describes the details of how we compute the variables described in Table 3. Other than the first two columns in Table 3, all other columns contain cross-sectional averages. Consider the column, "Number of stocks," as an example. First, to be included in the sample at time $t$ an investor must have a portfolio that contains at least two stocks on $t-1$, have at least twenty-four non-missing return observation between month $t-60$ and $t-1$, and finally have traded $x$ times during the last twenty-four months (time $t-24$ through $t-1$.) Table 3 reports results where each row corresponds to $x$ between 0 and 6, between 7 and 12, between 13 and 18, and between 19 and 24. If an investor satisfies the selection criteria, we retain the number of stocks held by this investor at time $t$. Second, using the time-series of months for which the given investor satisfies the selection criteria, we compute a time-series average of the number og stocks held in this investor's portfolio. Columns three through nine in Table 3 reports the cross-sectional average of these time-series averages.

The columns labeled "Jensen's alpha", "Momentum matched" and "BEME matched" report abnormal performance computed as described in section 4.2. The column labeled "Purchase Turnover" reports the percent of the portfolio turned over due to purchases. Purchase turnover is value-weighted and is measured as the value of all stocks purchased during a period divided by the value of the portfolio at the end of the period:

$$\sum_{j=1}^{J_{it}} \frac{P_{jt-1}N_{ijt}}{V'_{it-1}} \times \frac{B_{ijt}}{N_{ijt}}$$

where $B_{ijt} = aN_{ijt} - N_{ijt-1}$ is the split adjusted number of stocks purchased by investor $i$ in stock $j$ during month $t$ ($a \in [0, 1]$ is the adjustment factor) and

$$V'_{it-1} = \sum_{j=1}^{J_{it}} aP_{jt-1}N_{ijt}.$$

The column labeled "Sales Turnover" reports the percent of the portfolio turned over due to sales. Sales turnover is value-weighted and is measured as the value of all stocks sold during a period divided by the value of the portfolio at the beginning of the period:

$$\sum_{j=1}^{J_{it}} \frac{P_{jt-1}N_{ijt}}{V_{it-1}} \times \frac{S_{ijt}}{N_{ijt}}$$

where $S_{ijt} = N_{ijt-1} - aN_{ijt})$ is the split adjusted number of stocks sold by investor $i$ in stock $j$ during month $t$. The column labeled "Number of Stocks" reports the number of stocks held by this investor at the end of month $t$. The column labeled "Avg. Stock Value" reports the value weighted average firm size, in million Norwegian Kroner, over all firms in the portfolio at $t$:

$$\sum_{j=1}^{J_{it}} \frac{(P_{jt}N_{ijt})(P_{jt}N_{jt})}{V_{it}}$$

where $J_{it}$ is the number of stocks in investor $i$'s portfolio at time $t$, $P_{jt}$ is the price of stock $j$ at time $t$, $N_{ijt}$ is the number of shares owned by investor $i$ in stock $j$ at time $t$, $N_{jt}$ is the number of shares outstanding of stock $j$ at time $t$, and

$$V_{it} = \sum_{j=1}^{J_{it}} P_{jt}N_{ijt}.$$

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## .1 Tables

Table 1: Descriptive statistics for the Oslo Stock Exchange

Panel A reports monthly average returns for the equally weighted market portfolio (EW $R_m$), the value weighted market portfolio (VW $R_m$), the risk-free rate ($R_f$) and average risk-premiums associated with firm size, book-to-market ratio, and stock return momentum. The size (SMB) and book-to-market factors (HML) are constructed following the approach of Fama and French (1993). The momentum factor (MOM) is constructed following the approach outlined in Ken French's web-site. In particular, six value-weighted portfolios are constructed from the intersection of three portfolios formed using return momentum over months $t-12$ through month $t-2$ and two portfolios formed using market capitalization from month $t-1$. MOM is the average return on the two high momentum portfolios minus the average return on the two low momentum portfolios. The "Number of Securities" column report the time-series average number of common stocks that traded at least once during the current month and that in the previous month had a market capitalization larger than the 10th percentile. The sample period is January 1993 through July 2005.

