



Who trades on momentum? ☆

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ABSTRACT

Using unique data with the complete ownership structure of the German stock market, we study the momentum and contrarian trading of different investor groups. Foreign investors and financial institutions, especially mutual funds, are momentum traders, whereas private investors are contrarians. The disposition effect only partly explains the aggregate contrarian trading of private investors. We document a substantial increase in sales of past loser stocks by momentum traders during the market decline associated with the recent financial crisis 2007–2009. Evidence indicates that these excessive sales pushed prices below their fundamental value and are predictive of the momentum crash in 2009.

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1. Introduction

Stocks that have performed best in the past tend to continue to perform well, whereas stocks that performed worse 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 United States.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 in Germany, the country we study, 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

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

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 et al. (2012) and Daniel and Moskowitz (2016).

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 researchers have analyzed whether institutional investors exploit the momentum anomaly.³ Not all investors can simultaneously follow the momentum strategy. The 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.

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 2007–2009. 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. In contrast to previous work, we study slightly longer-run past stock performance and investors' trading behavior. One exception is Campbell et al. (2014), who look at different style-tilts over a longer horizon including momentum, but focus their analysis around private investors. Moreover, we analyze the time variation of momentum trading in different economic states, and ask 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 investors 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 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 investors to the capital gains overhang to test whether the disposition effect explains the contrarian trading of private investors. Evidence indicates that the disposition effect is not the sole driver of investors' trading on past stock performance. 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 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) offer interesting models in this context, in that they 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). We find evidence in line with Grinblatt and Han (2005) as both capital gain and loss overhang are negatively related to households' trading as predicted by their model. However, the contrarian trading to past returns remains economically and statistically significant, suggesting that other factors may play a role in explaining households' negative tilt towards momentum stocks.

According to Hong and Stein (1999) and Stein (2009), arbitrageurs try to exploit the 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) on crowded trades and recent empirical evidence by Lou and Polk (2014). However, other explanations as to why institutions excessively sold losers during the financial crisis also come to mind, such as stop-loss orders or career concerns of money managers (e.g. Dasgupta et al., 2011b). We provide empirical evidence in support of Vayanos and Woolley's (2013) model, in which institutional investors and delegated portfolio management play a key role in explaining price 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 transaction data (Grinblatt and Keloharju, 2000, 2001) and Taiwanese transaction data (Barber et al., 2009a). Second, the German stock market, which is the seventh largest in the world and the third

² The U.S. data are from Kenneth French's website. The German data are from Brückner et al. (2015). The figures refer to a WML strategy based on a (2×3) 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, for example, Lakonishok et al. (1992), Grinblatt et al. (1995), Falkenstein (1996), Nofsinger and Sias (1999), Gompers and Metrick (2001), Badrinath and Wahal (2002), and Bennett et al. (2003). For a summary and discussion of the different results regarding the momentum trading of institutional investors, see Sias (2007).

⁴ For overreaction models, see De Long et al. (1990); for underreaction models, see Barberis et al. (1998) and Grinblatt and Han (2005); for underreaction models followed by overreaction, see Daniel et al. (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) and Andrei and Cujean (2017).

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., 2003b; Chui et al., 2010).

Our study contributes to several strands of literature on the behavior of different investor groups in isolation. For example, there is one strand of literature on the behavior of institutional or private investors.⁶ In the literature on institutional ownership and trading (e.g., Gompers and Metrick, 2001; Bennett et al., 2003; Dasgupta et al., 2011a), quarterly SEC filings are used in most studies. 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. We also document the sizable heterogeneity among different types of institutions, notably, mutual funds, banks, insurance companies, and pension funds. Most studies of trading by individual investors use proprietary brokerage data, as introduced 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 investor groups in the market, but with the exceptional data from Finland (Grinblatt and Keloharju, 2000, 2001) and Taiwan (Barber et al., 2009a), as well as German holdings data, it is possible to study the trading of all investors in the market.

