Sharks and chum? On the trading in momentum stocks by various investor types

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[WORK IN PROGRESS]

Abstract

Controlling for the trading activity of more and less sophisticated investors ("sharks" and "chum"), past returns alone no longer predict that future returns will move in the same direction. I.e. momentum seems to be generated through the trading activity of these two groups. I find that past and current buying pressure of sharks positively relate to current returns; past and current selling pressure from chum positively relate to current returns. This is consistent with sharks being simply better able to identify good investment objects at any point in time; chum naivly go in the opposite direction.

Introduction

Samuelson (1965) asserts that for operators in an efficient equity market "...there is no way of making an expected profit by extrapolating past changes in the future price, by chart or any other esoteric device of magic or mathematics". An intriguing challenge to this position is therefore empirical evidence showing that the trivially simple trading strategy of buying past winning stocks with the proceeds from selling past losing stocks generates an expected profit. Jegadeesh and Titman (1993) establised this momentum effect, and numerous studies have reproduced the result both out of the original sample period and in equity markets outside of North-America; Fama and French (2008) label it the "premier anomaly". Indeed, a seemingly provocative profit opportunity. How do actual investors relate to this phenomenon; can their trading activity help explain its existence? Or, more bluntly, do investors react to or create the momentum effect?

Assume that we are able to rank investors by investment sophistication; from the least sophisticated ("chum") to the most sophisticated ("sharks"). To the extent that chum push prices away from fundamental value through their trading activity, do sharks profit from trading against these positions? Consider further that we know the fundamental value of a firm, and that we are able to space out relevant time intervals. Now, for some reason unrelated to fundamentals, chum investors start intense selling of a stock, triggering a negative price pressure. As the market price of the stock now deviates more and more from the fundamental value, shark investors have more and more to profit from trading against this position. At the end of the first period sharks start this process of buying stocks. This buying pressure increases the price towards fundamental value. Then chum investors take the recent price increase as a signal that they should buy. This buying pressure increases the price over the third time interval. As the price deviation from fundamental value becomes higher and higher, sharks have more and more to profit from trading against this position. Over the fourth period they do just that; push prices back down towards fundamental value. Then chum investors take the recent price decrease as a negative signal and start selling the stock. This price pressure without fundamental information pushes prices even further down; below fundamental value. Momentum could be fully explained by such an interaction between sharks and chum. The buying pressure of sharks leading the price of the stock back up to fundamental value would correspond to the formation period. Here we would see an increase in the price over the period, leading the stock to enter the winner group. In the next period, chum investors would take over the buying pressure, leading to price deviating from fundamental value and offering momentum returns. As the sharks come in the subsequent period to trade in the opposite direction, we have a reversal of the momentum returns, and this reversal is increased by the added selling pressure from chum in the period after that. If this story is true we would see momentum explained through buying pressure from sharks over the formation period positively related to future returns, and buying pressure from chum over the momentum period.

An alternative story would have sharks simply being better able to identify good investment objects at any point in time. Chum would naivly go in the opposite direction. If this is the case we would see past and current buying pressure of sharks positively related to current returns, with past and current selling pressure from chum positively related to current returns.

Both these stories would be consistent with momentum. Which of them is true?

If the first is true we need chum to be able to impact prices. Kogan, Ross, Wang and Westerfield (2006) show that irrational (optimistic or pessimistic) investors can have a long-lived impact on prices even if they are small in terms of wealth. Trading against such irrational traders is risky because they might become even more pessimistic or optimistic by the time better informed investors need to liquidate their position. This would explain the delay in response from sharks to the irrational positions of chum.