| | Number of Securities | EW $R_m$ | VW $R_m$ | $R_f$ | SMB | HML | MOM |
|---|---|---|---|---|---|---|---|
| | | | **A. Monthly averages** | | | | |
| 1993 | 128 | 7.78 | 4.40 | 0.61 | 2.86 | 2.89 | −2.36 |
| 1994 | 144 | 0.51 | 0.76 | 0.46 | 0.38 | 0.88 | −0.38 |
| 1995 | 144 | 1.99 | 0.84 | 0.45 | 0.98 | −1.68 | 1.78 |
| 1996 | 156 | 2.92 | 2.34 | 0.40 | 0.54 | 0.20 | 0.26 |
| 1997 | 180 | 2.06 | 2.39 | 0.30 | −0.71 | 0.57 | 1.79 |
| 1998 | 212 | −3.44 | −2.23 | 0.50 | −0.51 | −0.09 | 2.30 |
| 1999 | 207 | 4.05 | 3.20 | 0.55 | 1.64 | −0.58 | −0.91 |
| 2000 | 195 | 0.46 | 0.26 | 0.56 | 1.26 | 1.05 | 0.36 |
| 2001 | 192 | −0.72 | −0.87 | 0.60 | 0.34 | 0.34 | 2.62 |
| 2002 | 180 | −3.24 | −2.19 | 0.58 | −0.24 | 2.81 | 6.12 |
| 2003 | 167 | 5.48 | 3.63 | 0.35 | 0.06 | 2.22 | −1.48 |
| 2004 | 164 | 3.20 | 2.75 | 0.17 | −0.51 | 1.46 | 0.71 |
| 2005 | 175 | 4.23 | 4.09 | 0.17 | −0.39 | 1.38 | 4.40 |
| 1993–2005 | 179 | 1.87 | 1.40 | 0.45 | 0.47 | 0.86 | 1.06 |
| | | | **B. Correlations** | | | | |
| EW $R_m$ | | 1.000 | | | | | |
| VW $R_m$ | | 0.887 | 1.000 | | | | |
| $R_f$ | | −0.166 | −0.219 | 1.000 | | | |
| SMB | | 0.117 | −0.252 | 0.157 | 1.000 | | |
| HML | | −0.181 | −0.099 | 0.058 | −0.263 | 1.000 | |
| MOM | | −0.271 | −0.188 | −0.012 | 0.002 | 0.082 | 1.000 |

Table 2: Pricing of stock portfolios sorted on size, book-to-market ratio, and six-month momentum

The rows denoted "Jensen's alpha" report abnormal performance based on the intercepts from regressions using the three Fama-French factors plus a momentum factor. The rows denoted "Size and momentum matched" report abnormal performance measured using size and six-month momentum matched firms. The rows denoted "Size and BEME matched" report abnormal performance measured using size and book-to-market ratio (BEME) matched firms. Section 4.2 provides the details of the abnormal performance measures. The test assets are five size-sorted portfolios, five book-to-market ratio sorted portfolios, and five six-month momentum sorted portfolios. The sample period is January 1993 through July 2005. Parentheses contain t-values.

| | Portfolio ranking | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| **A. Size sorted portfolios (ranked from small to large)** | | | | | |
| Portfolio return | 2.52 | 1.95 | 2.04 | 1.61 | 1.33 |
| Jensen's alpha | 0.39 ( 0.87) | −0.10 (−0.37) | 0.40 ( 1.82) | −0.01 (−0.06) | −0.13 (−1.04) |
| Size and momentum matched | 0.47 ( 1.29) | 0.02 ( 0.10) | 0.14 ( 0.74) | −0.10 (−0.78) | −0.08 (−0.40) |
| Size and BEME matched | 0.41 ( 1.18) | 0.01 ( 0.02) | 0.24 ( 1.25) | −0.33 (−1.91) | 0.19 ( 0.73) |
| **B. Book-to-market ratio sorted portfolios (ranked from low to high)** | | | | | |
| Portfolio return | 1.28 | 1.17 | 1.60 | 1.77 | 1.88 |
| Jensen's alpha | −0.04 (−0.10) | −0.49 (−1.71) | −0.15 (−0.46) | 0.18 ( 0.70) | −0.25 (−0.76) |
| Size and momentum matched | −0.17 (−0.40) | −0.14 (−0.26) | −0.14 (−0.32) | 0.24 ( 0.73) | 0.52 ( 1.41) |
| Size and BEME matched | 0.53 ( 1.25) | −0.19 (−0.37) | 0.21 ( 0.74) | 0.27 ( 0.80) | 0.01 ( 0.03) |
| **C. Six-month momentum sorted portfolios (ranked from negative to positive)** | | | | | |
| Portfolio return | 1.01 | 1.66 | 1.56 | 1.33 | 1.94 |
| Jensen's alpha | −0.07 (−0.15) | 0.26 ( 0.84) | 0.06 ( 0.24) | −0.11 (−0.37) | −0.57 (−1.37) |
| Size and momentum matched | −0.02 (−0.05) | 0.15 ( 0.46) | 0.00 ( 0.00) | 0.01 ( 0.02) | 0.20 ( 0.60) |
| Size and BEME matched | −0.36 (−0.67) | 0.07 ( 0.17) | 0.51 ( 1.14) | −0.44 (−1.08) | 0.95 ( 2.04) |