Several studies document behavioral biases in household 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 et al., 2009b,c). With our data set, we can quantify the aggregate demand of private investors in the stock market.⁷ 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; Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016), 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 momentum crash in 2009. In contrast with the dynamic momentum trading strategies proposed by Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016), 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, we are 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 et al., 2004).

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 2007–2009, along with the biggest economic downturn in Germany's postwar history.

The remainder of the paper is structured as follows. In Section 2, we introduce the data set and provide descriptive statistics of our sample. In Section 3, we discuss the trading on past stock returns for different types of investors. In Section 4, we analyze the time series variation of momentum trading and the predictability of the momentum crash in 2009. A final section concludes.

2. Data and descriptive statistics

Our analysis is based on the rich ownership structure of German stocks obtained from the SHS and financial market data from Thomson Reuters Datastream. In this section, we detail the advantages of the data set and highlight some of the key characteristics of our sample.

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>.

⁶ Depending on the aggregation level of investor information, the literature can be divided in studies on the stock-level trades of investor groups (e.g., Choe et al., 1999; Gompers and Metrick, 2001; Griffin et al., 2003a) and individual investors (e.g., Grinblatt and Keloharju, 2000, 2001; Calvet et al., 2009; Campbell et al., 2014; Betermier et al., 2017), respectively.

⁷ 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., 2009b). See Subsection 2.1 for a detailed discussion.

2.1. Description of data sources

We obtain stock holdings data from the SHS for the mandatory quarterly filings by German financial institutions. The SHS is a centralized register of security ownership maintained by the Deutsche Bundesbank. It collects data through a full census of all relevant financial institutions in Germany including those that offer the service of safe custody of securities. Financial institutions are required to report their own securities holdings, along with those of their customers. Customers' securities holdings are broken down by investor sector and customer nationality.⁸

The full census and investor categorization represent the main differences between the SHS and the U.S. 13-F SEC filings, which is 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 \$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 date for which data are available, 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)⁹ and institutional. Moreover, the SHS provides 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' 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 differentiate different types of foreign investors. However, the overwhelming majority of foreign investors tend to be institutional investors, as noted by Dahlquist and Robertson (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 SHS ownership data with securities characteristics from Thomson Reuters Datastream. To merge the two databases, we follow the studies that rely on international or German stock market data (e.g., Schmidt et al., 2011; Karolyi et al., 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.¹⁰ We then merge the resulting stocks with the holdings data of the SHS database, using historical International Securities Identification Numbers (ISINs).¹¹ 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

⁸ For technical documentation on the SHS database, see Amann et al. (2012).

⁹ We use the terms private investors and households interchangeably.

¹⁰ 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.

¹¹ 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.

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 percentiles. Panel A also reports the time series average of the value-weighted ownership share. The sample period is 2005:Q4–2012:Q4.

Investor group	Mean	Std. Dev.	Percentiles			Value-weighted mean
			25th	50th	75th	
Panel A: Ownership share OS_{ij} (percentage)						
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 ΔOS_{ij} (percentage points)						
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	

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 stock i 's shares outstanding. 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.¹² 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) and foreign investors (predominantly financial investors). This large-cap preference is consistent with the 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). To mitigate the spurious effect of large outliers, particularly in small stocks, we winsorize changes in the ownership share at 2.5%. 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 portfolios 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%. In the momentum strategy, winners are bought and losers are sold over a holding period of one quarter. With regard to the momentum profits, our approach thus is more conservative than commonly applied procedure. First, rebalancing takes place 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, as well as the coverage of the 2009 momentum crash, yields a statistically and economically significant return. Momentum strategies based on the past two and four quarters yield annualized returns of

¹² 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.