The second story for how trading activity would explain the existence of momentum, also has support in the literature. By construction good things have happened to the stocks with the highest return over the formation period; either revealed through public or private information. To the extent that investors differ in how informed they are, both public and private information may drive the trading activity of the better informed investors; with the less informed investor types going in the opposite direction. For privat information this is clear, as trading is the only way through which this information may be impounded into prices. New evidence also show that less informed investors may trade in the wrong direction on the release of public information due to delayed response, whereby better informed and faster responding investors trade against ”stale” limit orders (Linnainmaa, 2007). This indicates that over the ranking period informed investors should be buying stocks ending up as winners by the end of the ranking period, and selling those that end up as losers. Less informed investors should trade in the opposite direction. Furthermore, Grinblatt and Keloharju (2000) also show that more sophisticated investors seem to trade with momentum, whereas less sophisticated investors trade in the opposite direction. Using a 2-year investor level panel of daily trade flows on the Helsinki Stock Exchange in Finland, they find that more sophisticated investors (non-domestic traders; large foreign institutions) tend to trade with the momentum. I.e. on each trading day these investors tend to buy more stocks with high past returns than stocks with past low returns. Domestic investors, and in particular household investors, tend to trade in the opposite direction. As a measure of the performance of each investor type, they show that foreign investors seem to pick future winning stocks more frequently than domestic investors do, even after adjusting for momentum. In the following I use the classification foreign investors as ”sharks” and household as ”chum”.

Thus, the trading activity of sharks and chum may be directly related to the return pattern of the momentum strategy. In this paper I test the hypothesis that by including measures of the trading activity of these two investor types, the explanatory power of past returns alone on future returns disappears. Using a new individual investor-level panel dataset of all stock holdings and stock trades from the Oslo Stock Exchange in Norway for the six years 2002 to 2007, I set out to test this hypothesis.

Several papers have investigated the relation between the trading activity of investor types and returns, but the literature is severely handicapped by the low frequency at which the data is available. Nofsinger and Sias (1999) investigate institutional trade flows at the annual frequency. They find that there is a strong positive concurrent correlation between returns and institutional trade flows. However, due to the low frequency of their flow data they do not know exactly when the change in ownership occurs. Thus, they are unable to track the trading in the portfolio of stocks that enter the momentum strategy, which is re-balanced monthly. The heavily researched CDA/Spectrum database on holdings by institutions covered by 13-F regulation in the US reports at quarterly frequencies, and therefore meets the same short-coming.

Much research has therefore involved how to generate proxies for trading at higher frequency by various investor types. This is often done through first identifying the direction of each trade through the algorithm developed by Lee and Ready (1991). In essence this algorithm aims to determine the side from which the market order generating each trade came from: buy side or sell side. A common approach is then, based on some cut-off value, to classify large orders as proxying institutional trades, and small orders as proxying household investor trades. A recent example is Hvidkjaer (2006) who relates buying and selling pressure from small and large trades to momentum returns. He finds that there is an initial small-trade buying pressure for loser stocks, which gradually converts into an intense small-trade selling pressure. Large trades, by contrast, seem to have little impact on subsequent returns. This suggests that momentum could partly be driven by the behaviour of small trades, mostly consistent with the first story sketched above.

It is tempting to equate small orders with the trading activity of houseshold investors (and large order to institutional investors). Barber, Odean and Zhu (2009) find that small trade order imbalances correlate well with order imbalance based on trades from investors in one retail broker from which they have data records. However, Campbell, Ramadorai and Schwartz (2009) show that classifying trades to investor types based on a simple trade-size cut-off point can be misleading. In particular, institutions frequently use small orders, and increasingly so with the rise in algorithmic trading. Campbell et al. (2009) develop a regression method based on all trade sizes in intraday trade flow data. Their resulting measure of daily institutional trading explain from 10% to 15% of the variance of quarterly changes in institutional ownership. This is superior to the match achieved from classification based on a trade-size cut-off point alone. This makes the results in Hvidkjaer (2006) hard to interpret, at least in terms the relative impact of investor types in momentum returns. If it is the characteristics of the investor behind the trade, i.e. household or institution, that may help shed light on momentum, then further investigation with a detailed high-frequency investor-level panel dataset is necessary. This would enable us to investigate the actual trading by each investor group in each of the actual stocks that enter the momentum portfolios each month. This is what I do below.

I proceed as follows. First, I briefly describe the investor level data from the Norwegian Central Securities Depository "Verdipapirsentralen ASA" (VPS), the institutional setup of VPS and how it relates to the trading platform at the Oslo Stock Exchange (OSE). Second, I offer descriptive statistics on OSE. Third, I test whether there is a momentum effect on OSE over the sample period. Fourth, I investigate how each of the investor groups trade in the stocks that enter the momentum portfolios each month; both during the formation period and the periods following portfolio formation. Fifth, I investigate whether inference on momentum changes when controlling for trading activity as discussed above, before I conclude.