Table 3: Descriptive statistics for individual investors

The table reports descriptive statistics for investors on the Oslo Stock Exchange. The numbers reported in columns 3 to 9 are cross-sectional averages and are computed as follows. For each investor we compute time-series averages from monthly observations. To be included in the time-series at month $t$ the investor must satisfy the following criteria: The investor's portfolio must contain at least two stocks on $t-1$, have at least 24 non-missing return observation between month $t-60$ and $t-1$. In addition, the cross-sectional averages are computed over investors that have made at least one trade in between 0 and 6 months, between 7 and 12, between 12 and 18, and between 19 and 24 times during the last 24 months. The first column in the Table refer to the number of trades. The "Jensen's alpha" column reports average abnormal performance based on the intercepts from regressions using the three Fama-French factors plus a momentum factor. The "Size and momentum matched" column reports average abnormal performance measured using size and six-month momentum matched firms. The "Size and BEME matched" column reports average abnormal performance measured using size and book-to-market ratio matched firms. Section 4.2 provides the details of the abnormal performance measures. "Number of Investors" is the number of investors used to compute the cross-sectional averages (this number vary slightly from statistic to statistic), "Purchase turnover" and "Sales turnover" are the percent of the portfolio turned over due to purchases and sales, respectively. "Number of stocks" is the number of stocks in the portfolio. "Avg. stock value" is the average size (in million NOK) of firms in the portfolio. Appendix A provides more detail on these variables. Because our sampling require at least 24 non-missing return observation between month $t-60$ and $t-1$, the sample period is January 1995 through June 2003.

| | | Cross-sectional averages | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Trades | Number of Investors | Jensens-alpha | Size and momentum matched | Size and BEME matched | Purchase Turnover | Sales Turnover | Number of Stocks | Avg. stock Value |
| 0–6 | 193,461 | 0.53 | 0.42 | 0.61 | 1.06 | 1.23 | 2.63 | 19,568 |
| 7–12 | 70,531 | 0.10 | -0.15 | 0.07 | 3.75 | 2.48 | 4.80 | 16,592 |
| 13–18 | 30,032 | -0.09 | -0.56 | -0.10 | 7.84 | 3.42 | 6.92 | 11,219 |
| 19–24 | 12,473 | -0.06 | -0.63 | -0.19 | 14.08 | 3.52 | 10.36 | 8,806 |

Table 4: Cross-sectional performance persistence regressions for individual investors

The table reports estimates and Newey-West t-values for:

$$\gamma_\tau \equiv \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_{t,\tau}$$

The estimates $\hat{\gamma}_{t,\tau}$, for $t = 1, \ldots T$, are obtained by rolling forward the following cross-sectional regression:

$$AR_p(t, t+\tau) = \theta_{t,\tau} + \gamma_{t,\tau} X_{pt-2} + \epsilon_p(t, t+\tau) \quad p = 1, \ldots, N$$

where $AR_p(t, t+\tau)$ is average abnormal performance for months $t$ through $t+\tau$. Abnormal performance is measured using Jensen's alpha, size and six-month momentum matched firms, and size and book-to-market ratio matched firms. The abnormal performance measures are described in section 4.2. The return horizons are given in the column headings. For the column "Months 1–3 " returns are averaged over three months. The right-hand side variable, $X_{pt-2}$, is performance for portfolio $p$ measured over months $t-61$ through $t-2$, using a minimum of 24 observations. Performance is measured using the Appraisal ratio (Jensen's alpha divided by the standard deviation of the portfolio's idiosyncratic risk). Because we require at least 24 observations to compute the measures of past performance, the sample includes investor portfolios observed over the period January 1995 through June 2003. Abnormal performance is measured until July 2005.

