Who trades on momentum?

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Keywords: momentum anomaly, momentum crash, investor behavior, institutional investors, individual investors

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1 Introduction

Stocks that have performed best in the past tend to continue to perform well, whereas stocks that performed worst in the past generally continue to perform poorly. This momentum effect in stock returns, first documented by Jegadeesh and Titman (1993), is economically significant, continues to be evident even after its discovery, and, with few exceptions, is also present outside the U.S.[1] During 1965-2012, a strategy of buying past winning stocks and selling past losing stocks would have earned an average annual return of 8.82% (t-value: 3.89) in the U.S., and similarly in Germany – the country we study in the following – an average annual return of 9.97% (t-value: 4.29). Despite the average strong performance of this "Winner-Minus-Loser" (WML) strategy, it performed extremely poorly following the recent financial crisis. During April-September 2009, a WML strategy would have yielded a cumulative return of -50.77% in the U.S. and -42.01% in Germany.[2] Other episodes of momentum crashes are documented by Daniel, Jagannathan, and Kim (2012) and Daniel and Moskowitz (2013).

Discussions on the momentum anomaly are closely intertwined with literature on institutional investors' trading. The very motivation for Jegadeesh and Titman (1993) is the practice of professional investors to trade on past prices. Since then, a multitude of studies have analyzed whether institutional investors exploit the momentum anomaly.[3] Not all investors can simultaneously follow the momentum strategy. Market clearing condition dictates that for every buyer, there must be a seller. If one investor buys winners and sells losers, another investor has to sell winners and buy losers.

[1] Jegadeesh and Titman (2001) confirm the profitability of the momentum strategy even after the publication of their original paper. Rouwenhorst (1998) and Griffin, Ji, and Martin (2003) provide evidence of the momentum effect in international stock markets (it is weakest in Asia, especially in Japan), and Asness, Moskowitz, and Pedersen (2013) document that momentum is present in not only stocks but other asset classes as well.

[2] The U.S. data are from Kenneth French's homepage. The German data are from Brückner, Lehmann, Schmidt, and Stehle (2013). The figures refer to a WML strategy based on a (2x3) sort on market capitalization and the past 2-11 months return as described by Fama and French (2012). Returns are in the local currency.

[3] See e.g. Lakonishok, Shleifer, and Vishny (1992), Grinblatt, Titman, and Wermers (1995), Falkenstein (1996), Nofsinger and Sias (1999), Gompers and Metrick (2001), Badrinath and Wahal (2002), and Bennett, Sias, and Starks (2003). For a summary and discussion of the different results regarding momentum trading of institutional investors, see Sias (2007).

Using the newly established Securities Holdings Statistics (SHS), which cover virtually the entire holdings structure of the German stock market, we *simultaneously* study the investment decisions of various investor types before, during, and after the financial crisis of 2008-2009. By observing the entire ownership structure of the market we can determine who trades on momentum, and – possibly a more interesting question – which investors are on the other side of the momentum trading strategy. Moreover, we analyze whether and how momentum trading relates to the momentum crash of 2009.

Our main findings are as follows: We find strong evidence that financial institutions, in particular mutual funds and foreign investors (which generally are also institutional investors) are momentum traders. Private households instead are contrarians. These trading patterns are robust over various past return formation periods (one to four quarters) for which the momentum anomaly is profitable. The results persist even when we control for different variables that are related to investors' trading (Bennett et al., 2003). When looking at winner and loser stocks separately, we find that momentum trading is particularly strong among losers. We also relate the trading behavior of private investors to measures of investor sophistication and thereby document that the degree of contrarian trading declines with private investors' sophistication as proxied by financial wealth and home bias. Furthermore, in a time-series analysis, we show that aggregate momentum trading in the market is anti-cyclical, such that it increases during market downturns and in high volatility phases. When separating winner and loser stocks, we find that only the sale of losers increases during bad economic states, but the purchase of winners is largely unrelated to the business cycle, the state of the market, or volatility. Finally, we document that excessive selling of loser stocks by institutions predicts reversals of the momentum strategy, even after controlling for several state variables employed in prior studies.

In relating these findings to existing behavioral theories about momentum profits, we note that in general momentum profits can be explained by overreaction to information, underreaction or a combination.[4] Hong and Stein (1999) and Grinblatt and Han (2005)

[4]For overreaction models, see De Long, Shleifer, Summers, and Waldmann (1990); for underreaction models, see Barberis, Shleifer, and Vishny (1998) and Grinblatt and Han (2005); for underreaction models

offer interesting models in this context, in that they explicitly model the interaction between different agents in the market to explain the momentum anomaly. Our finding that private investors are strongly contrarian is consistent with Grinblatt and Han's (2005) evidence that investors prone to the disposition effect (private investors) generate price distortions, underpricing winners and overpricing losers, which in turn are exploited by rational investors (institutional and foreign investors). Because the momentum trading strategy yields a positive average return in Germany, the momentum trading of institutions can be regarded as sophisticated. The finding that, within the group of private investors, less sophisticated investors are more contrarian corroborates this view. According to Hong and Stein (1999) and Stein (2009), arbitrageurs try to exploit underreactions to news by other investors. However, excessive momentum trading in the market can lead to an overreaction of arbitrageurs, pushing prices above/below their fundamental values and leading to a (long-term) reversal of returns. Our evidence of the excessive sales of loser stocks by institutional investors followed by the momentum reversal in 2009 is consistent with the models of Hong and Stein (1999) and Stein (2009). However, other explanations as to why institutions excessively sold losers during the financial crisis also come to mind, such as stop-loss orders. We provide empirical evidence in support of Vayanos and Woolley's (2013) model, which stresses the role of institutional investors and delegated portfolio management for explaining momentum and reversals. Particularly, we find that the sale of loser stocks by institutions and foreign investors in bad economic states forecasts reversals in the momentum strategy.

Data from the SHS offer several advantages for studying both the momentum and contrarian trading by different investors. First, it offers information on the holdings of *all* market participants, with very few exceptions, whereas the widely used 13-F filings of the U.S. Securities and Exchange Commission (SEC) are restricted to the holdings of large institutions. Data sets that cover all investors in the market include Finnish

followed by overreaction, see Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999). In addition to behavioral models of the momentum anomaly, there are also some rational explanations, such as that by Conrad and Kaul (1998).

transaction data (Grinblatt and Keloharju, 2000, 2001) and Taiwanese transaction data (Barber, Lee, Liu, and Odean, 2009). Second, the German stock market, which is the seventh largest in the world and the third largest in Europe,[5] provides a broad range of stocks, which is a necessary precondition to test trading on the cross-sectional momentum return anomaly. Third, Germany is appropriate for studying investors' momentum trading, because the momentum strategy is highly profitable in this market, unlike in Asia, where the momentum effect is weak or non-existent (e.g., Griffin et al., 2003; Chui, Titman, and Wei, 2010).

In turn, this study contributes to several strands of literature that tend to investigate the behavior of different investor groups in isolation. For example, different strands of literature separately study the behavior of institutional or private investors. Literature on institutional ownership and trading (e.g., Gompers and Metrick, 2001; Bennett et al., 2003) mostly uses quarterly SEC filings. Some studies focus on a subset of institutional investors, such as trading by pension funds (e.g., Lakonishok et al., 1992) or mutual funds (e.g., Grinblatt et al., 1995; Wermers, 1999). Evidence about the momentum trading of institutions is mixed (Sias, 2007). We add to this literature by showing strong evidence of momentum trading by financial institutions but also documenting the sizable heterogeneity among different types of institutions, notably, mutual funds, banks, and insurance companies and pension funds. Most studies of trading by individual investors use proprietary brokerage data, as introduced by the seminal works by Odean (1998, 1999). Although highly detailed, brokerage data cover only a small fraction of all private investors and often are limited to shorter sample periods. Thus, in contrast with institutional ownership literature, studies of trading by private investors mostly uses higher frequencies. Overall, different data sources and sample periods make it difficult to comprehend the interplay among the existing investor groups in the market, but with the exceptional data from Finland (Grinblatt and Keloharju, 2000, 2001) and Taiwan (Barber et al., 2009), as

[5]This ranking is based on the total market capitalization of domestic corporations listed on the country's stock exchange at the end of 2012. Source: World Development Indicators 2014, The World Bank. http://data.worldbank.org/indicator/CM.MKT.LCAP.CD/countries/1W

well as German holdings data, it is possible to study the trading of *all* investors in the market.

Several studies document also behavioral biases in households' trading (e.g., Odean, 1998), leading many researchers to regard private investors as noise traders. If their trading is uncorrelated, the price effect would cancel out within the group of private investors and be negligible. However, if private investors' trading is correlated, it could affect prices due to limits to arbitrage (Shleifer, 2000; Barber, Odean, and Zhu, 2009a,b). With our data set, we can quantify the aggregate demand of private households in the stock market.[6] We thus contribute to the literature by documenting that private investors' demand does not cancel out but instead can be considered systematic. In particular, we find that private investors' demand relates strongly negatively to past prices, even across wider horizons.

Recent literature also notes the phenomenon of momentum crashes (e.g., Daniel et al., 2012; Daniel and Moskowitz, 2013; Barroso and Santa-Clara, 2014), focusing on the predictability of such crashes and their hedging. We add to this literature by studying the momentum trading of market participants around the crash in 2009. In contrast with the dynamic momentum trading strategies proposed by Daniel and Moskowitz (2013) and Barroso and Santa-Clara (2014), which would reduce exposure to momentum in volatile periods, institutional investors actually increased their momentum trading during that time. Moreover, we find that the strong sales of loser stocks relate significantly to time-varying momentum profits, after controlling for the economic state variables. To the best of our knowledge, this study is the first to employ excessive momentum (loser) trading to forecast reversals in the momentum strategy. Our findings that momentum trading in the loser portfolio increases during market downturns and volatile times and also forecasts momentum returns thus contributes to research into time-varying momentum profits (e.g., Chordia and Shivakumar, 2002; Cooper, Gutierrez, and Hameed, 2004).

[6] The complement to the aggregated institutional holdings from the 13-F SEC filings does not represent small individual investors, because large holdings by households, small institutions, and smaller positions of institutions are not subject to SEC filings (cf. Barber et al., 2009a). See Section 2.1 for a detailed discussion.

Although our study reveals some links to Grinblatt and Keloharju (2000), it differs in several important respects. Whereas Grinblatt and Keloharju (2000) use transaction data about all market participants, we employ holdings data. Moreover, the studies differ in the frequency and horizon over which momentum is measured. Grinblatt and Keloharju (2000) study daily trading by different investor types in the Finnish stock market over two years, using a sample of 16 stocks and focusing on short-term momentum. In contrast, we study quarterly ownership changes in the vast cross-section of the entire German stock market over seven years, considering momentum measured over a horizon of one to four quarters. Finally, our sample period enables us to study momentum trading at different stages of the economy, because the time period covers not just prosperous economic periods but also the global financial crisis of 2008/2009, along with the biggest economic downturn in Germany's postwar history.

2 Data and descriptive statistics

2.1 Description of data sources

We obtain stock holdings data from the mandatory quarterly filings by German financial institutions with the SHS, a centralized register of security ownership maintained by the Deutsche Bundesbank. The SHS are collected through a full census of all relevant financial institutions located in Germany including those that offer the service of safe custody of securities. Financial institutions are obliged to report their own securities holdings, along with those of their customers. Customers' securities holdings are broken down by investor sector and customer nationality.[7]

The full census and investor categorization represent the main differences between the SHS and the U.S. 13-F SEC filings, which are a commonly used data source in the ownership literature. Whereas the SHS provide a full census of all institutional and individual investors, only large institutional investors with an investment discretion of

[7]For technical documentation on the SHS database, see Amann, Baltzer, and Schrape (2012).