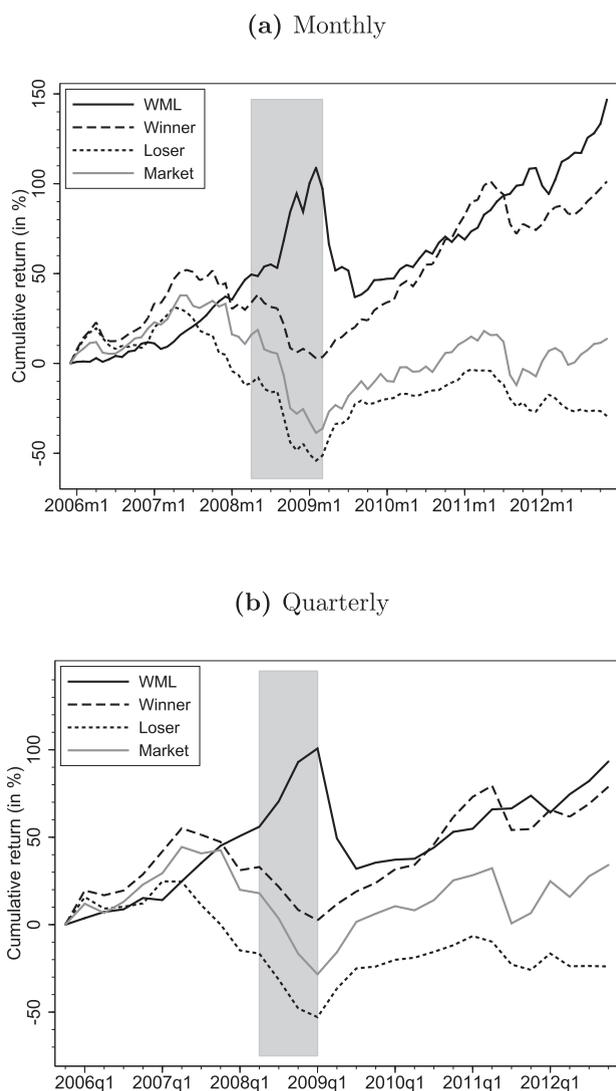


Fig. 1. Performance of the momentum strategy over time. This figure displays the cumulative return (in percent) of the momentum strategy in the German stock market. Stocks are sorted on the basis of their past return over four quarters, held for one month (Fig. 1(a)) and one quarter (Fig. 1(b)). The 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.

9.39% (t -value: 2.00) and 11.19% (t -value: 1.82), respectively.¹³

Although the momentum strategy performed very well on average, it also suffered large losses during our sample period, as Fig. 1 reveals, according to its performance 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, 2016).

¹³ 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 (2×3) sort on market capitalization and the past 2–11 months return, as described by Fama and French (2012), $WML = 1/2(\text{SmallWinner} + \text{BigWinner}) - 1/2(\text{SmallLoser} + \text{BigLoser})$, 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. (2015).

3. Which investor types are momentum traders?

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 in our sample, how demand for a stock relates to its past returns. Moreover, we distinguish between the trading on past positive and negative returns and relate our findings to the disposition effect.

3.1. Trading on past returns

To measure investor type-specific stock demand, we employ the aggregate change in stock holdings for each investor group, which is a well-established measure in the institutional trading literature (e.g., [Bennett et al., 2003](#); [Sias, 2007](#)). We regress this change in ownership on cumulative past returns and account for several control variables from the literature (e.g., [Gompers and Metrick, 2001](#)), as follows:

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

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. 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 addition we include a plethora of control variables to answer the question of who trades on momentum. The stock-specific control variables are the natural logarithm of firm's total market capitalization (*Size*), the natural logarithm of the ratio between the firm's book and market value (*B/M*), stock's market beta measured over a five-year horizon of monthly returns (*Beta*), stock's return volatility measured over a five-year horizon of monthly returns (*Vola*), the natural logarithm of the number of months since firm's foundation (*Age*), the natural logarithm of firm's annualized dividend yield (*Dividend yield*), the natural logarithm of firm's share price (*Price*), a dummy for membership in one of the four major German stock indices¹⁴ (*Index*), and the natural logarithm of stock's quarterly turnover measured by trading volume relative to firm's shares outstanding (*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, for 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. Notably, by exploiting the heterogeneity within each investor type separately, we control for any time-invariant unobservable characteristic specific to particular investor types, such as differences in preferences and beliefs. 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.¹⁵