| | Return horizon | | | | | |
|---|---|---|---|---|---|---|
| | Month 1 | Months 1–3 | Months 1–6 | Months 1–12 | Months 7-12 | Months 13-24 |
| **A. Investors that traded in 24 out of the last 24 months** | | | | | | |
| Cross-sectional obs. | 361 | 362 | 362 | 362 | 356 | 345 |
| Jensen's alpha | 0.216 (2.50) | 0.067 (3.36) | 0.033 (3.86) | 0.014 (2.83) | 0.024 (1.96) | 0.013 (2.05) |
| Size/Momentum matched | 0.213 (2.50) | 0.064 (2.41) | 0.029 (2.13) | 0.011 (1.50) | 0.020 (1.29) | 0.020 (2.03) |
| Size/BEME matched | 0.216 (2.04) | 0.076 (2.65) | 0.036 (2.57) | 0.012 (1.51) | 0.013 (0.77) | 0.007 (0.69) |
| **B. Investors that traded at least 18 out of the last 24 months** | | | | | | |
| Cross-sectional obs. | 3,190 | 3,204 | 3,207 | 3,209 | 3,137 | 3,036 |
| Jensen's alpha | 0.154 (2.42) | 0.051 (3.52) | 0.026 (3.59) | 0.011 (2.84) | 0.021 (2.71) | 0.004 (0.96) |
| Size/Momentum matched | 0.105 (1.75) | 0.037 (2.53) | 0.020 (2.70) | 0.008 (2.01) | 0.016 (1.87) | 0.009 (1.94) |
| Size/BEME matched | 0.156 (2.01) | 0.052 (2.80) | 0.027 (2.96) | 0.011 (2.21) | 0.023 (2.14) | 0.007 (1.60) |
| **C. Investors that traded at least 12 out of the last 24 months** | | | | | | |
| Cross-sectional obs. | 8,746 | 8,788 | 8,800 | 8,808 | 8,578 | 8,293 |
| Jensen's alpha | 0.141 (2.17) | 0.044 (3.25) | 0.022 (3.37) | 0.009 (2.70) | 0.016 (2.41) | 0.002 (0.65) |
| Size/Momentum matched | 0.164 (2.42) | 0.053 (3.24) | 0.025 (3.16) | 0.009 (2.17) | 0.013 (1.42) | 0.006 (1.33) |
| Size/BEME matched | 0.155 (1.92) | 0.049 (2.71) | 0.026 (2.96) | 0.011 (2.39) | 0.020 (2.10) | 0.006 (1.42) |
| **D. Investors that traded at least 6 out of the last 24 months** | | | | | | |
| Cross-sectional obs. | 24,142 | 24,262 | 24,298 | 24,326 | 23,751 | 23,121 |
| Jensen's alpha | 0.137 (1.64) | 0.044 (2.06) | 0.022 (2.11) | 0.009 (2.08) | 0.015 (1.93) | 0.000 (0.04) |
| Size/Momentum matched | 0.251 (2.39) | 0.078 (2.66) | 0.036 (2.60) | 0.011 (1.63) | 0.007 (0.47) | 0.002 (0.34) |
| Size/BEME matched | 0.148 (1.33) | 0.050 (1.72) | 0.028 (1.77) | 0.011 (1.91) | 0.016 (1.19) | 0.000 (0.02) |

Table 5: Cross-sectional performance persistence regressions for individual investors that traded in at least 12 out of the last 24 months

The table reports estimates and Newey-West t-values for:

$$\gamma_\tau \equiv \frac{1}{T}\sum_{t=1}^{T} \hat{\gamma}_{t,\tau}$$

The estimates $\hat{\gamma}_{t,\tau}$, for $t = 1, \dots T$, are obtained by rolling forward the following cross-sectional regression:

$$AR_p(t, t+\tau) = \theta_{t,\tau} + \gamma_{t,\tau} X_{pt-2} + \epsilon_p(t, t+\tau) \quad p = 1, \dots, N$$

where $AR_p(t, t+\tau)$ is average abnormal performance for months $t$ through $t+\tau$. Abnormal performance is measured using Jensen's alpha, size and six-month momentum matched firms, and size and book-to-market ratio matched firms. The abnormal performance measures are described in section 4.2. The return horizons are given in the column headings. For the column "Months 1–3 " returns are averaged over three months. The right-hand side variable, $X_{pt-2}$, is performance for portfolio $p$ measured over months $t-61$ through $t-2$, using a minimum of 24 observations. Performance is measured using the Appraisal ratio (Jensen's alpha divided by the standard deviation of the portfolio's idiosyncratic risk). Because we require at least 24 observations to compute the measures of past performance, the sample includes investor portfolios observed over the period January 1995 through June 2003. Abnormal performance is measured until July 2005.