$100 million or more are 13-F filers. Small institutional holdings, with fewer than 10,000 shares and less than $200,000, do not have to file this form. Moreover, institutions may be exempted from 13-F filings (Badrinath and Wahal, 2002; Lewellen, 2011). An additional limitation of 13-F filings, as noted by Del Guercio (1996), is that managers typically pool all client accounts in one filing. For example, bank trust accounts can contain holdings of wealthy individuals and corporate pension plan clients, which are subject to different regulations. The reporting to the SHS instead separates the banks' own holdings and breaks down customer accounts into different investor types, following the European System of Accounts (ESA95) standards. The standardized SHS categorization enables us to distinguish the holdings of different institutional investors consistently over time, which represents another advantage over 13-F filings. Furthermore, the categorization of different institutional investors by the Thomson Reuters CDA/Spectrum database is potentially faulty, as noted by Bennett et al. (2003) and Lewellen (2011). In particular, Lewellen (2011) notes time inconsistencies in the investor categorization provided by Thomson Reuters from 1998 onwards. The 13-F filings are publicly disclosed; the holdings reported to the SHS are not. Holdings are not only filed by institutions to the SHS but also screened by the statistics department of the Deutsche Bundesbank, using multiple plausibility checks. Potential mistakes undergo reviews by the Bundesbank's staff, who contact the respective banks if necessary. This screening ensures that SHS holdings data are of very high quality.

From these filings, we extract the aggregate quarterly share holdings pertaining to the banks' own portfolios and their customers' portfolios, starting the fourth quarter of 2005, the earliest available date, to the fourth quarter of 2012, on a security-by-security basis. In our investor categorization, we follow ESA95 standards. We first distinguish between foreign and domestic investors. We divide domestic investors into private (or households)[8] and institutional. Moreover, the SHS provide greater detail about the rather heterogeneous composition of institutional investors: We can distinguish between non-financial and financial investors, and we can divide financial institutions further into banks'

[8]We use the terms private investors and households interchangeably.

own holdings, mutual funds, insurance companies and pension funds, as well as a group of other financial investors. Appendix A provides the details of this investor categorization.

We cannot apply the same detailed classification system to foreign investors. Most of the foreign customer groups are classified as "foreign banks" or "foreign central securities depositories", both of which might contain portfolios for different types of foreign investors. Thus, similar to Grinblatt and Keloharju (2000), we cannot disentangle different types of foreign investors. However, the overwhelming majority of foreign investors tend to be institutional investors, as noted by Dahlquist and Robertsson (2001). Even if foreign investors cannot be classified by investor type, the majority of foreign investors' shares are registered in the SHS because they are being held in safekeeping at a German bank or central securities depository. Domestic and foreign owners in the SHS together make up 94.1% of the shares outstanding on average and 95.7% of the total market capitalization of German stocks. The remaining shares are likely held in safekeeping outside Germany, so we classify them as foreign investors as well.

We merge the ownership data of the SHS with securities characteristics from Thomson Reuters Datastream. To merge the two databases, we follow previous literature that relies on international or German stock market data (e.g. Schmidt, Von Arx, Schrimpf, Wagner, and Ziegler, 2011; Karolyi, Lee, and van Dijk, 2012) and start with the Datastream research lists of German stocks, including currently traded and delisted stocks. We apply several filters to obtain stocks classified as domestic common equity and protect against possible data errors in Datastream (Ince and Porter, 2006), as we detail in Appendix A. The resulting universe of the German stock market is comparable to that used in other international studies.[9] We then merge the resulting stocks with the holdings data of the SHS database, using historical International Securities Identification Numbers

[9]We exclude Volkswagen from our sample to prevent the 2008 short squeeze from affecting our results. That is, in October 2008, a short squeeze briefly made Volkswagen the most valuable company in the world. See *The Economist*: "VW and hedge funds: Squeezing the accelerator", October 29, 2008.

(ISINs).[10] The average percentage of stocks matched is 98.7%, or 99.8% in terms of market capitalization.

2.2 Descriptive statistics

Table 1 provides summary statistics for the ownership structure in the German stock market. For each stock i, we calculate the ownership share of investor group j: $OS_{i,j,t} = N_{i,j,t}/N_{i,t}$, where $N_{i,j,t}$ is the number of shares of stock i held by investor group j at time t, and $N_{i,t}$ is the total number of shares outstanding. To mitigate the spurious effect of large outliers, particular in small stocks, we winsorize changes in the ownership share at 2.5%. As Panel A reveals, the average fractional ownership share of foreign investors is 34.5%, that of private investors is 29.4%, and that of institutional investors is 34.9%, with a relatively large fraction of non-financial institutional investors (27.6%) compared with financial investors (7.3%). This relatively large fraction of non-financial institutional investors is a special feature of the German corporate ownership landscape. On the one hand, non-financial investors' shares can represent cross-holdings, which were widespread in Germany and are still quite common.[11] On the other hand, family-owned company shares are usually classified as non-financial, because they are often held through an investment company, which is then classified as non-financial by ESA95. Thus non-financial investors generally can be regarded as strategic, long-term investors. The value-weighted average differs considerably, indicating 56.3% foreign investors, 12.7% private investors, 15.1% non-financial institutional investors, and 13.8% financial institutional investors. The difference between the equally and value-weighted average holdings shares indicates a preference for large-cap stocks by financial investors (banks, mutual funds and insurance companies)

[10] We thank Christopher Fink, Thomas Johann, Erik Theissen, and Christian Westheide for providing us with the matching tables of historical and current ISINs for the German regulated market (CDAX). We manually collected the remaining historical ISINs from the Deutsche Börse Xetra Newsboard.

[11] Corporate cross-holdings result from a specific German phenomenon, the "Deutschland AG", which was predominant until the end of twentieth century. Most German companies listed on the stock exchange were mutually owned by a relatively small network of other companies and banks, to control one another and ensure that outsiders could not gain excessive influence by purchasing shares. Although these insular, cross-shareholding structures have been breaking down in recent decades, we still find a relatively high ownership share of non-financial corporations in our data.

and foreign investors (predominantly financial investors). This large-cap preference is consistent with prior literature (e.g., Dahlquist and Robertsson, 2001; Bennett et al., 2003; Sias, 2007).

Our variable of interest is the change in fractional ownership share: $\Delta OS_{i,j,t} = OS_{i,j,t} - OS_{i,j,t-1}$, which measures investor groups' demand for a specific stock (Sias, 2007). We provide the descriptive statistics about the change in ownership share in Panel B of Table 1. Because the change in ownership depends on the level of ownership, the standard deviation and interquartile range of ΔOS vary considerably across investor groups, which we account for throughout our analyses.

As mentioned previously, the momentum investment strategy is highly profitable in Germany. With our quarterly data frequency, we consider a slightly modified momentum strategy, such that we base the winner and loser portfolio on the past returns over one to four quarters. Following Jegadeesh and Titman (1993), we form equally weighted portfolios (winners and losers) of the top 30% and bottom 30%. The momentum strategy buys winners and sells losers over a holding period of one quarter. With regard to the momentum profits, our approach thus is more conservative than commonly applied procedures: First, rebalancing takes place only each quarter, instead of every month. Second, we do not skip one month between the ranking period and the formation date to avoid the short-run reversal documented by Jegadeesh (1990) and Lehmann (1990). Despite our conservative approach, the short sample period, and the coverage of the 2009 crash, the momentum investment strategy described above yields a statistically and economically significant return. Momentum strategies based on the past two and four quarters yield annualized returns of 9.39% (t-value: 2.00) and 11.19% (t-value: 1.82), respectively.[12]

[12]The momentum effect is robust across different formation and holding periods. Table A.1 in the Internet appendix contains further details. We apply equal-weighting in this study, but the momentum effect is also present for different weighting schemes. For example, an investment strategy based on value-weighted portfolios from a (2x3) sort on market capitalization and the past 2-11 months return, as described by Fama and French (2012), $WML = 1/2(\text{Small Winner} + \text{Big Winner}) - 1/2(\text{Small Loser} + \text{Big Loser})$, also yields an economically large return. The annualized return of such a strategy is 11.94% (t-value: 1.65) in the seven-year sample period, comparable to the overall return of 9.97% (t-value: 4.29) in the sample period 1965-2012. See Brückner et al. (2013).

Although the momentum strategy performed very well on average, it also suffered large losses during our sample period, as Figure 1 reveals, according to the performance of the momentum investment strategy over time, employing monthly and quarterly portfolio formations. In the second and third quarter of 2009, the WML strategy yielded returns of -25.62% and -11.63%, respectively. The momentum crash occurred at a point in time when the German stock market was rebounding; the crash resulted when the loser portfolio suddenly outperformed the winner portfolio, with returns of 34.64% and 18.11% in the second and third quarters of 2009, compared with returns of 9.02% and 6.48% in the winner portfolio. The course and magnitude of the momentum crash in Germany were remarkably similar to those in the U.S., which also occurred around the time the market started to recover (Daniel and Moskowitz, 2013).

3 Which investor types are momentum traders?

3.1 Portfolio sorts

Considering the strong performance of the momentum strategy, a natural question that arises is which investor groups trade on stocks that exhibit price momentum. We examine, for each investor group, how demand for a stock relates to its past returns. To measure investor type-specific stock demand, we compute the aggregate change in stock holdings for each investor group, which is a well-established measure in institutional trading literature (e.g., Bennett et al., 2003; Sias, 2007).

As a first test to identify investor types that are momentum traders on average, we conduct a simple sort of the stock universe according to past performance (cf. Sias, 2007). We form three portfolios using the 30th and 70th percentile of the lag cumulative return as breakpoints, which we refer to as the loser, middle, and winner portfolio, respectively. Within each portfolio, we compute the stocks' average change in ownership for each investor type and the difference between the winner and loser portfolios. A positive (negative) difference in investor ownership change between the winner and loser portfolio indicates momentum (contrarian) trading. In contrast with Sias (2007), we measure the ownership change after the momentum formation period. The rationale for using lagged quarterly returns instead of contemporaneous or overlapping formation period returns, is that we want to strictly identify trading in response to past returns. Using (partially) contemporaneous returns does not allow for a clear inference and interpretation of results. By using only the past return as a sorting criterion, we take a conservative approach that ensures the availability of public information at the time of portfolio formation.

The results in Table 2 report the average change in ownership for the loser, middle, and winner portfolios, as well as the difference between the winner and loser portfolios. By sorting stocks according to their returns of the previous one, two, and four quarters (Panels A to C of Table 2), we uncover initial evidence of momentum trading by foreign investors. The results show a strong positive relation between the change in foreign ownership and the cumulative past return. For example, considering the results of the two-quarter formation period, we find that foreign investors, on average, decrease their ownership share in loser stocks by 0.35 percentage points of the stocks' market capitalization, whereas the average demand for winner stocks is around 0.12 percentage points. The difference between the ownership change of foreign investors in the upper and lower lag return portfolio thus is 0.47 percentage points, which is statistically significant at the 1% level. Overall, with a longer time period, a much larger cross-section of stocks, and a different methodology than Grinblatt and Keloharju (2000), we confirm their findings about momentum trading by foreign investors.