[Table 2](#) reports the regression results using the previous two quarters' returns and controls as explanatory variables for investor ownership changes. In column (1), we uncover strong evidence of momentum trading by foreign investors. The results show a significant positive relation between the stock's cumulative past return and the change in foreign ownership. The difference between the foreign investors' ownership change in a loser stock with a past return that is one standard deviation below the mean return, and a winner stock with a past return that is one standard deviation above the mean return is 0.30 percentage points.¹⁶ This shift from loser stocks to winner stocks 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 investors completely account for the contrarian trading of domestic investors. A one standard deviation increase in the past two-quarter return decreases private investors' net purchases by 0.12 standard deviations or a demand differential of -0.48 percentage points, making it by far the most important determinant of households' trading among all incorporated firm and stock characteristics. This finding from column (3) is in accordance with literature on the disposition effect and the trading of private 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

¹⁴ The four major German stock indices are DAX, MDAX, SDAX, and TecDAX.

¹⁵ Instead of pooled OLS regressions with standardized variables in each quarter, we also 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 \(1987\)](#). Overall, the [Fama and MacBeth \(1973\)](#) estimations yield qualitatively similar results as our baseline OLS estimations (see [Table A.2](#) in the [Internet Appendix](#)).

¹⁶ The magnitude of the momentum trading of foreign investors is calculated by employing the standardized regression coefficient, the distance between the loser and winner stock of two standard deviations, and the standard deviation of the ownership change: $0.05 \times 2 \times 3.02$.

Table 2

Determinants of ownership share changes. This table provides the results of the pooled OLS regressions of ownership changes of different investor types on a list of stock characteristics. The stock-specific control variables are the natural logarithm of firm's total market capitalization (*Size*), the natural logarithm of the ratio between the firm's book and market value (*B/M*), stock's market beta measured over a five-year horizon of monthly returns (*Beta*), stock's return volatility measured over a five-year horizon of monthly returns (*Vola*), the natural logarithm of the number of months since firm's foundation (*Age*), the natural logarithm of firm's annualized dividend yield (*Dividend yield*), the natural logarithm of firm's share price (*Price*), a dummy for membership in one of the four major German stock indices (*Index*), and the natural logarithm of stock's quarterly turnover measured by trading volume relative to firm's shares outstanding (*Turnover*). 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.