1 Institutional setup of VPS

The Norwegian Central Securities Depository "Verdipapirsentralen ASA" (VPS) handles registration of direct ownership of securities, corporate actions in relation to end-investors and clearing and settlement between brokers. For our purposes, it is important to note that VPS is the only company with a licence to run a securities depository in Norway. Therefore, the aggregate holdings of Oslo Stock Exchange (OSE) registered stocks in VPS investor accounts is equivalent to the universe of stocks registered with the OSE. The VPS thereby accounts for who owns each of these stocks on any day. The data I use in this study are the daily VPS transactions from the six years 2002 to 2007. Below is an brief description of how an OSE trade generates a VPS transaction, and a brief presentatin of key figures for the Oslo Stock Exchange over this sample period.

1.1 From agreement on OSE to a transaction in VPS

Customer orders are placed at the OSE by brokers. Following a match between two such orders, a trade at the OSE results. The broker on each side of the trade reports two transaction to VPS: (1) The broker to broker transaction at OSE, and (2) the broker to customer transaction. Thus, in general, for each trade at OSE there are a total of four transactions reported to VPS, two on each side of the trade.

Once the broker to broker transactions are matched in the VPS system, the VPS account of the broker on the buying side is debited with the shares of the transaction, and the VPS account of the broker on the selling side is correspondingly credited. Then the second level of the transaction, broker to customer, is performed. On the buying side, the broker's account is now credited and the customer's account debited with the shares of the transaction. The end result is a net flow of zero on the brokers account and a positive flow to the buying customer's account. Symmetrically on the selling side. It is of course possible for a transaction to result from customers of the same broker. If brokers match orders outside OSE, the transaction is reported and registered with VPS as above.

1.2 Transactions in the VPS dataset

Entries in the transaction table hold the following information: trade date, VPS settlement date (normally trade date + 3 days), transaction price, volume (positive for buy and negative for sell), value, isin, investor id, function type (type of VPS transaction). An additional dummy variable indicates whether price on the transaction is the actual transaction price, or inferred by VPS from volume and value or close price of stock on trade date/registration date.

The data constitutes all account flows in the VPS system. The VPS registration system carefully and electronically keeps a log of all movements on all accounts. As outlined above, some of these movements will be temporary flows of stocks on broker accounts before the stocks are set against the account of the end-customer on each side of the trade.

Each VPS account is linked to an organisation number or a social security number. In the data constructed by the VPS for this study each of these investors is identified by an anynomised investor id. Each investor is also allocated to a sector. The sector allocation is standard European Union and United Nations classification, and is aggregated into the following six sector categories: Household, finance and insurance institution, non-financial corporation, general government, non-profit institution, and foreign investor. If an investor has several VPS accounts, the flows are linked to the same anynomous investor id. Thus, the data tracks investors and not VPS accounts.

However, foreign investors can trade on so-called nominee accounts, i.e. where the broker trades in the investor's name. We do not know how many foreign investors enter each of these nominee accounts, and each foreign investors is also able to spread trading across various nominee accounts. Therefore, data on foreign investors using such nominee accounts do not constitute an individual level panel of investor trades. Many foreign investor do not use such nominee accounts. It is not possible for domestic investors to trade on such nominee accounts, and for these investors, therefore, the VPS data therefore constitute a panel of individual investor trades. In the analysis below I use aggregate trade flows for each investor type, not individual investor entries, and therefore this is not an issue.

2 OSE over the sample period

Figures 3 plot the Oslo Stock Exchange All Share Index (OSEAX)[1]. Table 1 gives key figures for OSE over the sample period.