Because foreign investors are momentum traders, domestic investors must be contrarians, due to the market clearing condition. Yet a closer look at the structure of domestic investors, however, reveals that private households completely account for the contrarian trading of domestic investors. This finding is in accordance with literature on the disposition effect and the trading of retail investors, as initially documented by Odean (1998). He shows that retail investors of a large U.S. discount brokerage house tend to realize winners and stick to losers.

Furthermore, the sorting exercise indicates that domestic institutional investors increase their ownership in stocks that have performed well and decrease their holdings of stocks that have performed poorly. This finding is in line with a series of studies that analyze the trading of institutional investors (e.g., Bennett et al., 2003; Sias, 2007; Yan and Zhang, 2009). According to Table 2, mutual funds in particular engage in momentum trading. This finding confirms previous studies of mutual funds and their positive trading on past returns in the U.S. equity market (Grinblatt et al., 1995; Badrinath and Wahal, 2002). Overall, investor groups considered (more) sophisticated (i.e., foreign financial institutions and domestic mutual funds) are more likely to engage in momentum trading, at the expense of individual investors. Contrarian trading by private investors is economically substantial, with a demand differential between winner and loser stocks of 0.57 percentage points. To put this figure into perspective, we compare it to the inter-quartile range of private investors' ownership change, which amounts to 0.77 percentage points.

Surprisingly, the portfolio sorts show that non-financial investors engage partly in momentum trading, which is puzzling: non-financial investors are generally long-term, strategic investors. However, Table 2 only provides initial evidence about heterogeneity in momentum trading across different investor types, so we need to treat these results with caution. Other stock characteristics, closely related to past returns, could induce the correlation between lag return and change in ownership. For example, according to Bennett et al. (2003) and Sias (2007), institutional investors prefer larger stocks which might have increased in market capitalization due to their large past returns. In this case, it would not be the lagged return that drives stock demand but rather the size of the firm. Thus, in the next step we employ regression estimations with a plethora of control variables to answer the question asked in the heading of this section.

3.2 Regression approach

We regress the change in ownership on cumulative past returns and account for several control variables from prior literature (e.g., Gompers and Metrick, 2001), as follows:

$$\Delta OS_{i,j,t} = \alpha + \beta_1 Ret_{i,t-k,t-1} + \gamma Controls_{i,t-1} + \varepsilon_{i,j,t}, \tag{1}$$

where $\Delta OS_{i,j,t}$ is the ownership change in stock i during quarter t of investor group j, and $Ret_{i,t-k,t-1}$ is the cumulative return over the past k quarters. The stock-specific controls are the size, book-to-market ratio, beta, volatility, age, dividend yield, share price, a dummy for membership in four major German stock indices (DAX, MDAX, SDAX, and TechDAX), and turnover. We lag all explanatory variables by one quarter to ensure that investors can react on the information available at the time of their trade. Explanatory variables are winsorized at the 1% level, to mitigate any spurious effect of outliers. To make the regression coefficients comparable across investor groups (and time) we follow Bennett et al. (2003) and standardize both the dependent and the independent variables (except the index dummy) at each point of time. That is, in each quarter, we subtract the cross-sectional average and divide by the cross-sectional standard deviation of the variable. In addition to the comparability of the estimation coefficients across variables and investor types, we naturally introduce time-fixed effects by virtue of the cross-sectional standardization. We estimate coefficients using pooled ordinary least squares (OLS). To account for autocorrelation and cross-correlation of the error terms, we compute t-statistics with two-way clustered standard errors (by stock and quarter), as suggested by Petersen (2009). Procedurally, we use the methodology that Thompson (2011) proposes to calculate the variance-covariance matrix.[13]

[13] Alternatively, we use the Fama and MacBeth (1973) regression framework and run, for each quarter, cross-sectional regressions of standardized changes in investor ownership on standardized past returns and the control variables. Then, we calculate the time-series average of the cross-sectional regression coefficients, along with standard errors adjusted according to Newey and West (1987). When there is only a time effect (no firm effect) the standard errors estimated by Fama and MacBeth (1973) are unbiased. Newey and West (1987) standard errors account for serial autocorrelation in error terms. Overall, the Fama and MacBeth (1973) estimations yield qualitatively similar results as our baseline OLS estimations (see Table A.2).

Table 3 reports the regression results using the previous two quarters' returns and controls as explanatory variables for investor ownership changes. We largely confirm the results from Section 3.1 regarding the degree of momentum trading of different investor groups, even after controlling for several other variables. Foreign investors are momentum traders. Purchases by foreign investors are sales by domestic investors, so the latter must be contrarian investors. However, not all domestic investors are contrarian; again, the contrarian trading is driven mainly by private households. Institutional investors as a group are momentum traders, which supports the findings in the U.S. market (e.g. Bennett et al., 2003), Sias (2007) and Yan and Zhang (2009). Momentum trading is mainly pursued by financial investors, in particular mutual funds and banks. However, there is no evidence that insurance companies and pension funds, and other financial institutions are momentum traders.

In addition to past returns, other variables are important determinants of net purchases by different investor groups. Similar to Dahlquist and Robertsson (2001), we find that foreign investors have a lower, albeit insignificant, preference for dividends relative to private households, which show a strong preference for high-dividend stocks. Foreign investors are also net buyers of stocks listed in one of the leading German stock market indices, even after controlling for turnover as a liquidity proxy, which indicates that visibility or index tracking have important influences on foreign investors' investment decisions.

In contrast with the portfolio sorts, momentum trading by institutional investors is mainly driven by financial institutions. Non-financial institutions do not trade on momentum. Bearing the portfolio sorts in mind, this result highlights the importance of controlling for other firm and stock characteristics that might falsely drive the (non)existent relationship between stocks' past returns and investors' stock preference. Furthermore, a larger cross-section (as opposed to three portfolios sorted by past returns) offers a more powerful analysis to be made and paints the complete picture of each effect.

The degree of momentum trading is by no means homogeneous across different types of financial institutions. As we documented previously, momentum trading is mostly followed by mutual funds, with a coefficient of 0.06 and an economic magnitude equivalent to three times the size of banks' momentum trading.

Overall, past returns are an important determinant of net purchases across the investigated investor groups. A one standard deviation increase in the past two-quarter return decreases private investors' net purchases by 0.12 standard deviations, making it by far the most important determinant of private households' trading among all incorporated firm and stock characteristics.

To confirm that these results are not driven by the choice of the momentum formation period, we perform the regressions in Table 3 using different horizons of cumulative past returns. Specifically, we employ the cumulative return of the past one, two, three, and four quarters and the contemporaneous return as our main explanatory variable. Table 4 contains a summary of the coefficients to the lag return variables, omitting the remaining control variables for brevity. The momentum trading of foreign investors and mutual funds is robust and strong across all horizons of the formation period. Both investor types' trading even relates positively to the stock's contemporaneous quarterly return. The results from these different specifications thus strengthen the findings of the portfolio sorts.

The contrarian trading of private households decreases with the length of the formation period. This finding is in line with, but distinct from Barber et al.'s (2009b) findings. They reveal strong contrarian trading by private investors only in the short run; we find that this behavior is very strong in the short run and decreases with the horizon but still remains significant for at least four quarters.

Evidence on banks' trading behavior is somewhat less clear. For all formation period horizons, we find a positive coefficient to lagged returns, significant across all four specifications. In contrast with the momentum trading on lagged returns, we find a negative coefficient for the contemporaneous quarterly return. This finding suggests that banks serve as liquidity providers for foreign and domestic institutional investors that demand immediacy. Finally, the results for mutual funds and banks are reflected in the trading behavior of financial institutions that are momentum traders, using past returns up to four quarters, but that do not show any reaction to contemporaneous returns. We confirm the results of the previous regression and find that non-financial investors are neutral to trading on past returns. With the exception of the marginally significant positive loading on one past quarter's return, we observe neither momentum nor contrarian trading on the part of non-financial institutions.

In summary, our regression analysis identifies strong contrarian trading behavior by private investors. On the other side of these trades are financial institutions, in particular mutual funds and foreign investors – which are predominantly financial investors as well – that engage in momentum trading.

These findings resonate with the model of Grinblatt and Han (2005), according to which investors prone to the disposition effect (Shefrin and Statman, 1985) hold on to their losing stocks too long and sell their winners too soon, thereby creating selling pressure for winner stocks and buying pressure for loser stocks. This demand distortion leads to an information underreaction, where winners are undervalued and losers overvalued. Rational investors exploit this mispricing, but due to limits of arbitrage, the prices only converge slowly, giving rise to momentum profits.

Grinblatt and Han (2005) do not specify which investors are prone to the disposition effect, but empirical evidence suggests that the disposition effect is stronger among private investors than among institutional investors (e.g., Barber, Lee, Liu, and Odean, 2007; Choe and Eom, 2009). If we aggregate all investors that exhibit a stronger disposition effect (relative to other market participants), their aggregate demand is contrarian. Thus, our findings are consistent with Grinblatt and Han's (2005) theory. Investors that exhibit a pronounced disposition effect (private investors) express a positive aggregate demand for loser stocks and a negative demand for winner stocks. More sophisticated investors (institutions and foreign investors) exploit this behavior by following a momentum trading strategy.

3.3 Buying winners or selling losers?

The momentum strategy consists of buying winners and selling losers. In the context of this study, a natural question is whether investors' momentum trading differs between the winner and loser portfolios. To answer this question, we perform piece-wise linear regressions with the median of the cumulative lag return as a knot:

$$\begin{aligned}\Delta OS_{i,j,t} &= \alpha + \beta_1 Ret_{Loser,i,t-k,t-1} + \beta_2 Ret_{Winner,i,t-k,t-1} \\ &\quad + \gamma Controls_{i,t-1} + \varepsilon_{i,j,t},\end{aligned} \tag{2}$$

where $Ret_{Loser,i,t-k,t-1} = min(Ret_{i,t-k,t-1}; \widetilde{Ret}_{t-k,t-1})$ and $Ret_{Winner,i,t-k,t-1} = max(Ret_{i,t-k,t-1} - \widetilde{Ret}_{t-k,t-1}; 0)$, such that $\widetilde{Ret}_{t-k,t-1}$ represents the median cumulative return. The piece-wise linear regression – widely used in the flow-performance literature of mutual funds (see Sirri and Tufano, 1998) – enables us to estimate two different regression coefficients for the past return variable. One estimated slope refers to the segment below the median past return, whereas the other slope refers to the segment above the median. Stocks above (below) the cross-sectional median are winner (loser) stocks. A positive coefficient associated with the above (below) median sample indicates that the investor group buys winners (sells losers) on average. The estimation procedure is similar to the initial regression framework, in Equation (1), but it allows for a kink in the regression line at the lag median return.

Table 5 reports the standardized regression coefficients for the lag return variables. Again, we omit the control variables for brevity. The regressions reveal a clear pattern: Momentum/contrarian trading is stronger among loser stocks than among winner stocks. However, there are notable differences among investor groups. Regarding private households, the influence of past returns on the change in ownership is impressive if a stock's past return is below the median. For example, a decrease in the return of the past two quarters increases the change in ownership of private investors by more than one fourth of its standard deviation. The effect of contrarian trading is much weaker for well-performing stocks (selling winner stocks). Foreign investors and mutual funds are on the other side of these trades, and the momentum trading of foreign investors is limited to the loser portfolio. For winners, the coefficient is insignificant and small in economic terms. In contrast, mutual funds are momentum traders in both the winner and loser portfolios, though momentum trading among winners is not as pronounced. Our finding that mutual funds buy winners and sell losers stands in contrast with Grinblatt et al.'s (1995) finding of significant momentum trading only on the winner's side.