| | Return horizon | | | | | |
|---|---|---|---|---|---|---|
| | Month 1 | Months 1–3 | Months 1–6 | Months 1–12 | Months 7-12 | Months 13-24 |
| **A. Investors with above median performance** | | | | | | |
| Cross-sectional obs. | 4,375 | 4,395 | 4,401 | 4,404 | 4,289 | 4,148 |
| Jensen's alpha | 0.165 (1.82) | 0.047 (2.41) | 0.024 (2.42) | 0.011 (2.61) | 0.023 (2.23) | 0.004 (0.65) |
| Size/Momentum matched | 0.290 (2.59) | 0.085 (3.12) | 0.036 (3.12) | 0.013 (3.33) | 0.020 (1.77) | 0.005 (0.89) |
| Size/BEME matched | 0.160 (1.34) | 0.050 (1.65) | 0.025 (1.61) | 0.013 (2.09) | 0.030 (1.81) | 0.011 (2.26) |
| **B. Investors with below median performance** | | | | | | |
| Cross-sectional obs. | 4,370 | 4,392 | 4,399 | 4,403 | 4,288 | 4,145 |
| Jensen's alpha | 0.142 (2.07) | 0.049 (3.70) | 0.021 (4.52) | 0.008 (2.90) | 0.011 (1.54) | 0.000 (0.14) |
| Size/Momentum matched | 0.064 (0.83) | 0.027 (1.80) | 0.013 (2.10) | 0.004 (1.14) | 0.002 (0.28) | 0.002 (0.46) |
| Size/BEME matched | 0.126 (1.55) | 0.046 (2.15) | 0.021 (2.42) | 0.007 (1.68) | 0.008 (0.82) | 0.002 (0.41) |

Table 6: Average abnormal portfolio returns for top and bottom performing individual investors, using investors that traded in at least 12 out of the last 24 months

For each month $t$ all investors that have traded in at least twelve out of the last twenty-four months are ranked based on performance over the period $t-60$ through $t-1$. Past performance is measured using the Appraisal ratio (Jensen's alpha divided by the standard deviation of the portfolio's idiosyncratic risk). Top performing investors for month $t$ are the investors that rank above the 90th Appraisal ratio decile and bottom performing investors rank below the 10th Appraisal ratio decile. For all investors ranked in month $t$, we compute the average abnormal portfolio returns starting in month $t+1$ at the earliest. The Table report results for the horizons: $t+1$ through $t+\tau$ for $\tau \in \{1, 3, 6, 12, 24\}$ as well as for the horizons $t+7$ through $t+12$ and $t+13$ through $t+24$. Abnormal portfolio returns are measured using Jensen's alpha, size and six-month momentum matched firms, and size and book-to-market ratio matched firms. The measurements of abnormal portfolio returns are described in section 4.2. Abnormal portfolio returns are averaged over all individuals ranked in month $t$. Using all available months, we obtain a time-series of abnormal returns for all past performance deciles. The Table reports the time-series average of these abnormal portfolio returns. The column labeled "Top − Bottom" reports the time-series average of the differences between the abnormal returns for top performers and the abnormal return for bottom performers. The parentheses contains Newey and West (1987) t-statistics. Because we require at least 24 observations to compute the measures of past performance, the sample includes investor portfolios observed over the period January 1995 through June 2003. Abnormal performance is measured until July 2005.