3 Is there a momentum effect at OSE?

I want to find the returns to a momentum strategy at OSE in event time, over the sample period. For each month t in the sample period, I use the close stock price at the last day of each month. Then I rank the stocks over the formation period $(t-J, t)$, based on prices adjusted for splits, reverse splits and dividend payments. Stocks that do not have enought data enabling this calculation are excluded. The remaining stocks are ranked in ascending order according to cumulative return over the formation period. Using this ranking I then divide the stocks into quintiles. The first quintile, i.e. the 20% stocks with the lowest cumulative return over the formation period, is labelled the "loser" group; the last quintile the "winner" group. So, I now have the stocks that make up the loser and winner group in the current month (based on past returns over the formation period). For each of the following 24 months I then calculate the return of the equal weighted portfolio of winners and an equal weighted portfolio of the losers. The momentum

[1]The Oslo Børs All Share Index consists of all shares listed on Oslo Børs. The index is adjusted for corporate actions daily and the current outstanding number of shares is applied in the index. The OSEAX index is adjusted for dividend payments.

strategy return is then the return to the winner portfolio minus the return to the loser portfolio.

These raw excess returns are then also held against two common risk factors: the market ($R_{m,t} - R_{f,t}$) and size factors (SMB_t). The market factor is calculated as the return on the strategy of buying the market factor with the proceeds of the short sale of the risk-free rate. The market proxy is the log-return on the OSEAX monthly close value. The risk-free rate is proxied by the log-return on the Norwegian government 1/4 year bond yield index (ST1X) monthly close value. The size factor is the value weighted return on the portfolio of firms with a market value below the median-valued firm on the market, minus the value weighted return on the portfolio of firms with a market value equal to or higher than that of the median-valued firm. Thus, using the momentum strategy trading profit time series for the k^{th} month following each of the formation dates ($t = 1, \ldots, T$) over the sample period ($W_{k,t} - L_{k,t}$), I estimate the regression

$$W_{k,t} - L_{k,t} = \alpha_k + \beta_k[R_{m,t} - R_{f,t}] + \gamma_k SMB_t + \epsilon_{k,t}$$

The risk adjusted trading profits to the momentum strategy in the k^{th} month after the portfolio formation date is then the resulting α_k from this regression.

3.1 Results

Based on a formation period of 12 months table 2 offers the standard results: momentum returns with reversal after about a year, and risk adjustment leaving these excess returns largely unchanged. The event time excess returns load negatively on both the size and market factors. Figure 4 plots the average cumulative excess returns to the momentum strategy.

4 How do the different investor types trade in momentum stocks?

I now look at how each investor type trades in the stocks that make up the winner and loser portfolios of the momentum strategy. As a measure of trading activity I calculate the net buy ratio for each each investor type n, stock i and each trading day d:

$$\text{net buy ratio}_{n,i,d} = \frac{\text{buy}_{n,i,d} - \text{sell}_{n,i,d}}{\text{buy}_{n,i,d} + \text{sell}_{n,i,d}}$$

This offers a variable with values between negative and positive unity. Thus, if all the investors of a particular types, say, foreign investors, only buy a particular stock on a particular day, the resulting net buy ratio would be equal to 1. Symmetrically, if they all sold this particular stock the net buy ratio would be equal to -1.

4.1 Results

Figure 5 offers plots of the average daily trading activity of each investor type over the sample period in the winner and loser groups. We see that household investors systematically sell less losers and sell more winners over the formation period. Foreign investors systematically buy more winners and sell more losers over both the formation period and thereafter.

5 What is the price impact of this trading activity?

I want to measure how each investor group changed position in a stock over a period. To do this I first calculate the net turnover for each investor type n, each stock i and each tradedate d

$$\text{turnover}_{n,i,d} = \frac{\text{buy}_{n,i,d} - \text{sell}_{n,i,d}}{\text{shares outstanding}_{i,d}}$$

This is a useful measure as it both captures the relative change in the investor group's holding in the stock and controls for split/reverse split at the same time. Moreover, it is easy to measure how the position was changed over various time horizons simply by adding up the turnover observations for the relevant period.

Thus, at each month t I am interested in the following relationship

$$\begin{aligned} R_{i,(t,t+12)} &= \alpha + \beta_1 R_{i,(t-12,t)} + \beta_2 \log(size_{i,t}) \\ &\quad + \gamma_1 \text{turnover}_{H,i,(t,t+12)} + \gamma_2 \text{turnover}_{F,i,(t,t+12)} \\ &\quad + \lambda_1 \text{turnover}_{H,i,(t-12,t)} + \lambda_2 \text{turnover}_{F,i,(t-12,t)} \\ &\quad + \epsilon_{i,(t,t+12)} \qquad i = 1, \ldots, N \end{aligned}$$

β_1 captures the momentum effect and should therefore be positive, β_2 captures the effect of size and should be negative. As argued above, I want to test whether the inclusion of the measures of trading activity alter inferences on past returns. At the same time we are able to test which of the two trading stories that are consistent with momentum.