3.4 Financial sophistication and contrarian trading of private investors

In the preceding analysis, aggregate private investors' demand relates negatively to past stock performance, in accordance with Grinblatt and Han's (2005) model, in which less sophisticated investors prone to the disposition effect (i.e., private investors) underreact to information, giving rise to momentum profits.

A general assumption in prior literature indicates that institutional investors are more sophisticated than private investors. Selling losers and buying winners is a highly profitable strategy, supporting the notion that momentum trading by institutions reflects investor sophistication. To confirm this link between contrarian trading and investor sophistication, we investigate the differences in households in more detail. Substantial literature already links the disposition effect to investor sophistication (Feng and Seasholes, 2005; Dhar and Zhu, 2006) and reveals a negative relationship between the two variables. Consequently, we expect the degree of contrarian trading of private investors to depend strongly on their sophistication.

To test the effect of investor sophistication on the degree of momentum trading, we disaggregate the change in the ownership share of private investors using bank-stock-level data from the SHS. That is, we look at the change in ownership share of the private investors in each bank for each stock, rather than the aggregate change in ownership of the investors at the stock level. The bank-specific definition of private investors' stock demand creates cross-sectional heterogeneity across private investors and allows us to assign a bank-related proxy for investor sophistication to each bank-stock observation.

We employ two proxies for investor sophistication: investors' average financial wealth and equity home bias (French and Poterba, 1991). Both variables have been used previously as proxies for the financial sophistication of investors (Dhar and Zhu, 2006; Kimball and Shumway, 2010). For each bank, we calculate average financial wealth as the total market value of all assets of private investors, divided by the total number of accounts. To compute the home bias, we divide the domestic equity share by the share of the German stock market in worldwide market capitalization. We take the natural logarithm of both variables to avoid a skewed distribution of the proxies.[14]

In contrast with our previous tests, for which we used the change in ownership share of each investor group as the main dependent variable, in this section we account for the large difference in aggregate private investor portfolios across banks. That is, due to the greater number of customers in large banks relative to smaller banks, the variation of the change in ownership share for each stock is driven mainly by banks with a larger number and/or greater size of private investor portfolios. To avoid misleading inferences, we scale the ownership share change of banks' private investors by the level of ownership share of the very same banks' private investors in the previous quarter. This variable can be interpreted as the relative change in ownership share.

To test whether the contrarian trading of private investors relates to investors' sophistication, we run a pooled OLS regression with time-fixed and bank-type-fixed effects:

$$\begin{aligned}\frac{\Delta OS_{i,j=PO,l,t}}{OS_{i,j=PO,l,t-1}} =& \alpha + \beta_1 Ret_{i,t-k,t-1} + \beta_2 Ret_{i,t-k,t-1} \times I_{l,t-1} + \beta_3 I_{l,t-1} \\ &+ \gamma Controls_{i,t-1} + \varepsilon_{i,j=PO,l,t}\end{aligned} \quad (3)$$

[14]Summary statistics on the sophistication proxies are available in Table A.3 in the internet appendix.

where $\frac{\Delta OS_{i,j=PO,l,t}}{OS_{i,j=PO,l,t-1}}$ denotes the relative change in the ownership share of private investors of bank l in stock i, and $I_{l,t-1}$ is either the financial wealth or home bias related to private investors of bank l. The remaining variables are defined as in the previous regression framework (see Section 3.2).

First, in line with the results for the aggregate stock-level regression of the change in private ownership share, we expect to observe contrarian trading within the sample of private investors and the β_1 coefficient to have a negative sign. Second, if the contrarian trading of private investors weakens with their financial sophistication, we expect that the coefficient of the interaction term, β_2, should have a positive (negative) sign when we replace the interaction variable I with average financial wealth (equity home bias). Third, we control for investor sophistication and all the standard control variables from the previous sections.

Table 6 provides the regression coefficients for the past return variable, the coefficients for the interaction terms, and the sophistication of the investors. Using two (Panel A) and four (Panel B) quarters as formation periods for the lag return, we find that the relative change in ownership share relates negatively to the lag stock performance. As expected, the result of the first specification in Column (1) confirms the previous results on contrarian trading of private investors at the aggregate stock level. In Column (2), we use financial wealth as the investor sophistication proxy and find a highly significant, positive regression coefficient of the interaction term. In Column (3), the interaction term with equity home bias, which proxies for investors' lack of sophistication, reveals a negative coefficient. The regression results thus are in line with our expectations: Increasing average home bias (decreasing investor sophistication) among investors is associated with stronger contrarian trading by private investors. Even when we account for both interaction terms in one specification, as in Column (4), the results remain largely unchanged.

The effect of investors' financial wealth and equity home bias on their contrarian trading also indicates a sizable economic magnitude. Using the interquartile range of the logarithmized average financial wealth (0.55), multiplied by the interaction coefficient estimate (0.07), we document a 55% decline in contrarian trading for the formation period of four quarters (Panel B). For the formation period horizon of four quarters, a decline in the home bias by its inter-quartile range is associated with a drop in private investors' contrarian trading by about 23%. Regarding the pervasive and strong average returns of the momentum strategy in Germany, our findings raise concerns about the contrarian trading of private investors, particularly those associated with lower financial wealth and stronger home bias.

4 Momentum trading over time

4.1 Momentum trading and economic state variables

Thus far we have established which investors are momentum or contrarian traders on average over the entire sample period. However, several studies find that momentum profits vary considerably over time (e.g., Chordia and Shivakumar, 2002; Cooper et al., 2004; Wang and Xu, 2010). The momentum crash of 2009 in our sample period represents an extreme example of time-varying momentum profits. Thus, we investigate how trading on the momentum anomaly develops over time and how it relates to the profitability of the momentum strategy.

Prior literature proposes several state variables to predict momentum profits.[15] Chordia and Shivakumar (2002) find that the momentum strategy is profitable during expansions but not in recessions. Antoniou, Doukas, and Subrahmanyam (2010) relate investor sentiment positively to momentum profits. Cooper et al. (2004) find that momentum profits depend on the state of the market, such that the momentum strategy is profitable following positive market returns but unprofitable after negative market returns. Wang and Xu (2010) and Barroso and Santa-Clara (2014) find that the realized volatility of the market and the WML portfolio predicts low momentum profits. From a risk-based

[15] For a survey, see Jegadeesh and Titman (2011).

perspective, these findings are puzzling though, because a momentum strategy generates high returns following good times and low returns following bad ones.

In our analysis, we study trading by all private households (contrarian traders) and their counterparts, institutional and foreign investors (momentum traders), over time. We focus on momentum trading by all non-households (i.e. all institutional investors plus all foreign investors), such that the reciprocal of our measure is contrarian trading of households, by construction. To measure the degree of momentum trading over time, we proceed as in Section 3.1 and Table 2 by sorting stocks into winner and loser portfolios, according to their past returns. The portfolio cutoffs again are the 30th and 70th percentiles, and past returns are measured over different formation horizons of one to four quarters. At each point in time, we calculate the average demand (i.e., change in ownership share) of non-household investors in the winner and loser portfolios, as well as the demand differential between winners and losers. Figure 2 displays the results of this exercise.

Two key findings emerge from Figure 2(a), which shows the difference in demand between the winner and loser portfolios over time. First, the momentum trading measure for non-households is generally positive during the sample period. In no time periods is this relationship inverted. That is, we do not observe considerable contrarian trading by this investor group, even though at some points in time, the demand differential between winners and losers is close to zero. Second, the degree of momentum trading varies remarkably over time, such that it increased rapidly and considerably above its sample average during the Great Recession and the accompanying market downturn, just before the momentum crash. The time series average of the momentum trading measure for a formation period of two quarters is 0.57 (see Table 2, Panel B), but it increased above 1.5 during the recession.

Figures 2(b) and 2(c) separately display the ownership changes in the winner and loser portfolios, revealing that time variation in momentum trading is considerably stronger in the loser portfolio than in the winner portfolio. The peak in momentum trading during the Great Recession can be attributed entirely to the sale of losers. Thus, there was excessive selling of losers by foreign and institutional investors during the recession, which was followed by the momentum crash in 2009, when losers suddenly outperformed winners (Daniel and Moskowitz, 2013). This sequence of events supports overreaction as an explanation for the momentum crash. Strong selling pressures pushed the prices of losers below their fundamental value, leading to a strong reversal in 2009.

To relate momentum trading to various state variables that predict momentum profits, we run univariate time-series regressions of the momentum trading measure on these state variables. We include the following conditioning variables: real GDP growth; two economic sentiment indices provided by the Centre for European Economic Research (Zentrum für Europäische Wirtschaftsforschung, ZEW), Mannheim, and the Ifo Institute for Economic Research, Munich, both based on surveys of future economic expectations; the 12-month market return; and the realized volatility of the market return and the WML portfolio. The regression results are in Table 7.

The observations from Figure 2 are confirmed by considering the contemporaneous relationship of our momentum trading measure with the state variables. Panel A shows how momentum trading - that is, the demand differential between the winner and loser portfolio - relates to the aforementioned state variables. It relates negatively to GDP growth, the two economic sentiment variables, and the market return. Furthermore, momentum trading is positively associated with the realized volatility of both the market and the WML strategy. State variables that predict low momentum profits thus are positively related to momentum trading, and state variables that predict high momentum profits are negatively related to it. In Panels B and C, we look at the winner and loser portfolios separately, which reveals a discernable pattern: The sale of losers is strongly related to stock market and business cycle state variables, but the purchase of winners is unrelated to these variables. The coefficients for the regression of ownership change in the loser portfolio on the state variables GDP growth, economic sentiment, and market return are positive, whereas they are negative for the volatility measures, such that non-households reduce their ownership share in losers in bad economic states. The vast majority of coefficients for the time-series regression of momentum trading in the winner portfolio instead are insignificant.[16]

The large time variation in momentum trading is of interest for research into dynamic momentum strategies. Hedging the time-varying market risk in the momentum strategy (Grundy and Martin, 2001) can only partly alleviate the momentum crash, so both Barroso and Santa-Clara (2014) and Daniel and Moskowitz (2013) suggest dynamic momentum strategies, in which the weight on the momentum strategy depends on volatility as a state variable. Such a strategy would reduce momentum trading in volatile times and lower exposure to crashes. For example, in the dynamic momentum strategy posited by Barroso and Santa-Clara (2014), the weight averages around 0.90 but declines to 0.20 in the turbulent 2008-2009 era. The actual trading we observe behaves in precisely the opposite manner, with an extensive increase in momentum trading during that time.

4.2 Momentum trading and time-varying momentum profits

Our previous results show extensive selling of losers by foreign and institutional investors during bad times (recession, market downturns, and times of high volatility). The strong correlation between economic state variables that predicts momentum profits and momentum trading of institutional investors thus raises question: Can excessive momentum trading of institutional investors predict momentum reversals? Theory suggests a link between trading and momentum profits: Stein (2009) argues that sophisticated investors might engage in "crowded trading" in the presence of uncertainty about how many other investors follow the same strategy, such that they push prices away from fundamentals. Moreover, Vayanos and Woolley (2013) propose a model in which institutional investors and delegated portfolio management effectively explain momentum and reversals. Lou (2012) finds supportive empirical evidence for their theory by showing a positive link between expected flow and momentum profits.

[16]When the momentum trading measure forms over a horizon of four quarters, some state variables relate statistically significantly to momentum trading in the winner portfolio, but when compared with the trading in the loser portfolio, the explained variation is small.