| | Past performance decile | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Horizon | Bottom | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Top | Top − Bottom |
| | | | | | **A. Jensen's alpha** | | | | | | |
| Month 1 | −0.20 | −0.07 | −0.05 | 0.01 | 0.04 | 0.03 | 0.09 | 0.12 | 0.11 | 0.28 | 0.48 (2.17) |
| Months 1–3 | −0.19 | −0.09 | −0.03 | 0.01 | 0.05 | 0.07 | 0.09 | 0.09 | 0.11 | 0.26 | 0.45 (3.57) |
| Months 1–6 | −0.17 | −0.07 | −0.02 | −0.01 | 0.04 | 0.06 | 0.11 | 0.09 | 0.12 | 0.26 | 0.42 (3.83) |
| Months 1–12 | −0.09 | −0.03 | 0.01 | 0.03 | 0.07 | 0.08 | 0.14 | 0.11 | 0.12 | 0.25 | 0.34 (2.93) |
| Months 1–24 | −0.12 | −0.03 | −0.01 | −0.03 | 0.02 | 0.06 | 0.11 | 0.11 | 0.14 | 0.28 | 0.40 (2.30) |
| Months 7–12 | −0.05 | −0.02 | −0.01 | 0.04 | 0.06 | 0.06 | 0.12 | 0.11 | 0.10 | 0.21 | 0.25 (2.37) |
| Months 13–24 | 0.12 | 0.09 | 0.09 | 0.12 | 0.11 | 0.14 | 0.16 | 0.13 | 0.12 | 0.19 | 0.07 (0.59) |
| | | | | | **B. Size and momentum matched** | | | | | | |
| Month 1 | −0.52 | −0.40 | −0.43 | −0.42 | −0.36 | −0.42 | −0.34 | −0.28 | −0.18 | −0.05 | 0.47 (2.11) |
| Months 1–3 | −0.47 | −0.43 | −0.39 | −0.39 | −0.32 | −0.33 | −0.32 | −0.25 | −0.17 | −0.06 | 0.41 (2.85) |
| Months 1–6 | −0.44 | −0.37 | −0.35 | −0.34 | −0.29 | −0.29 | −0.23 | −0.20 | −0.15 | −0.03 | 0.40 (2.77) |
| Months 1–12 | −0.31 | −0.26 | −0.27 | −0.28 | −0.23 | −0.22 | −0.15 | −0.12 | −0.12 | −0.01 | 0.30 (1.93) |
| Months 1–24 | −0.12 | −0.03 | −0.01 | −0.03 | 0.02 | 0.06 | 0.11 | 0.11 | 0.14 | 0.28 | 0.40 (2.30) |
| Months 7–12 | −0.28 | −0.23 | −0.29 | −0.31 | −0.27 | −0.25 | −0.18 | −0.13 | −0.19 | −0.09 | 0.18 (1.34) |
| Months 13–24 | −0.19 | −0.19 | −0.19 | −0.17 | −0.14 | −0.11 | −0.04 | −0.02 | −0.05 | 0.02 | 0.21 (1.46) |
| | | | | | **C. Size and BEME matched** | | | | | | |
| Month 1 | −0.29 | −0.13 | −0.07 | −0.07 | −0.05 | −0.02 | 0.05 | 0.11 | 0.18 | 0.26 | 0.55 (1.97) |
| Months 1–3 | −0.29 | −0.14 | −0.06 | −0.08 | −0.02 | 0.02 | 0.04 | 0.08 | 0.16 | 0.22 | 0.51 (2.80) |
| Months 1–6 | −0.28 | −0.12 | −0.08 | −0.10 | −0.02 | 0.02 | 0.09 | 0.11 | 0.16 | 0.25 | 0.53 (2.83) |
| Months 1–12 | −0.17 | −0.05 | −0.03 | −0.04 | 0.01 | 0.06 | 0.12 | 0.13 | 0.16 | 0.29 | 0.46 (2.28) |
| Months 1–24 | −0.12 | −0.03 | −0.01 | −0.03 | 0.02 | 0.06 | 0.11 | 0.11 | 0.14 | 0.28 | 0.40 (2.30) |
| Months 7–12 | −0.15 | −0.03 | −0.08 | −0.04 | −0.03 | 0.03 | 0.08 | 0.10 | 0.10 | 0.26 | 0.40 (2.26) |
| Months 13–24 | −0.06 | −0.02 | −0.04 | −0.03 | 0.00 | 0.02 | 0.06 | 0.05 | 0.09 | 0.26 | 0.32 (2.16) |

Table 7: Average abnormal returns for portfolios of top and bottom performing individual investors, using investors that traded in at least 6 out of the 24 last months, sorted by portfolio value

For each month $t$ all investors that have traded in at least six out of the last twenty-four months are ranked based on performance over the period $t-60$ through $t-1$. Top performing investors for month $t$ are the investors that rank above the 90th decile and bottom performing investors rank below the 10th decile. The table ranks investors based on the Appraisal ratio (Jensen's alpha divided by the standard deviation of the portfolio's idiosyncratic risk), the Sharp ratio, and a portfolio weight based performance measure ($\Delta$W(6,6).) For all investors ranked in month $t$, we compute the average abnormal portfolio return as the difference between the average return over horizon $t+1$ through $t+\tau+1$ less the average return, using returns from months $t+1$ through $t+\tau+1$, on a portfolio of size and momentum matched stocks. These abnormal returns are averaged over all individuals ranked in month $t$. Using all available months, we obtain a time-series of abnormal returns for top and bottom performing investors. The return horizons are $\tau = 1, 3, 6, 12, 24$, and 36—corresponding to the columns in the table. The rows labeled "Bottom performers" and "Top performers"reports the time-series average return using only bottom performing investors and top performing investors, respectively. The row labeled "Top − Bottom" reports the time-series average of the differences between the abnormal returns for top performers and the abnormal return for bottom performers. The rows labeled "T-statistic" report a Newey and West (1987) t-statistic. Because we require at least 24 observations to compute the performance measures, the sample period is January 1995 through June 2003.