5.1 Results

Figure 1 offers the results from the panel regressions with only past returns and size as explanatory variables. We see that each of them have the expected sign: higher past returns predict higher future returns; smaller size predicts higher future returns. Figure 2 offers the same panel regressions now including the trading activty measures. We see that high past returns no longer predicts high future returns; the size effect remains as expected. The coefficents on the trading variables have the expected sign in both periods: foreign investor buying pressure in past and current period relates positively to current returns; household investor past and current selling pressure is positively related current returns. These results are consistent with the story where shark investors are better able than chum to pick good stocks.

6 Conclusion

Controlling for the trading activity of more and less sophisticated investors ("sharks" and "chum"), past returns alone no longer predict that future returns will move in the same direction. I.e. momentum seems to be generated through the trading activity of these two groups. I find that past and current buying pressure of sharks positively relate to current returns; past and current selling pressure from chum positively relate to current returns. This is consistent with sharks being simply better able to identify good investment objects at any point in time; chum naivly go in the opposite direction.

Table 1: Key figures OSE, 2001 - 2007

Description	2001	2002	2003	2004	2005	2006	2007
OSEBX (year-end)	167.2	115.2	171.0	236.7	332.5	440.4	490.8
Percentage change OSEBX	-14.6	-31.1	48.4	38.4	40.5	32.4	11.5
Market capitalisation (NOK billion, year-end)	677	503	690	932	1403	1916	2157
Trading days	249	249	250	253	253	251	250
New Issues (NOK billion)	28	6	7	9	28	57	54
Total dividends (NOK billion)	20	20	23	37	49	51	69
Total turnover (NOK billion)	555	442	549	902	1506	2578	3211
Number of transactions (thousands)	2489	2012	2322	3366	5425	8797	12056
Turnover velocity	86.4	74.7	97.7	110.3	128.9	153.7	153.2
Listed companies	212	203	178	188	219	229	241
Listings (incl. demerger)	17	6	5	22	46	32	30
De-listings (incl. merger)	19	15	30	12	15	22	18
Foreign companies	26	24	20	22	28	33	31

Source: OSE. Turnover velocity: Average of annualized turnover per month divided by market value at the end of each month. Only capital registered in the VPS. Dividends paid during the year: Only dividends in companies listed at year end are included.

Table 2: MOMENTUM STRATEGY EXCESS RETURNS IN EVENT TIME: MEAN RETURN OF STRATEGY IN THE K'TH MONTH FOLLOWING PORTFOLIO FORMATION, 12 MONTHS RANKING PERIOD, PORTFOLIO REBALANCED END OF EACH MONTH: JANUARY 1999 - NOVEMBER 2008