We adopt a different approach to investigate how institutional trading relates to the momentum crash. The excessive sale of losers in bad economic states might lead to overreaction, pushing prices below fundamentals, which then revert afterwards. Therefore, if momentum crashes or reversals occur due to initial overreaction in the sale of loser stocks, we expect that strong excessive selling of past losers predicts reversals in momentum profits (or future outperformance of past losers).

To examine the predictive ability of institutional momentum trading on momentum returns, we leave a time of at least one quarter between measuring the return and the demand for winner and loser stocks. This timeline ensures that the returns are not influenced by price pressure induced by herding of institutional trades (Sias, Starks, and Titman, 2006) and that we do not partially capture a previously documented, positive link between flows and stock returns (Lou, 2012). The formation period of both the trading variable and the momentum strategy is 12 months. To increase the power of our test and to be consistent with prior studies (e.g., Daniel and Moskowitz, 2013; Barroso and Santa-Clara, 2014), we run the estimations using monthly momentum returns and keep the variables with a quarterly frequency constant within each quarter.

Table 8 shows the results of the predictive regressions. The first specification reports the estimated coefficient of the univariate regression of momentum profits on momentum trading, lagged by two quarters. Strong previous momentum trading negatively predicts future momentum profits, in line with overreaction explanations of momentum and not necessarily in conflict with previous empirical findings of a positive link between institutional trading and momentum profits in the short-run due to herding behavior or informed trading. However, disentangling the explanatory variable into trades of past losers and past winners, we uncover an interesting pattern. In Column (2), only the institutions' sales of loser stocks predict momentum profits. Strong decreases in the ownership of losers have positive predictive ability for the reversal of the momentum strategy. Moreover, the demand for winner stocks is unrelated to future momentum profits. Therefore, this finding is in line with the notion that excessive selling pressure on loser stocks pushes prices below their fundamentals, resulting in a stronger future reversal (outperformance) of loser stocks than winner stocks. To confirm that trading of loser stocks is not just a proxy for the state variables introduced in prior studies, we control for each of them in Columns (3) - (9). The coefficient for our variable remains unchanged or even becomes slightly stronger.

A caveat of our analysis is the relatively short sample period. Nevertheless, the findings suggest that the state variables provide a reasonable proxy for capturing the selling pressure in the loser portfolio in times when the discrepancy between asset prices and fundamentals is higher. They also provide initial evidence that trading on momentum, particularly the sale of loser stocks, might have an impact or at least predictive ability for momentum profits.

5 Discussion

With this article, we document two stylized facts. First, we observe contrarian trading by private, especially unsophisticated, investors. Institutional and foreign investors, in contrast, are momentum traders. Second, we observe excessive selling of loser stocks by institutional and foreign investors before the momentum crash. These documented trading patterns in turn relate to different theories about the momentum anomaly. A multitude of models, mostly behavioral, try to explain momentum profits; we focus on the models of Hong and Stein (1999) and Grinblatt and Han (2005), which explicitly model the interaction of different investors. In this section, we briefly summarize each model and discuss how our results relate to them.

First, Grinblatt and Han (2005) consider two types of investors, one that is rational, and another that is subject to the disposition effect. Investors that exhibit the disposition effect are reluctant to realize losses and thereby create selling pressure for winner stocks and buying pressure for loser stocks. This demand distortion leads to an information underreaction, where winners are undervalued and losers are overvalued. Rational investors exploit this mispricing, but due to arbitrage limits, prices converge slowly, giving rise to momentum profits. Our first stylized fact thus is consistent with Grinblatt and Han

(2005), because private investors, which exhibit a severe disposition effect, are strong contrarians. Contrarian trading by private investors can be exploited by institutional investors. Because the momentum trading strategy yields a positive return on average, the momentum trading of institutions can be regarded as sophisticated. The finding that less sophisticated private investors are more contrarian corroborates this view.

Second, Hong and Stein (1999) model the behavior of another two types of investors, namely, “newswatchers” who underreact to information and “momentum traders” who exploit this underreaction. Because momentum traders focus solely on past prices, the initial underreaction results in an overreaction. Similarly, Stein (2009) predicts that uncertainty about how many other investors follow the momentum strategy results in a “crowded trade” effect, pushing prices away from fundamentals. The investor categorization of newswatchers and momentum traders does not easily translate to our investor categorization, but the excessive selling of losers, followed by a reversal in momentum profits, such that losers suddenly outperform winners, is in line with a crowded trade effect. This crowded trade effect arises due to a coordination problem, in that too many investors try to exploit the momentum anomaly. Other possible explanations also might describe the excessive sale of losers during the market downturn. For example, institutional settings, such as stop-loss orders, might force institutional investors to sell stocks with large negative returns (De Long et al., 1990). Finally, our results are in line with Vayanos and Woolley’s (2013) model which assigns a predominant role to institutions for explaining momentum and reversals.

6 Concluding remarks

Using a unique data set of equity holdings from Germany, we investigate which investor types trade on momentum. We find robust evidence of negative feedback trading by private households. Financial institutions and foreign investors, especially mutual funds, are on the other side of these trades and strongly engage in momentum trading. Considering that momentum trading is highly profitable, why would private investors trade in the opposite direction? We believe this behavior can best be understood as the result of behavioral biases among private investors. In particular, the disposition effect, which is very pronounced among individual investors, can generate negative aggregate demand for past winners and positive aggregate demand for past losers (Grinblatt and Han, 2005). A more detailed look at differences in private households supports this view. Contrarian trading is stronger among less sophisticated private investors, with financial sophistication proxied by financial wealth and equity home bias.

Although the momentum strategy is highly profitable on average, it crashed in 2009, when losers suddenly outperformed winners. By looking at the momentum trading of institutional and foreign investors over time, we determine that the selling of losers is anti-cyclical: It increases during market downturns and in high-volatility phases. The buying of winners instead is mostly unrelated to the state of the market or the economy. The extensive selling of losers in 2008 preceded the strong reversal in momentum profits in 2009, which is in support of an overreaction explanation for the momentum crash.

A Data appendix

Ownership data from the Securities Holdings Statistics (SHS) database

The reporting template of the Securities Holdings Statistics (SHS) is based on the European System of Integrated Economic Accounts (ESA95), which is the legally binding conceptual reference framework within the European Union.[17] We broadly follow this classification. For domestic investors, we group private households as "private," which corresponds to ESA code S.14. We contrast this investor group with institutional investors, including both non-financial corporations (ESA code S.11) and financial corporations (S.120). We do not explicitly feature small investor groups as "non-profit institutions" (S.15) or "general government" (S.13), because they are negligible when investigating stock investments. However, disregarding these groups explains why the sum of private and institutional investors is not equal to the reported overall domestic share. For financial investors, the reporting template includes more detailed information than indicated by ESA95. The sector of "insurance companies" that we use corresponds to S. 125, "insurance corporations and pension funds," and "banks" comply with the ESA95 sector S.122 ("MFIs"), with one exception. We bundle money market funds included in S.122 with investment funds that are assigned to sector S.123 ("other financial institutions") to create a separate category, "mutual funds." Adding the remaining investors of "other financial institutions" to "financial auxiliaries" (S.124) constitutes our last financial group "other financial," featuring a range of different investors not fitting into any of the other categories, such as proprietary holdings of investment companies, special-purpose vehicles, or financial auxiliaries linked to the credit and insurance industry. We do not separate central banks

[17] For a technical documentation of the SHS database, see Amann et al. (2012). Note that ESA95 was recently updated to ESA2010, changing the sector numeration somewhat (http://epp.eurostat.ec.europa.eu/portal/page/portal/product_details/publication?p_product_code=KS-02-13-269).

in our classification because they have no role in stock investments in this period. All investors classified as foreign are grouped together to form a single sector, "foreign."

Security data from Thomson Reuters Datastream

To specify our data universe, we download security data using constituent lists maintained by Thomson Reuters Datastream that cover the German market. We use the lists named *FGER1*, *FGER2*, *FGERDOM*, and *FGERKURS* for securities currently trading on German exchanges and, to avoid any survivorship bias, *DEADBD1-DEADBD6* for securities that are no longer traded. After dropping duplicates and securities that have not been traded since 2005Q4, the starting point of our analysis, we double-check our remaining sample in static screens for regional code ("Germany") and for asset class ("common equity"). We further reduce the data set by choosing the quotation of the security, which proves to be the most significant in terms of the market value and liquidity of the respective company (*MAJOR*). We also follow Ince and Porter (2006) and search the variable *NAME* for key words or phrases that might indicate that a security is not common equity, such as participating certificates and real estate investment trusts (REITs). For each term, we manually examine each equity name that contain the focal term before removing it from the screened sample. We also exclude all stocks for which we lack any time-series information. Following Ince and Porter (2006), we drop stocks with prices of less than 10 cents, to avoid anomalous return observations.

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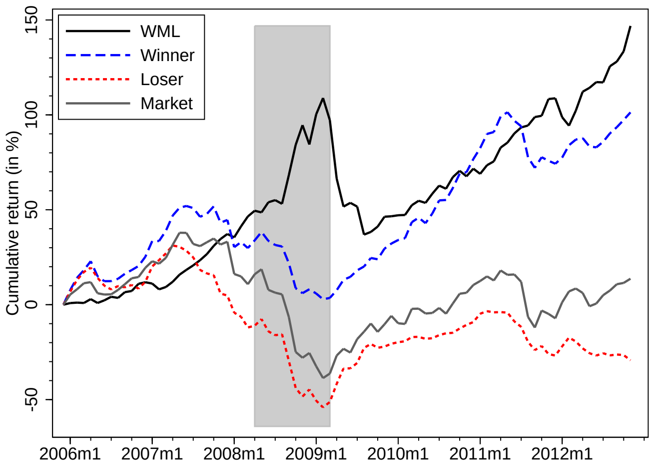
(a) Monthly



(b) Quarterly

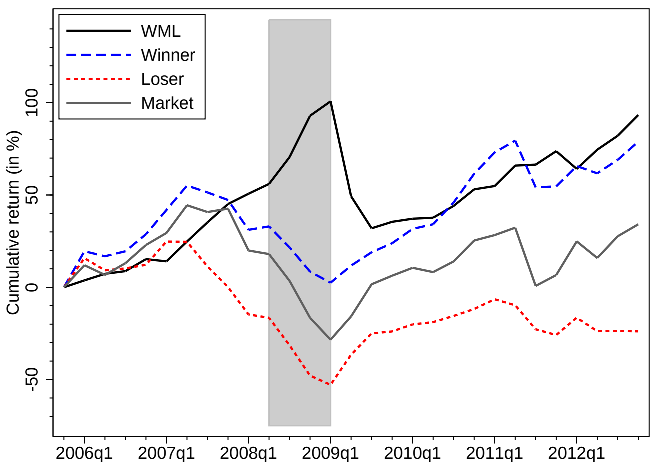
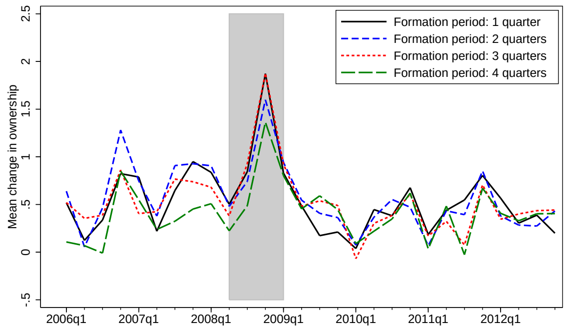
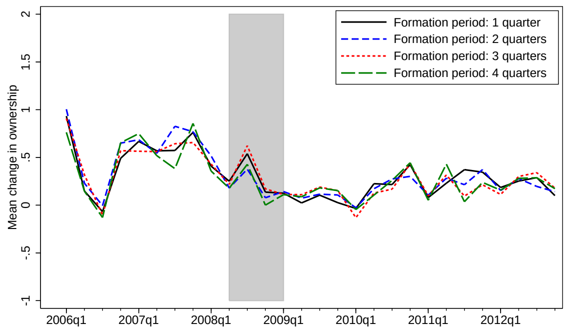


Figure 1:
Performance of the momentum strategy over time
This figure displays the cumulative return (in percent) of the momentum strategy in the German stock market. Stocks are sorted on the basis of their past return over four quarters, held for one month (Figure 1(a)) and one quarter (Figure 1(b)). The winner portfolio is the equally weighted return of the top 30% stocks, and the loser portfolio is the equally weighted return of the bottom 30% stocks. The WML ("Winner-Minus-Loser") portfolio is long in winners and short in losers. The graph also displays the cumulative value-weighted market return. The sample period is 2006:Q1 - 2012:Q4. The shaded area indicates the economic recession period in Germany, defined as a quarter-to-quarter GDP contraction over at least two consecutive quarters.