| | Return horizon | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 month | 3 months | 6 months | 12 months | 18 months | 24 months | 36 months |
| **A. Past performance measured using the Appraisal ratio** | | | | | | | |
| *Quartile of individual investors with small portfolios* | | | | | | | |
| N | 433 | 420 | 402 | 364 | 329 | 296 | 236 |
| Top − Bottom | 0.48 | 0.55 | 0.41 | 0.16 | 0.12 | 0.05 | 0.15 |
| T-statistic | 1.16 | 2.20 | 2.01 | 0.96 | 0.63 | 0.46 | 1.15 |
| *Quartile of individual investors with large portfolios* | | | | | | | |
| N | 421 | 419 | 416 | 402 | 380 | 357 | 294 |
| Top − Bottom | 0.45 | 0.49 | 0.50 | 0.43 | 0.40 | 0.36 | 0.33 |
| T-statistic | 1.36 | 2.20 | 2.71 | 2.76 | 2.98 | 3.24 | 3.43 |
| **B. Past performance measured using Sharpe ratio** | | | | | | | |
| *Quartile of individual investors with small portfolios* | | | | | | | |
| N | 522 | 508 | 487 | 444 | 406 | 371 | 306 |
| Top − Bottom | 0.35 | 0.46 | 0.49 | 0.07 | 0.06 | -0.08 | 0.03 |
| T-statistic | 0.64 | 1.71 | 1.66 | 0.25 | 0.05 | -0.24 | 0.15 |
| *Quartile of individual investors with large portfolios* | | | | | | | |
| N | 385 | 383 | 380 | 368 | 349 | 326 | 269 |
| Top − Bottom | 0.29 | 0.41 | 0.39 | 0.38 | 0.36 | 0.32 | 0.26 |
| T-statistic | 0.82 | 1.82 | 2.05 | 2.32 | 2.92 | 2.95 | 4.04 |
| **C. Past performance measured using a portfolio weigh based measure, $\Delta$W(6,6)** | | | | | | | |
| *Quartile of individual investors with small portfolios* | | | | | | | |
| N | 530 | 513 | 486 | 431 | 383 | 340 | 265 |
| Top − Bottom | 0.37 | 0.42 | 0.41 | 0.41 | 0.34 | 0.20 | 0.04 |
| T-statistic | 1.56 | 2.83 | 2.75 | 2.61 | 2.55 | 1.57 | 0.37 |
| *Quartile of individual investors with large portfolios* | | | | | | | |
| N | 303 | 301 | 297 | 285 | 269 | 250 | 204 |
| Top − Bottom | 0.17 | 0.13 | 0.15 | 0.15 | 0.20 | 0.20 | 0.23 |
| T-statistic | 1.08 | 1.04 | 1.37 | 1.72 | 2.13 | 2.30 | 2.90 |

Table 8: Average returns for portfolios of stocks favored by top performing and bottom performing individual investors that traded in at least 6 out of the 24 last months

The table reports portfolio time-series average returns. The portfolio returns are constructed as follows. For each month $t$ all investors that have traded in at least six out of the last twenty-four months are ranked based on performance over the period $t-60$ through $t-1$. Top performing investors for month $t$ are the investors that rank above the 90th decile and bottom performing investors rank below the 10th decile. The table ranks investors based on the Appraisal ratio (Jensen's alpha divided by the standard deviation of the portfolio's idiosyncratic risk), the Sharp ratio, performance relative to a portfolio of size and momentum matched stocks (style matched), and a portfolio weight based performance measure ($\Delta$W(6,6).) A stock is favored by top-performing investors if the stock is held by twice as many top-performers as bottom-performers. The opposite is true for stocks favored by bottom-performers. We construct an $H$-month holding period portfolio, $R^H_{pt}$, from stocks favored by top-performers as follows. For month $t$, the portfolio contains stock favored by investors that was classified as top-performers in months $t-H$ through $t-1$. This way of populating a portfolio with stocks follows Jegadeesh and Titman (1993). Portfolio returns are computed as the weighted average of the returns on the stocks in the portfolio where the weight for stock $j$ is number of top-performers holding stock $j$ divided by total number of top-performing investors. Returns on a portfolio of stocks favored by bottom-performers are computed in a similar way. The columns report average returns for monthly holding periods H in $\{1, 3, 6, 12, 18, 24, 26\}$. Because we require at least 24 observations to compute the performance measures, the sample period is January 1995 through June 2003.