k	mean $(W_k - L_k)$	t(mean)	α_k	$t(\alpha_k)$	β_k	$t(\beta_k)$	γ_k	$t(\gamma_k)$	R^2
1	0.0355	4.41	0.0292	4.26	-0.37	-3.73	-0.96	-6.36	0.31
2	0.0345	4.39	0.0273	4.11	-0.34	-3.63	-0.98	-6.61	0.32
3	0.0373	4.78	0.0295	4.59	-0.34	-3.72	-1.03	-7.23	0.36
4	0.0303	4.06	0.0227	3.66	-0.26	-2.98	-0.98	-7.16	0.34
5	0.0256	3.56	0.0189	3.07	-0.29	-3.38	-0.86	-6.40	0.31
6	0.0207	3.02	0.0147	2.44	-0.23	-2.70	-0.77	-5.84	0.27
7	0.0190	2.52	0.0118	1.84	-0.26	-2.90	-0.91	-6.52	0.31
8	0.0148	1.88	0.0073	1.07	-0.26	-2.76	-0.90	-6.11	0.29
9	0.0107	1.43	0.0041	0.63	-0.26	-2.80	-0.82	-5.79	0.27
10	0.0092	1.27	0.0021	0.36	-0.25	-2.98	-0.91	-7.09	0.35
11	0.0087	1.30	0.0024	0.43	-0.25	-3.16	-0.79	-6.50	0.32
12	0.0054	0.77	-0.0007	-0.13	-0.25	-3.11	-0.91	-7.18	0.37
13	0.0057	0.80	-0.0007	-0.12	-0.19	-2.19	-0.85	-6.29	0.30
14	0.0032	0.50	-0.0028	-0.51	-0.18	-2.40	-0.79	-6.56	0.32
15	0.0020	0.30	-0.0035	-0.59	-0.07	-0.85	-0.68	-5.15	0.23
16	0.0014	0.21	-0.0042	-0.69	-0.13	-1.56	-0.69	-5.18	0.23
17	0.0000	0.00	-0.0053	-0.98	-0.05	-0.72	-0.66	-5.57	0.26
18	-0.0026	-0.40	-0.0074	-1.29	-0.06	-0.76	-0.63	-4.97	0.22
19	-0.0088	-1.50	-0.0122	-2.20	0.04	0.56	-0.43	-3.57	0.15
20	-0.0088	-1.41	-0.0120	-2.01	0.09	1.10	-0.39	-3.01	0.13
21	-0.0065	-1.07	-0.0093	-1.56	0.11	1.35	-0.30	-2.30	0.10
22	-0.0106	-1.63	-0.0128	-2.05	0.24	2.77	-0.17	-1.26	0.12
23	-0.0078	-1.16	-0.0094	-1.41	0.21	2.29	-0.11	-0.74	0.08
24	-0.0070	-1.10	-0.0080	-1.25	0.16	1.78	-0.07	-0.49	0.05