(a) Winner-Loser portfolio



(b) Winner portfolio



(c) Loser portfolio

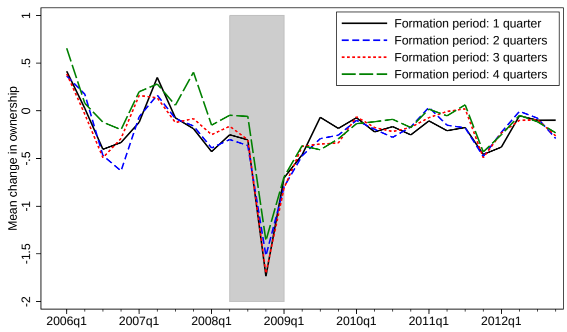


Figure 2:
Momentum trading over time
This figure displays the degree of momentum trading in the stock market by foreign and institutional investors. At each point in time, we calculate the cross-sectional average change in ownership by non-households in the winner and loser portfolios, with portfolio cutoffs at the 30th and 70th percentiles of past returns. Past returns are measured over formation horizons of one to four quarters. Figure 2(a) shows the difference in ownership change between the winner and loser portfolio; Figures 2(b) and 2(c) display the ownership change in the winner and loser portfolios, respectively. The shaded area indicates the economic recession period in Germany, defined as a quarter-to-quarter GDP contraction over at least two consecutive quarters.

Table 1:
Summary statistics: Ownership and changes in ownership
This table provides summary statistics for the ownership shares (Panel A) and changes in ownership (Panel B) of different investor groups. The table provides time-series averages of the cross-sectional mean, standard deviation, and 25th, 50th, and 75th percentile. Panel A also reports the time-series average of the value-weighted ownership share. The sample period is 2005:Q4-2012:Q4.

Panel A: Ownership share $OS_{i,j}$ (percentage)

			Percentiles			Value-weighted
Investor group	Mean	Std. Dev.	25th	50th	75th	Mean
Foreign	34.5	29.9	8.3	26.3	56.9	56.3
Domestic	65.5	29.9	43.1	73.7	91.7	43.7
Private	29.4	25.6	7.9	21.1	47.0	12.7
Institutional	34.9	30.4	9.0	25.6	57.2	28.9
Non-Financial	27.6	29.9	2.4	15.0	46.1	15.1
Financial	7.3	15.1	0.2	2.0	7.7	13.8
Banks	1.4	7.4	0.0	0.1	0.4	2.9
Mutual funds	2.3	3.9	0.0	0.1	3.2	7.0
Insurance companies	0.9	6.5	0.0	0.0	0.0	2.1
Other Financial	2.7	11.0	0.0	0.1	0.5	1.7

Panel B: Change in ownership share $\Delta OS_{i,j}$ (percentage points)

			Percentiles		
Investor group	Mean	Std. Dev.	25th	50th	75th
Foreign	-0.10	3.02	-0.50	0.00	0.45
Domestic	0.10	3.02	-0.45	0.00	0.50
Private	-0.05	1.95	-0.44	-0.02	0.33
Institutional	0.16	2.76	-0.33	0.01	0.41
Non-Financial	0.21	2.46	-0.07	0.00	0.19
Financial	-0.06	1.17	-0.21	0.00	0.14
Banks	-0.01	0.33	-0.03	0.00	0.02
Mutual funds	-0.03	0.59	-0.02	0.00	0.01
Insurance companies	-0.01	0.05	0.00	0.00	0.00
Other Financial	0.00	0.38	-0.02	0.00	0.01

Table 2:
Changes in ownership and past returns

This table shows the average change in fractional ownership $\Delta OS_{i,j,t} = OS_{i,j,t} - OS_{i,j,t-1}$ of investor group j in stock i, conditional on past return. The W-L column reports the difference in the ownership change of each investor type between the winner and loser portfolio. The t-statistics are reported in parentheses. For each quarter, we sort all stocks on the basis of the return over the previous quarter (Panel A), the previous two quarters (Panel B), and the previous four quarters (Panel C), into three different portfolios (loser, middle, and winner). The portfolio cutoffs are the 30th and 70th percentiles of the lag return. Then we calculate the average change in ownership within each portfolio for all investor types j. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Investor type	Loser (L)	Mid	Winner (W)	W-L	t-value
Panel A, Sorting variable: Lagged one quarter					
Foreign	−0.28	−0.08	0.05	0.34***	(3.41)
Domestic	0.28	0.08	−0.05	−0.34***	(−3.41)
Private	0.24	−0.10	−0.30	−0.54***	(−6.35)
Institutional	0.02	0.20	0.26	0.24***	(5.54)
Non-Financial	0.14	0.24	0.24	0.10***	(2.88)
Financial	−0.12	−0.05	0.01	0.13***	(6.68)
Banks	−0.02	−0.01	0.01	0.03***	(3.66)
Mutual funds	−0.07	−0.03	0.00	0.07***	(5.17)
Insurance companies	0.00	−0.01	−0.01	0.00**	(−2.54)
Other Financial	0.00	0.00	0.00	0.01	(0.73)
Panel B, Sorting variable: Lagged two quarters					
Foreign	−0.35	−0.09	0.12	0.47***	(4.82)
Domestic	0.35	0.09	−0.12	−0.47***	(−4.81)
Private	0.26	−0.12	−0.31	−0.57***	(−6.90)
Institutional	0.05	0.23	0.21	0.16***	(4.12)
Non-Financial	0.15	0.27	0.20	0.05	(1.15)
Financial	−0.10	−0.06	−0.01	0.09***	(6.78)
Banks	−0.02	−0.01	0.00	0.01**	(2.07)
Mutual funds	−0.07	−0.03	0.00	0.08***	(7.30)
Insurance companies	0.00	−0.01	−0.01	0.00*	(−1.85)
Other Financial	0.00	0.00	0.00	0.00	(0.57)
Panel C, Formation period: Previous four quarters					
Foreign	−0.22	−0.09	0.03	0.25***	(2.77)
Domestic	0.22	0.09	−0.03	−0.25***	(−2.77)
Private	0.13	−0.08	−0.28	−0.41***	(−6.76)
Institutional	0.04	0.17	0.30	0.26***	(4.56)
Non-Financial	0.16	0.22	0.24	0.08**	(2.16)
Financial	−0.12	−0.06	0.02	0.14***	(5.89)
Banks	−0.02	−0.01	0.00	0.01	(1.54)
Mutual funds	−0.08	−0.03	0.01	0.09***	(7.42)
Insurance companies	0.00	−0.01	0.00	0.00	(0.21)
Other Financials	0.00	0.00	0.00	0.00	(0.42)

Table 3:
Determinants of ownership share changes

This table summarizes the results of the pooled OLS regressions of ownership changes of different investor types on a list of stock characteristics. The table reports standardized regression coefficients (except for the index dummy) and t-values computed with two-way clustered standard errors (firm and time) in parentheses. The standardization of the variables in each quarter introduces time-fixed effects. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: Change in ownership $\Delta OS_{i,j,t}$ of investor group j									
	Foreign	Domestic								
	All	All	Private	Institutional						
			All	All	Non-Fin.	Financial				
Explanatory variables:					All	All	Banks	Funds	Insur.	Oth. Fin.
Lagged return (2 quarters)	0.05***	-0.05***	-0.12***	0.03***	0.01	0.04***	0.02**	0.06***	-0.00	0.01
	(5.17)	(-5.17)	(-9.04)	(2.87)	(1.28)	(2.98)	(2.23)	(5.31)	(-0.00)	(1.49)
Size	-0.02*	0.02*	0.01	0.02	0.02	-0.01	0.00	-0.00	-0.09***	-0.01
	(-1.71)	(1.67)	(0.45)	(1.53)	(1.37)	(-0.84)	(0.10)	(-0.32)	(-3.70)	(-0.56)
B/M	0.01	-0.01	-0.00	-0.02**	-0.02*	-0.01	-0.01	0.00	-0.02*	-0.00
	(1.44)	(-1.42)	(-0.04)	(-2.06)	(-1.94)	(-0.70)	(-1.54)	(0.35)	(-1.70)	(-0.26)
Vola	-0.01	0.01	0.02	-0.01	-0.01	0.02	0.00	0.02**	0.03***	0.01
	(-0.62)	(0.58)	(1.63)	(-0.50)	(-0.66)	(1.56)	(0.23)	(2.45)	(2.91)	(1.03)
Beta	0.00	-0.00	0.01	-0.01	-0.01	-0.01	0.01	-0.02*	0.02*	-0.01
	(0.31)	(-0.31)	(0.51)	(-1.30)	(-1.03)	(-1.08)	(0.77)	(-1.67)	(1.82)	(-1.52)
Age	0.02	-0.02	0.04**	-0.04***	-0.02*	-0.01	0.01	0.01	-0.04*	-0.04***
	(1.05)	(-1.05)	(2.33)	(-3.33)	(-1.79)	(-0.69)	(0.63)	(0.35)	(-1.90)	(-2.85)
Dividend yield	-0.01	0.01	0.04***	-0.02*	-0.01	-0.00	-0.01***	-0.01	-0.01	0.01*
	(-1.51)	(1.50)	(4.14)	(-1.87)	(-1.45)	(-0.03)	(-2.75)	(-0.68)	(-0.61)	(1.91)
Price	0.01	-0.01	-0.01	0.00	-0.01	0.02**	-0.00	0.01	0.06***	0.01
	(1.23)	(-1.22)	(-0.95)	(0.00)	(-0.88)	(2.38)	(-0.05)	(1.26)	(4.94)	(0.78)
Index dummy	0.05*	-0.05*	0.03	-0.07**	-0.04	-0.02	-0.03	0.01	-0.09	-0.02
	(1.81)	(-1.81)	(0.80)	(-2.52)	(-1.48)	(-0.71)	(-0.49)	(0.17)	(-1.52)	(-1.13)
Turnover	-0.01	0.01	0.01	-0.01	0.00	-0.03***	-0.02	-0.05***	-0.04*	-0.01
	(-0.89)	(0.90)	(0.86)	(-0.84)	(0.18)	(-2.87)	(-0.79)	(-3.20)	(-1.83)	(-0.70)