| | Return horizon | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 month | 3 months | 6 months | 12 months | 18 months | 24 months | 36 months |
| Time-series observations | 101 | 99 | 96 | 90 | 84 | 78 | 66 |
| **A. Past performance measured using the Appraisal ratio** | | | | | | | |
| Top performers | 2.01 | 1.72 | 1.63 | 1.33 | 1.15 | 0.85 | 0.43 |
| Bottom performers | 0.29 | 0.22 | 0.38 | 0.73 | 0.16 | 0.19 | -0.56 |
| **B. Past performance measured using Sharpe ratio** | | | | | | | |
| Top performers | 1.48 | 1.39 | 1.28 | 1.24 | 0.98 | 0.72 | 0.33 |
| Bottom performers | 0.93 | 0.40 | 0.49 | 0.91 | 0.03 | 0.48 | -0.65 |
| **C. Past performance measured using a portfolio weigh based measure, $\Delta$W(6,6)** | | | | | | | |
| Top performers | 0.72 | 1.16 | 1.08 | 0.79 | 0.47 | 0.14 | -0.11 |
| Bottom performers | -0.72 | -0.50 | -0.54 | -0.62 | -0.60 | -0.62 | -0.37 |

Table 9: Jensen's alphas for portfolios of stocks favored by top performing and bottom performing individual investors that traded in at least 6 out of the 24 last months

The table reports intercepts from the following time-series regression:

$$R_{pt}^{H} = \alpha_p + \beta(R_{mt} - R_{ft}) + sSMB_t + hHML_t + mMOM_t + \epsilon_{pt},$$

where the right-hand side variables are described in Table 2. The portfolio returns on the left-hand side are constructed as follows. For each month $t$ all investors that have traded in at least six out of the last twenty-four months are ranked based on performance over the period $t-60$ through $t-1$. Top performing investors for month $t$ are the investors that rank above the 90th decile and bottom performing investors rank below the 10th decile. The table ranks investors based on the Appraisal ratio (Jensen's alpha divided by the standard deviation of the portfolio's idiosyncratic risk), the Sharp ratio, performance relative to a portfolio of size and momentum matched stocks (Style matched), and a portfolio weight based performance measure ($\Delta$W(6,6).) A stock is favored by top-performing investors if the stock is held by twice as many top-performers as bottom-performers. The opposite is true for stocks favored by bottom-performers. We construct an $H$-month holding period portfolio, $R_{pt}^{H}$, from stocks favored by top-performers as follows. For month $t$, the portfolio contains stock favored by investors that was classified as top-performers in months $t-H$ through $t-1$. This way of populating a portfolio with stocks follows Jegadeesh and Titman (1993). Portfolio returns are computed as the weighted average of the returns on the stocks in the portfolio where the weight for stock $j$ is number of top-performers holding stock $j$ divided by total number of top-performing investors. Returns on a portfolio of stocks favored by bottom-performers are computed in a similar way. The columns report Jensen's alphas for monthly holding periods H in $\{1, 3, 6, 12, 18, 24, 26\}$. Because we require at least 24 observations to compute the performance measures, the sample period is January 1995 through June 2003. The parentheses contains White (1980) t-values.

| | Return horizon | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 month | 3 months | 6 months | 12 months | 18 months | 24 months | 36 months |
| Time-series observations | 101 | 99 | 96 | 90 | 84 | 78 | 66 |
| **A. Past performance measured using the Appraisal ratio** | | | | | | | |
| Top performers | 1.25<br>(3.25) | 0.92<br>(2.55) | 0.97<br>(2.58) | 0.81<br>(2.21) | 0.80<br>(2.07) | 0.72<br>(1.83) | 0.73<br>(1.66) |
| Bottom performers | 0.07<br>(0.09) | −0.20<br>(−0.25) | 0.08<br>(0.09) | 0.45<br>(0.60) | 0.04<br>(0.06) | 0.26<br>(0.42) | −0.23<br>(−0.39) |
| **B. Past performance measured using Sharpe ratio** | | | | | | | |
| Top performers | 0.77<br>(3.12) | 0.63<br>(2.75) | 0.67<br>(2.77) | 0.71<br>(2.90) | 0.59<br>(2.32) | 0.51<br>(1.91) | 0.45<br>(1.50) |
| Bottom performers | 0.87<br>(0.72) | 0.12<br>(0.11) | 0.32<br>(0.28) | 0.71<br>(0.75) | −0.09<br>(−0.12) | 0.67<br>(0.97) | −0.22<br>(−0.29) |
| **C. Past performance measured using a portfolio weigh based measure, $\Delta$W(6,6)** | | | | | | | |
| Top performers | −0.00<br>(−0.01) | 0.36<br>(1.05) | 0.24<br>(0.76) | −0.08<br>(−0.34) | −0.31<br>(−1.26) | −0.48<br>(−1.90) | −0.57<br>(−2.04) |
| Bottom performers | −0.61<br>(−0.53) | −0.43<br>(−0.37) | −0.46<br>(−0.40) | −0.67<br>(−0.58) | −0.46<br>(−0.41) | −0.39<br>(−0.35) | −0.19<br>(−0.16) |