Explanatory variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
Dependent variable: Change in ownership $\Delta OS_{i,j,t}$ of investor group <i>j</i>											
	Foreign		Domestic								
	All	All	Private	Institutional							
			All	All	Non-fin.	Financial					
				All	All	Banks	Funds	Insur.	Oth. Fin.		
<i>Ret</i> _{<i>i,t-2,t-1</i>}	0.05*** (5.17)	-0.05*** (-5.17)	-0.12*** (-9.04)	0.03*** (2.87)	0.01 (1.28)	0.04*** (2.98)	0.02** (2.23)	0.06*** (5.31)	-0.00 (-0.00)	0.01 (1.49)	
<i>Size</i>	-0.02* (-1.71)	0.02* (1.67)	0.01 (0.45)	0.02 (1.53)	0.02 (1.37)	-0.01 (-0.84)	0.00 (0.10)	-0.00 (-0.32)	-0.09*** (-3.70)	-0.01 (-0.56)	
<i>B/M</i>	0.01 (1.44)	-0.01 (-1.42)	-0.00 (-0.04)	-0.02** (-2.06)	-0.02* (-1.94)	-0.01 (-0.70)	-0.01 (-1.54)	0.00 (0.35)	-0.02* (-1.70)	-0.00 (-0.26)	
<i>Vola</i>	-0.01 (-0.62)	0.01 (0.58)	0.02 (1.63)	-0.01 (-0.50)	-0.01 (-0.66)	0.02 (1.56)	0.00 (0.23)	0.02** (2.45)	0.03*** (2.91)	0.01 (1.03)	
<i>Beta</i>	0.00 (0.31)	-0.00 (-0.31)	0.01 (0.51)	-0.01 (-1.30)	-0.01 (-1.03)	-0.01 (-1.08)	0.01 (0.77)	-0.02* (-1.67)	0.02* (1.82)	-0.01 (-1.52)	
<i>Age</i>	0.02 (1.05)	-0.02 (-1.05)	0.04** (2.33)	-0.04*** (-3.33)	-0.02* (-1.79)	-0.01 (-0.69)	0.01 (0.63)	0.01 (0.35)	-0.04* (-1.90)	-0.04*** (-2.85)	
<i>Dividend yield</i>	-0.01 (-1.51)	0.01 (1.50)	0.04*** (4.14)	-0.02* (-1.87)	-0.01 (-1.45)	-0.00 (-0.03)	-0.01*** (-2.75)	-0.01 (-0.68)	-0.01 (-0.61)	0.01* (1.91)	
<i>Price</i>	0.01 (1.23)	-0.01 (-1.22)	-0.01 (-0.95)	0.00 (0.00)	-0.01 (-0.88)	0.02** (2.38)	-0.00 (-0.05)	0.01 (1.26)	0.06*** (4.94)	0.01 (0.78)	
<i>Index</i>	0.05* (1.81)	-0.05* (-1.81)	0.03 (0.80)	-0.07** (-2.52)	-0.04 (-1.48)	-0.02 (-0.71)	-0.03 (-0.49)	0.01 (0.17)	-0.09 (-1.52)	-0.02 (-1.13)	
<i>Turnover</i>	-0.01 (-0.89)	0.01 (0.90)	0.01 (0.86)	-0.01 (-0.84)	0.00 (0.18)	-0.03*** (-2.87)	-0.02 (-0.79)	-0.05*** (-3.20)	-0.04* (-1.83)	-0.01 (-0.70)	

losers. Our results are also in line with the longer-run performance study by [Campbell et al. \(2014\)](#), who show that individual Indian investors tend to tilt negatively towards the momentum strategy.

Furthermore, the regression results in column (4) indicate 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](#)).

As evident from columns (5) and (6), momentum trading is mainly pursued by financial investors, while there is no such an evidence for non-financial institutions. The degree of momentum trading is by no means homogeneous across different types of financial institutions. 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 (columns (7) and (8)). 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](#)). In contrast, there is no evidence that insurance companies and pension funds, and other financial institutions are momentum traders. 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.¹⁷

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 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.

To confirm that these results are not driven by the choice of the momentum formation period, we perform the regressions for [Table 2](#) 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 variables. [Fig. 2](#) displays the coefficients to the lag return variables over different formation periods for the most impor-

¹⁷ Alternative to the regression approach, we also employ a simple sort of the stock universe according the returns in the previous quarters to identify investor types that on average are momentum traders (cf. [Sias, 2007](#)). Results are reported in the [Appendix](#) in [Table A.3](#). Consistent with our main results, we find that foreign and domestic institutional investors increase (decrease) their ownership in the past winner (loser) portfolio, while households trade in the opposite direction.