See text for details

Figure 1: Panel regressions: Momentum

```
. xtreg return_forward return_past log_size

Random-effects GLS regression                   Number of obs      =     14287
Group variable: isin_id                         Number of groups   =       299

R-sq:  within  = 0.1652                         Obs per group: min =         1
       between = 0.0010                                        avg =      47.8
       overall = 0.0120                                        max =        84

Random effects u_i ~ Gaussian                   Wald chi2(2)       =   2305.23
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
return_for~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 return_past |   .2954761   .0094984    31.11   0.000     .2768597    .3140925
    log_size |  -.3451332   .0072894   -47.35   0.000    -.3594201   -.3308463
       _cons |   6.931566   .1528644    45.34   0.000     6.631957    7.231175
-------------+----------------------------------------------------------------
     sigma_u |  .50786016
     sigma_e |  .55467061
         rho |  .45602972   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

See text for details.

Figure 2: Panel regressions: Momentum and trading activity

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. xtreg return_forward return_past log_size turnover_forward_* turnover_past_*

Random-effects GLS regression                   Number of obs      =      4883
Group variable: isin_id                         Number of groups   =       174

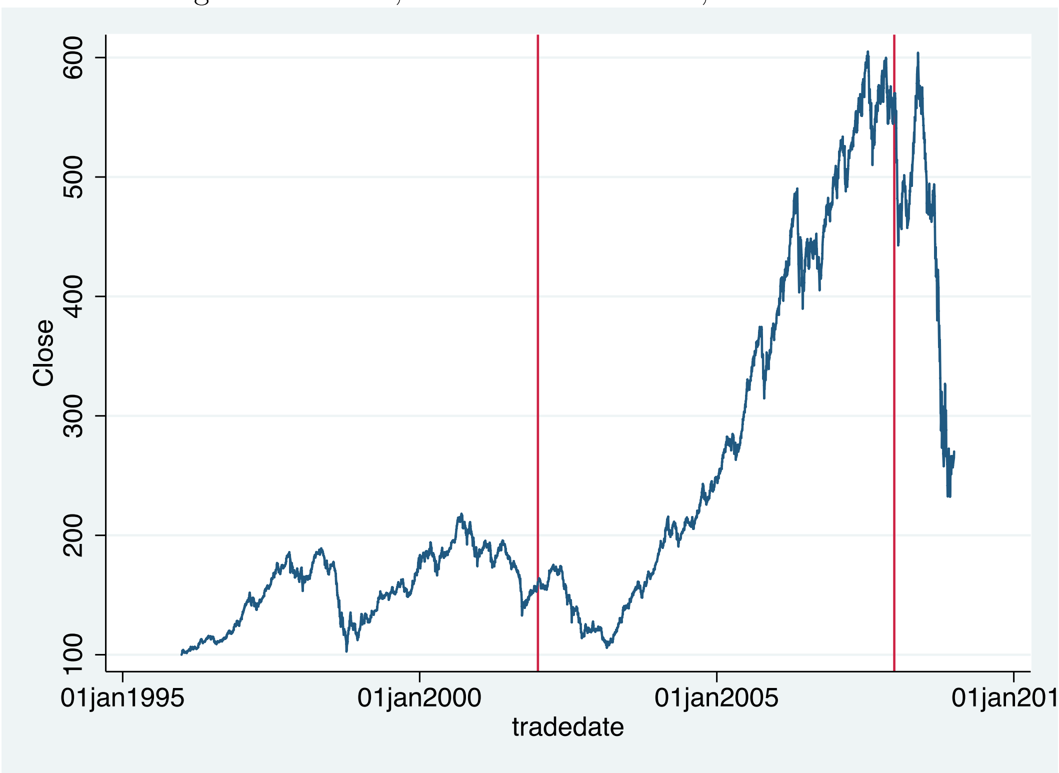
R-sq:  within  = 0.3838                         Obs per group: min =         1
       between = 0.0207                                        avg =      28.1