Table 4:
Lag return as a determinant of ownership change

This table reports the standardized regression coefficients for different lag return variables. We regress the change of ownership of different investor types on a list of control variables (see Table 3) and different lag return variables. The t-values computed with two-way clustered standard errors (firm and time) are reported in parentheses. For brevity, we do not repeat the coefficients of the control variables from Table 3. The standardization of the variables in each quarter introduces time-fixed effects. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: Change in ownership $\Delta OS_{i,j,t}$ of investor group j									
	Foreign	Domestic								
	All	All	Private	Institutional						
			All	All	Non-Fin.	Financial				
Explanatory variables:					All	All	Banks	Funds	Insur.	Oth. Fin.
Lagged return (4 quarters)	0.05***	-0.05***	-0.09***	0.02**	-0.01	0.05***	0.03***	0.06***	0.03***	0.01
	(5.37)	(-5.37)	(-7.22)	(2.29)	(-1.01)	(5.51)	(2.58)	(6.01)	(2.75)	(1.54)
Lagged return (3 quarters)	0.06***	-0.06***	-0.11***	0.02*	-0.01	0.05***	0.03***	0.06***	0.01	0.02*
	(5.25)	(-5.25)	(-7.58)	(1.83)	(-0.70)	(4.67)	(2.96)	(5.29)	(1.17)	(1.84)
Lagged return (2 quarters)	0.05***	-0.05***	-0.12***	0.03***	0.01	0.04***	0.02**	0.06***	-0.00	0.01
	(5.17)	(-5.17)	(-9.04)	(2.87)	(1.28)	(2.98)	(2.23)	(5.31)	(-0.00)	(1.49)
Lagged return (1 quarter)	0.04***	-0.04***	-0.11***	0.04***	0.02*	0.05***	0.04***	0.05***	-0.01	0.01
	(3.92)	(-3.92)	(-8.80)	(3.74)	(1.67)	(3.67)	(4.21)	(4.59)	(-0.52)	(1.01)
Contemporaneous return	0.07***	-0.07***	-0.13***	0.01	0.00	-0.00	-0.05***	0.03***	-0.06***	-0.02
	(6.24)	(-6.23)	(-7.83)	(1.15)	(0.43)	(-0.56)	(-4.01)	(3.46)	(-5.09)	(-1.43)

Table 5:
Lag return as a determinant of ownership change: Winner stocks and loser stocks separately

This table reports the standardized regression coefficients for different lag return variables using a piece-wise regression framework, with the median lag return as a knot. We regress the change of ownership of different investor types on a list of control variables (see Table 3) and different lag return variables. The t-values computed with two-way clustered standard errors (firm and time) are reported in parentheses. For brevity, we do not repeat coefficients of the control variables from Table 3. The standardization of the variables in each quarter introduces time-fixed effects. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: Change in ownership $\Delta OS_{i,j,t}$ of investor group j									
	Foreign	Domestic								
	All	All	Private	Institutional						
			All	All	Non-Fin.	Financial				
Explanatory variables:					All	All	Banks	Funds	Insur.	Oth. Fin.
Lagged return (4 quarters)	0.10***	-0.10***	-0.21***	0.08***	0.04	0.09***	0.05**	0.09***	0.07***	0.03
below median	(3.11)	(-3.10)	(-6.44)	(2.80)	(1.40)	(3.20)	(2.11)	(3.29)	(2.76)	(1.19)
Lagged return (4 quarters)	0.03**	-0.03**	-0.03**	-0.01	-0.03**	0.03***	0.01	0.05***	0.01	0.01
above median	(2.21)	(-2.23)	(-2.27)	(-0.57)	(-2.17)	(2.80)	(1.28)	(3.66)	(0.95)	(0.56)
Lagged return (3 quarters)	0.15***	-0.15***	-0.28***	0.07**	0.02	0.08***	0.06**	0.08***	0.03	0.01
below median	(4.06)	(-4.05)	(-9.74)	(2.29)	(1.04)	(3.04)	(2.34)	(3.41)	(1.48)	(0.37)
Lagged return (3 quarters)	0.02	-0.02	-0.03	-0.01	-0.02	0.03*	0.02	0.05***	0.00	0.02
above median	(1.18)	(-1.20)	(-1.63)	(-0.34)	(-1.46)	(1.78)	(1.58)	(2.94)	(0.16)	(1.57)
Lagged return (2 quarters)	0.14***	-0.14***	-0.27***	0.07***	0.05**	0.06**	0.03	0.07***	-0.01	0.02
below median	(4.28)	(-4.27)	(-9.27)	(2.72)	(2.00)	(2.57)	(1.25)	(3.94)	(-0.51)	(0.99)
Lagged return (2 quarters)	0.01	-0.01	-0.04**	0.01	-0.01	0.02	0.02	0.05***	0.01	0.01
above median	(0.43)	(-0.44)	(-2.02)	(0.41)	(-0.32)	(1.09)	(1.13)	(3.69)	(0.30)	(0.56)
Lagged return (1 quarter)	0.11***	-0.11***	-0.22***	0.07**	0.04**	0.06***	0.04***	0.07***	-0.01	0.01
below median	(3.95)	(-3.95)	(-9.18)	(2.44)	(2.31)	(2.63)	(2.96)	(2.82)	(-0.54)	(0.74)
Lagged return (1 quarter)	-0.00	0.00	-0.04**	0.02	-0.00	0.03**	0.04**	0.04***	-0.00	0.01
above median	(-0.04)	(0.04)	(-2.41)	(1.09)	(-0.01)	(1.96)	(2.19)	(2.75)	(-0.27)	(0.48)
Contemporaneous return	0.12***	-0.12***	-0.24***	0.05**	0.01	0.06***	-0.06**	0.12***	-0.02	-0.02
below median	(6.09)	(-6.09)	(-8.72)	(2.28)	(0.41)	(3.17)	(-2.45)	(7.29)	(-1.26)	(-1.20)
Contemporaneous return	0.04**	-0.04**	-0.06***	-0.01	0.00	-0.04***	-0.04**	-0.02*	-0.07***	-0.01
above median	(2.47)	(-2.47)	(-2.66)	(-0.46)	(0.17)	(-3.96)	(-2.39)	(-1.84)	(-5.00)	(-0.70)

Table 6:
Financial sophistication and contrarian trading of private investors

This table summarizes the results of the pooled OLS regressions of relative ownership changes of (bank-specific) private investors on lag return, lag-return-related interaction terms, and stock-specific control variables as in Table 4. We only show the coefficient estimates of lag returns and the interaction terms, for brevity, along with t-values computed with two-way clustered standard errors (firm×bank and time) in parentheses. The coefficients are multiplied by 1000. In all regressions, we add time-fixed and bank-type-fixed effects. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Lag return variable with formation period of two quarters				
Explanatory variables:	(1)	(2)	(3)	(4)
Lag return (2 quarters)	-0.20***	-0.19***	-0.20***	-0.19***
	(-2.72)	(-2.71)	(-2.71)	(-2.71)
Lag return × ln(financial wealth)		0.07***		0.07***
		(4.02)		(3.86)
Lag return × ln(home bias)			-0.17***	-0.11**
			(-3.78)	(-2.40)
Controls	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Bank-type-fixed effects	Yes	Yes	Yes	Yes

Panel B: Lag return variable with formation period of four quarters				
Explanatory variables:	(1)	(2)	(3)	(4)
Lag return (4 quarters)	-0.07**	-0.07**	-0.07**	-0.07**
	(-2.42)	(-2.40)	(-2.42)	(-2.40)
Lag return × ln(financial wealth)		0.07***		0.07***
		(5.20)		(5.13)
Lag return × ln(home bias)			-0.16***	-0.10*
			(-2.88)	(-1.96)
Controls	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Bank-type-fixed effects	Yes	Yes	Yes	Yes

Table 7:
Momentum trading and economic state variables

This table reports the univariate regression results of the measure of momentum trading of non-households on several economic state variables. In Panel A, the dependent variable is the difference in ownership change between the winner and loser portfolio; in Panel B, the ownership change in the winner portfolio; and in Panel C, it is the ownership change in the loser portfolio. The economic state variables include growth in real GDP, two economic sentiment variables provided by ZEW and Ifo, the 12-month market return, realized market volatility, and the WML strategy. The results for the momentum trading measure are reported for horizons of 1 to 4 quarters. For each regression, we report the slope coefficient β, its t-value, and its R^2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	GDP growth	Economic sentiment (ZEW)	Economic sentiment (Ifo)	12-month return (MKT)	Realized volatility (MKT)	Realized volatility (WML)
Panel A: Momentum trading (Winner - Loser)						
Horizon: 1 quarter						
β	-14.89**	-0.61***	-1.37***	-0.86***	2.29***	2.12***
	(-2.77)	(-3.59)	(-3.46)	(-3.62)	(4.40)	(3.94)
R^2 (in%)	22.8	33.2	31.5	33.5	42.7	37.4
Horizon: 2 quarters						
β	-13.11**	-0.51***	-1.11**	-0.66**	1.61**	1.54**
	(-2.45)	(-2.93)	(-2.70)	(-2.63)	(2.73)	(2.62)
R^2 (in%)	18.8	24.8	21.9	21.0	22.2	20.9
Horizon: 3 quarters						
β	-16.08***	-0.40**	-1.51***	-0.77***	2.03***	2.28***
	(-3.23)	(-2.17)	(-4.26)	(-3.26)	(3.82)	(4.76)
R^2 (in%)	28.6	15.3	41.1	29.1	35.9	46.5
Horizon: 4 quarters						
β	-13.87***	-0.24	-1.09***	-0.61***	1.46***	1.56***
	(-3.35)	(-1.50)	(-3.37)	(-3.00)	(3.04)	(3.41)
R^2 (in%)	30.1	7.9	30.4	25.7	26.2	30.9

Table 7 – Continued

	GDP growth	Economic sentiment (ZEW)	Economic sentiment (Ifo)	12-month return (MKT)	Realized volatility (MKT)	Realized volatility (WML)
Panel B: Momentum trading in the winner portfolio						
Horizon: 1 quarter						
β	3.16	-0.13	0.37	0.15	-0.48	-0.59
	(0.77)	(-0.95)	(1.17)	(0.77)	(-1.05)	(-1.33)
R^2 (in%)	2.2	3.4	5.0	2.2	4.1	6.4
Horizon: 2 quarters						
β	5.02	-0.07	0.56	0.26	-0.72	-0.77
	(1.16)	(-0.49)	(1.68)	(1.28)	(-1.49)	(-1.64)
R^2 (in%)	4.9	0.9	9.8	5.9	7.9	9.4
Horizon: 3 quarters						
β	3.29	-0.05	0.31	0.17	-0.62	-0.47
	(0.81)	(-0.37)	(0.98)	(0.86)	(-1.39)	(-1.05)
R^2 (in%)	2.5	0.5	3.5	2.8	6.9	4.1
Horizon: 4 quarters						
β	3.86	-0.04	0.54*	0.25	-0.99**	-0.85*
	(0.93)	(-0.28)	(1.73)	(1.31)	(-2.30)	(-1.95)
R^2 (in%)	3.2	0.3	10.3	6.2	16.9	12.8
Panel C: Momentum trading in the loser portfolio						
Horizon: 1 quarter						
β	18.05***	0.47**	1.74***	1.01***	-2.77***	-2.71***
	(3.57)	(2.55)	(5.08)	(4.65)	(-6.41)	(-6.26)
R^2 (in%)	32.9	20.0	49.8	45.4	61.3	60.2
Horizon: 2 quarters						
β	18.13***	0.43**	1.66***	0.93***	-2.32***	-2.31***
	(3.95)	(2.47)	(5.25)	(4.42)	(-4.96)	(-5.03)
R^2 (in%)	37.6	19.0	51.5	42.9	48.6	49.3
Horizon: 3 quarters						
β	19.37***	0.35*	1.82***	0.94***	-2.65***	-2.75***
	(4.02)	(1.77)	(5.64)	(4.12)	(-5.81)	(-6.58)
R^2 (in%)	38.3	10.7	55.0	39.5	56.5	62.5
Horizon: 4 quarters						
β	17.72***	0.20	1.63***	0.87***	-2.45***	-2.41***
	(3.65)	(1.02)	(4.77)	(3.78)	(-5.19)	(-5.18)
R^2 (in%)	33.8	3.8	46.7	35.4	50.9	50.8