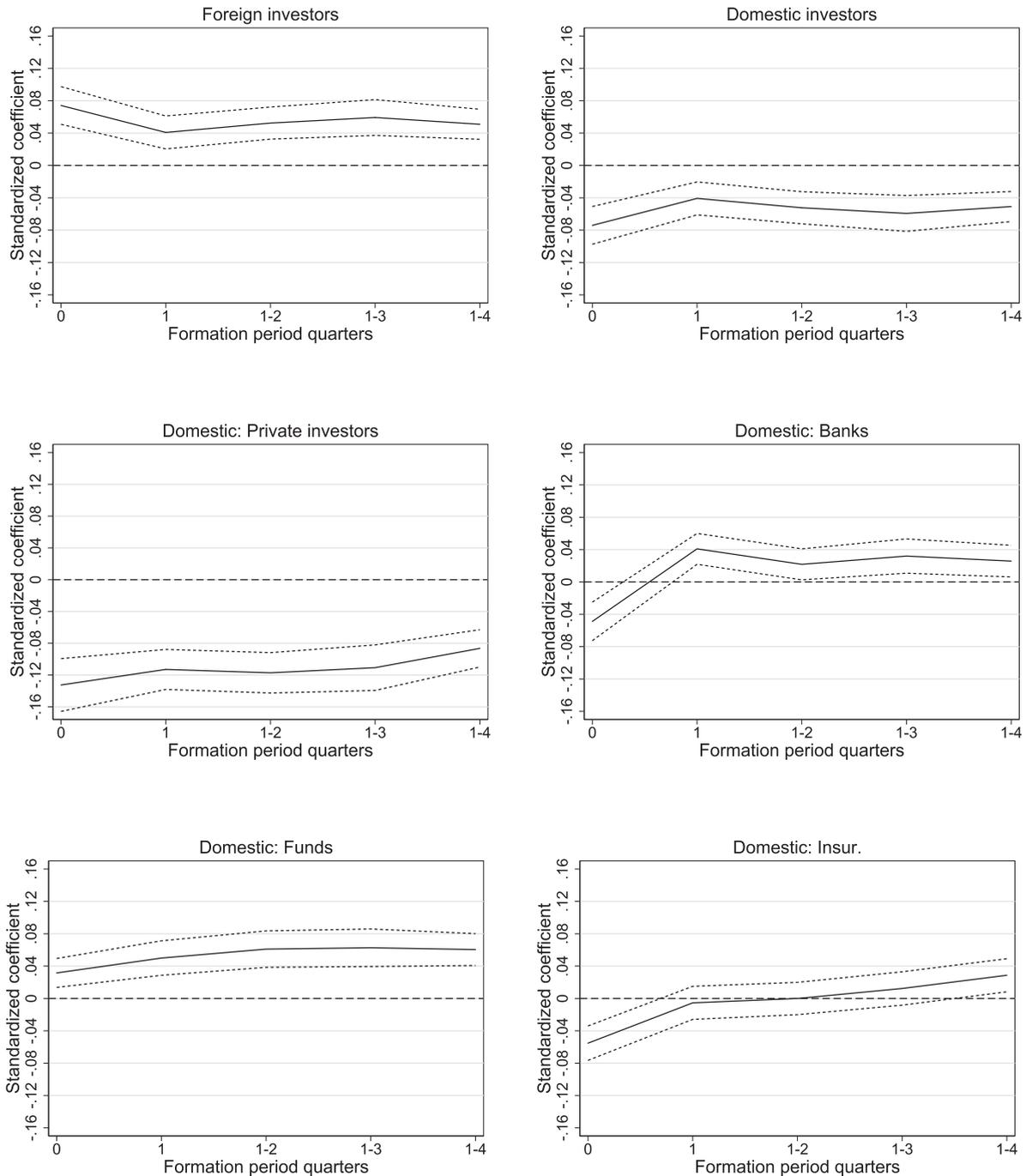


Fig. 2. Lag return as a determinant of ownership change. This graphs show the standardized regression coefficients of different investor types for different past return formations periods of momentum. We regress the change of ownership of different investor types on a list of control variables (see Table 2) and lag return variables of different formation periods. 0 indicates the return over the contemporaneous formation period (quarter 0), 1 the lagged 1-quarter return, 1-2 the lagged 2-quarter return, 1-3 the lagged 3-quarter return, and 1-4 the lagged 4-quarter return. 95% confidence intervals (dashed lines) are computed from two-way clustered standard errors (firm and time).

tant investor types.¹⁸ 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 contrarian trading of households decreases with the length of the formation period. This finding is in line with, but distinct from Barber et al.'s (2009c) 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.¹⁹

Mutual funds are strong momentum traders for all different formation periods. The evidence on banks' trading behavior is somewhat less clear. 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. Insurance companies and pension funds are not trading on momentum but - similar to banks - we find a negative coefficient for the contemporaneous quarterly return.