       overall = 0.0225                                        max =        49

Random effects u_i ~ Gaussian                   Wald chi2(6)       =   2036.70
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
return_for~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 return_past |    -.09098   .0099534    -9.14   0.000    -.1104882   -.0714718
    log_size |  -.2796204   .0089009   -31.41   0.000    -.2970659   -.2621749
turnover_f~4 |  -1.043413   .0532757   -19.59   0.000    -1.147832   -.9389947
turnover_f~6 |   .7758093   .0526975    14.72   0.000     .6725241    .8790944
turnover_p~4 |   -.352423   .0365868    -9.63   0.000    -.4241318   -.2807143
turnover_p~6 |   .3669855   .0544865     6.74   0.000     .2601938    .4737771
       _cons |   6.168471   .1884585    32.73   0.000     5.799099    6.537843
-------------+----------------------------------------------------------------
     sigma_u |  .25744371
     sigma_e |  .31605585
         rho |  .39885561   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

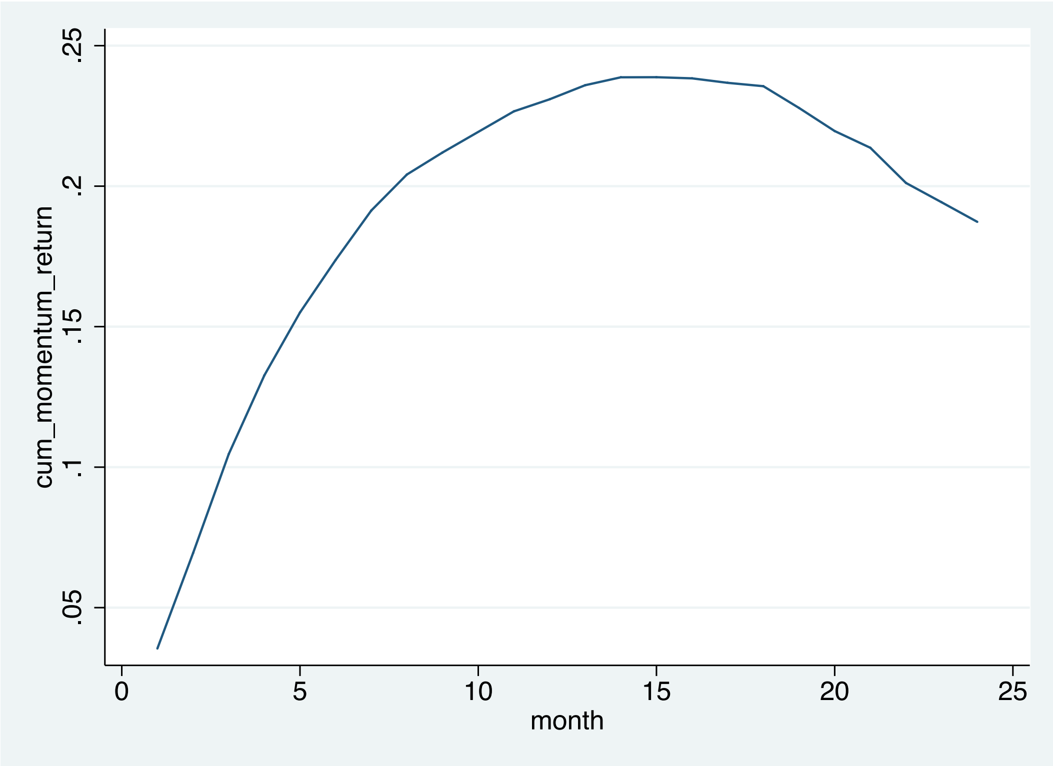
See text for details.

Figure 3: OSEAX, DAILY CLOSE VALUE, 1996-2008



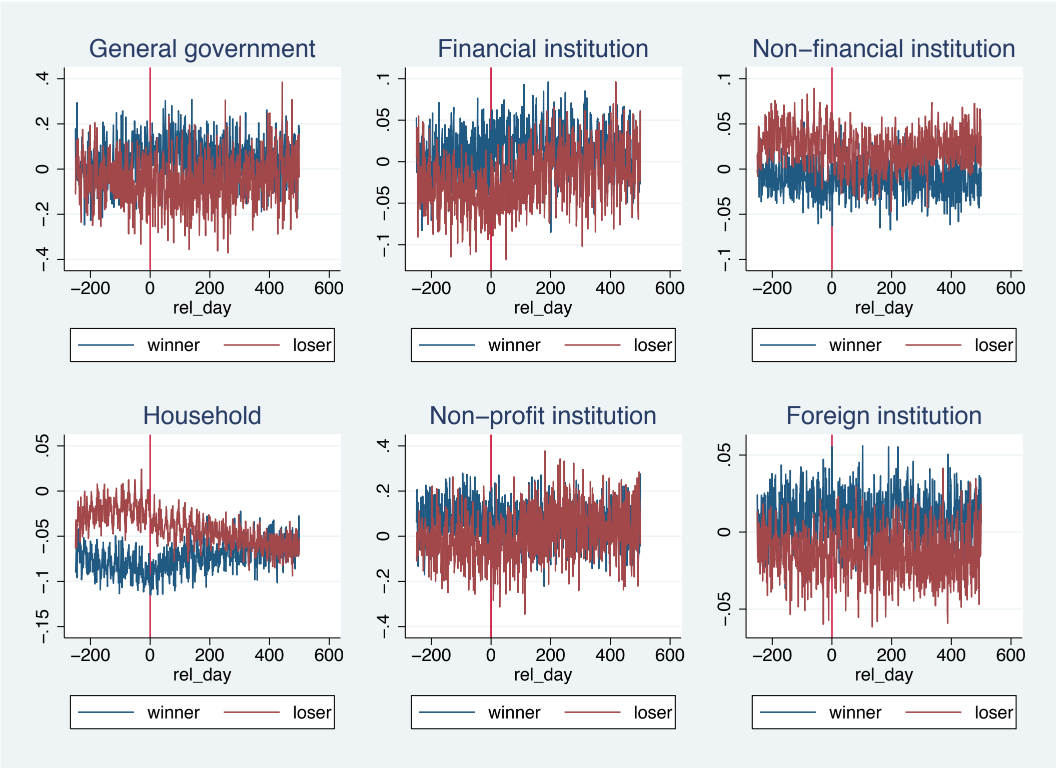
See text for details. Start date for the OSEAX series (index==100) is 29 December 1995. Vertical lines indicate the start and end dates of the daily VPS investor accounts data (28 December 2001 and 28 December 2007)

Figure 4: Average cumulative (raw excess) return to 12 months momentum at the Oslo Stock Exchange, 1999-2008



See text for details

Figure 5: Average daily net buy ratio of each investor group in momentum stocks



See text for details

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