Table 8:
Momentum trading as a predictor of time-varying momentum profits

This table reports the predictive regression results of the monthly momentum returns on momentum trading, winner and loser trading, and several economic state variables. The trading variables are measured at a quarterly frequency and lagged by two quarters. The economic state variables include growth in real GDP, two economic sentiment variables provided by ZEW and Ifo, the 12-month market return, realized market volatility, and the WML strategy. The formation period for both the trading variable and trading strategy is 12 months. For each regression, we report the slope coefficients and their t-values in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mom. Trading (W-L)	-1.59**								
	(-2.15)								
Mom. Trading (Loser)		1.94**	1.97**	2.24**	1.93***	2.07***	1.97***	2.07***	2.11**
		(2.54)	(2.59)	(2.58)	(2.68)	(2.67)	(2.71)	(2.86)	(2.37)
Mom. Trading (Winner)		0.02							
		(0.04)							
Market (12-month return)			-0.07						0.48
			(-0.12)						(0.73)
GDP growth				-0.38					-0.13
				(-0.48)					(-0.13)
Sentiment (ZEW)					-0.12				-0.15
					(-0.26)				(-0.29)
Sentiment (IfO)						-0.26			-0.23
						(-0.43)			(-0.32)
Realized volatility (MKT)							0.20		-0.35
							(0.53)		(-0.52)
Realized volatility (WML)								0.45	0.80
								(1.27)	(1.21)
Constant	1.19***	1.19***	1.19***	1.19***	1.18***	1.18***	1.18***	1.18***	1.22***
	(3.04)	(3.20)	(3.48)	(3.19)	(3.36)	(3.29)	(3.23)	(3.22)	(3.29)
N	78	78	78	78	78	78	78	78	78

Internet appendix accompanying

“Who trades on momentum?”

- Figure A.1 shows the ownership structure over time.
- Table A.1 displays momentum profits for different formation and holding periods (see Section 2.2).
- Table A.2 repeats the regression of the analysis of Table 3 using the Fama-MacBeth regression instead of pooled OLS, with two-way clustered standard errors.
- Table A.3 shows the summary statistics of the bank-stock-specific relative change of the private ownership share, as well as two proxies for investor sophistication.

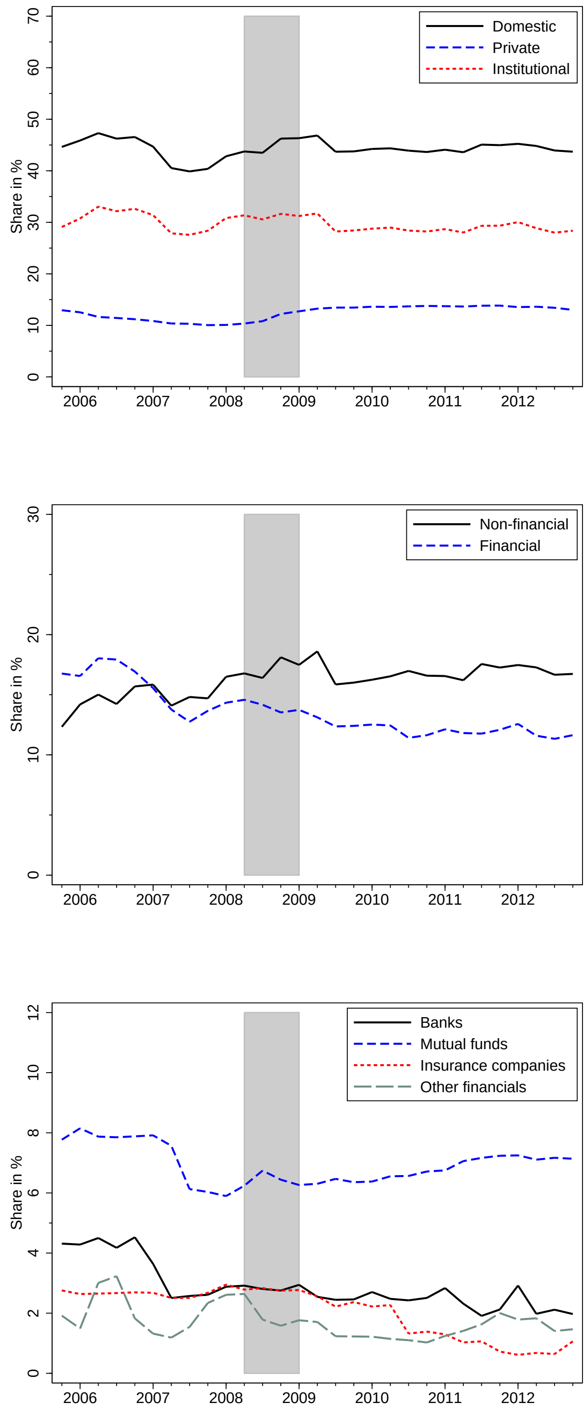


Figure A.1:
Ownership over time
These graphs show the fractional ownership shares of the different investor groups in the German stock market. The sample period is 2005:Q4-2012:Q4.

Table A.1:
Performance of momentum investment strategies

This table shows the average annualized return of different momentum investment strategies. Portfolios of winners and losers (top and bottom 30%) are formed on the basis of past returns over the horizon of one to four quarters (formation period) and held over the horizon of one to four quarters. The sample period is 2006:Q1-2012:Q4. The t-values are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Formation period	Holding period (in quarters)			
(in quarters)	1	2	3	4
1	7.94**	7.37**	7.03**	5.82**
	(2.12)	(2.47)	(2.50)	(2.15)
2	9.39*	9.22**	8.03*	6.75*
	(2.00)	(2.16)	(1.98)	(1.82)
3	11.66**	9.87*	8.81*	6.53
	(2.19)	(1.93)	(1.94)	(1.61)
4	11.19*	9.50*	7.49	4.92
	(1.82)	(1.71)	(1.46)	(1.05)

Table A.2:

Determinants of the change in ownership shares: Fama-MacBeth regression

This table repeats the analysis of Table 4 using the Fama and MacBeth (1973) regression approach instead of two-way clustered, pooled OLS. The table reports standardized regression coefficients (except for the index dummy), along with t-values in the parentheses, computed over the time series using Newey and West (1987) standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: Change in ownership $\Delta OS_{i,j,t}$ of investor group j									
	Foreign	Domestic								
	All	All	Private	Institutional						
			All	All	Non-Fin.	Financial				
Explanatory variables:					All	All	Banks	Funds	Insur.	Oth. Fin.
Lagged return (2 quarters)	0.04***	-0.04***	-0.12***	0.04***	0.03**	0.03**	0.02**	0.05***	-0.01	0.02
	(3.48)	(-3.48)	(-9.35)	(3.55)	(2.18)	(2.31)	(2.17)	(4.36)	(-1.51)	(1.51)
Size	-0.02	0.02	0.01	0.02	0.02	-0.01	-0.00	-0.01	-0.09***	-0.00
	(-1.54)	(1.50)	(0.91)	(1.26)	(1.37)	(-1.02)	(-0.04)	(-0.49)	(-3.50)	(-0.38)
B/M	0.01	-0.01	0.00	-0.01	-0.01	-0.01	-0.02	0.00	-0.02*	0.00
	(0.72)	(-0.71)	(0.06)	(-1.49)	(-1.16)	(-0.80)	(-1.38)	(0.29)	(-1.84)	(0.01)
Vola	-0.01	0.01	0.03**	-0.01	-0.01	0.02*	0.00	0.02***	0.02*	0.02
	(-0.95)	(0.91)	(2.27)	(-0.80)	(-1.02)	(1.71)	(0.11)	(3.03)	(2.03)	(1.30)
Beta	0.00	-0.00	0.00	-0.01	-0.01	-0.02	-0.00	-0.02	0.02	-0.02*
	(0.26)	(-0.26)	(0.35)	(-1.18)	(-0.80)	(-1.35)	(-0.24)	(-1.51)	(1.39)	(-1.72)
Age	0.01	-0.01	0.04***	-0.04**	-0.02	-0.01	0.01	0.01	-0.03	-0.04**
	(0.78)	(-0.78)	(2.91)	(-2.67)	(-1.48)	(-0.65)	(0.61)	(0.23)	(-1.41)	(-2.62)
Dividend yield	-0.01	0.01	0.03***	-0.02*	-0.01	0.00	-0.01	0.00	-0.01	0.01
	(-1.01)	(1.00)	(4.26)	(-1.73)	(-1.62)	(0.50)	(-1.29)	(0.11)	(-0.72)	(1.58)
Price	0.01	-0.01	-0.01	-0.00	-0.01	0.02*	-0.00	0.01	0.06***	0.01
	(1.35)	(-1.34)	(-1.08)	(-0.26)	(-1.09)	(2.01)	(-0.16)	(1.38)	(4.90)	(0.58)
Index dummy	0.04	-0.04	0.04	-0.05*	-0.03	-0.00	-0.02	0.02	-0.09	-0.02
	(1.21)	(-1.20)	(0.99)	(-1.72)	(-1.27)	(-0.05)	(-0.32)	(0.55)	(-1.66)	(-0.83)
Turnover	-0.00	0.00	0.00	-0.01	0.00	-0.04***	-0.02	-0.06***	-0.04*	-0.01
	(-0.23)	(0.24)	(0.00)	(-0.98)	(0.21)	(-2.83)	(-0.69)	(-3.72)	(-1.74)	(-1.25)

Table A.3:
Summary statistics: Relative change in private ownership and financial sophistication

This table provides summary statistics for the relative change in private ownership shares, as well as for the two financial sophistication proxies, financial wealth and home bias. For each bank, we calculate average financial wealth as the total market value of all assets of private investors, divided by the total number of accounts. To compute the home bias, we divide the domestic equity share by the share of the German stock market in worldwide market capitalization. The table provides time-series averages of the cross-sectional mean, standard deviation, and the 10th, 25th, 50th, 75th, and 90th percentile. The sample period is 2005:Q4-2012:Q4.

			Percentiles				
Bank-stock-specific characteristics	Mean	Std. Dev.	10th	25th	50th	75th	90th
$\frac{\Delta OS_{i,j=PO,l,t}}{OS_{i,j=PO,l,t-1}}$ (in %)	2.97	25.72	-8.52	-0.15	0.00	0.07	10.59
ln(financial wealth)	10.52	0.56	9.94	10.20	10.50	10.75	10.99
Financial wealth	47,020.21	61,729.26	20,732.04	26,984.10	36,581.48	46,641.64	59,648.51
ln(home bias)	3.12	0.09	3.02	3.08	3.13	3.18	3.21
Home bias	22.83	1.87	20.48	21.87	23.06	24.06	24.90