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.

3.2. 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 piecewise linear regressions with the median of the cumulative lag return as a knot:

$$\Delta OS_{i,j,t} = \alpha + \beta_1 Ret_{Loser,i,t-k,t-1} + \beta_2 Ret_{Winner,i,t-k,t-1} + \gamma Controls_{i,t-1} + \varepsilon_{i,j,t}, \quad (2)$$

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 piecewise linear regression, which is 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 suggesting momentum trading. Inversely, a negative coefficient of the two variables indicates contrarian trading. 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 3 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 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, although momentum trading among winners is not as pronounced. Our finding that mutual funds buy winners and sell losers stands in contrast to Grinblatt et al.'s (1995) finding of significant momentum trading only on the winner's side.

3.3. Momentum, contrarian strategies, and the disposition effect

In this subsection we link our findings to a highly debated result in prior work that investors tend to sell investments with unrealized gains and are reluctant to sell investments with unrealized losses, a behavior known as the disposition effect. Grinblatt and Han (2005) develop a model in which the disposition effect of individuals aggregates into demand that shows an opposing direction with regard to past gains and losses. This trading results in prices underreacting to past information, giving rise to return predictability and momentum profits. Recent evidence, however, calls this direct link between the disposition effect and momentum profits into question. Although the propensity to sell is indeed larger for unrealized gains than for unrealized losses, Ben-David and Hirshleifer (2012) emphasize that the investors' selling propensity is actually an asymmetric V-shaped function of unrealized gains as the selling propensity is increasing in the magnitude of both gains and losses. An (2016)

¹⁸ The corresponding Table A.4 is shown in the Internet Appendix.

¹⁹ In additional analyses on bank level, we employ average financial wealth and average inverse home bias of households as financial sophistication proxies and show that their contrarian trading decreases with increasing financial sophistication. However, the decrease in contrarian trading does not revert to momentum trading except with extremely large values of financial wealth. Results of these tests are depicted in Table A.5 and Figure A.2 of the Internet Appendix.

Table 3

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 piecewise 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 2) 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 2. The standardization of the variables in each quarter introduces time-fixed effects. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Explanatory variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable: Change in ownership ΔOS_{ijt} of investor group j										
	Foreign		Domestic							
	All	All	Private	Institutional						
			All	All	Non-fin.	Financial				
					All	Banks	Funds	Insur.	Oth. Fin.	
$Ret_{Loser,i,t-4,t-1}$	0.10*** (3.11)	-0.10*** (-3.10)	-0.21*** (-6.44)	0.08*** (2.80)	0.04 (1.40)	0.09*** (3.20)	0.05** (2.11)	0.09*** (3.29)	0.07*** (2.76)	0.03 (1.19)
$Ret_{Winner,i,t-4,t-1}$	0.03** (2.21)	-0.03** (-2.23)	-0.03** (-2.27)	-0.01 (-0.57)	-0.03** (-2.17)	0.03*** (2.80)	0.01 (1.28)	0.05*** (3.66)	0.01 (0.95)	0.01 (0.56)
$Ret_{Loser,i,t-2,t-1}$	0.14*** (4.28)	-0.14*** (-4.27)	-0.27*** (-9.27)	0.07*** (2.72)	0.05** (2.00)	0.06** (2.57)	0.03 (1.25)	0.07*** (3.94)	-0.01 (-0.51)	0.02 (0.99)
$Ret_{Winner,i,t-2,t-1}$	0.01 (0.43)	-0.01 (-0.44)	-0.04** (-2.02)	0.01 (0.41)	-0.01 (-0.32)	0.02 (1.09)	0.02 (1.13)	0.05*** (3.69)	0.01 (0.30)	0.01 (0.56)

builds on this observation and finds the net selling propensity measure that recognizes this V shape cannot explain price momentum.

To provide new information for this debate, we first re-run our estimations from equation (1) and Table 2 including Grinblatt and Han's (2005) capital gains overhang (CGO) measure into our specifications.²⁰ We are particularly interested in the CGO coefficient for the private investors. If they tend to sell stocks that have gained in value since purchase rather than those that have decreased, we expect that CGO will relate negatively to the change in ownership. Also, if the disposition effect of private investors entirely explains their contrarian trading, we expect that the cumulative past return will become redundant when controlling for CGO. For the sake of brevity, Panel A of Table 4 only reports the regression coefficients for stock's cumulative past return and CGO. Three important findings emerge. First, we find evidence in accordance with Grinblatt and Han's (2005) model: Relative to all remaining investor types, households increase their ownership with decreasing capital gains overhang. In other words, they tend to sell stocks with unrealized gains. Second, although the magnitude of the coefficient to past return decreases when accounting for the CGO, the disposition effect alone cannot explain the contrarian trading of private investors. Independent of the return formation period, past returns significantly and negatively predict the change in their stock ownership. Third, while CGO matters for households, it plays no role in explaining the momentum trading of foreign investors and mutual funds. This result suggests that these investors trade on the momentum strategy rather than being just mechanically on the other side of household trades.

Next, we decompose the effect of CGO into unrealized gains and losses as in An (2016) to control for a potential V-shaped disposition effect. For the sake of consistency and comparability, we also estimate the regression coefficient to past returns separately for positive and negative cumulative returns, similar to Table 3. This specification serves two purposes: First, we aim to test whether the effect of CGO on investors' trading is consistent for gains and losses. Second, we want to understand to which extent the asymmetry in private investors' contrarian trading reported in Subsection 3.2 is driven by unrealized capital gains and losses. Panel B of Table 4 shows the regression coefficients for the four variables of main interest. Although the slope for capital gains is indeed larger than for losses in the case of households' aggregate trading, there is no evidence of a V-shaped function of unrealized profits. In particular, we find that private investors are net buyers of stocks with unrealized losses and net sellers of stocks with unrealized gains, consistent with the original form of the disposition effect suggested in Grinblatt and Han (2005). More importantly, we document that the households' contrarian trading of past winners is subsumed by unrealized gains whereas the ownership increase of past losers remains economically and statistically meaningful even when we control for unrealized losses. Overall, unrealized profits affect the trading of private investors but do not seem to be the only driver of their contrarian trading.²¹

²⁰ A detailed description of the variable construction is provided in Appendix A.

²¹ Importantly, our results are not necessarily at odds with the recently documented V-shaped disposition effect. Namely, we observe the aggregate net trading behavior of different investor types while previous analyses on any form of the disposition effect focus mainly on the selling propensity for stocks the investors already hold. The V-shaped disposition effect could be present, but reversed by other effects when looking at the net buying of households. In other words, while private investors may exhibit a higher propensity to sell the loser stock they hold, on an aggregate level they may still be net buyers for this particular stock if the demand from all other private investors is higher relative to other investor types. Therefore, our analysis adds an important dimension to the discussion on contrarian trading and the disposition effect of private investors.

Table 4

Lag return and capital gains overhang as determinants of ownership change. This table reports the standardized regression coefficients for different lag return variables and capital gains overhang. In Panel A, we use the same specifications as in Table 2 but use the capital gains overhang (CGO), defined similarly to Grinblatt and Han (2005), as an additional control variable in the regression. In Panel B we use a piecewise regression framework, with the median lag return as a knot as in Table 3 but add the gain and loss overhang motivated by An (2016). 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 2. The standardization of the variables in each quarter introduces time-fixed effects. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Explanatory variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable: Change in ownership $\Delta OS_{ij,t}$ of investor group j										
	Foreign		Domestic							
	All	All	Private	Institutional						
			All	All	Non-fin.	Financial				
				All	All	Banks	Funds	Insur.	Oth. Fin.	
Panel A: Baseline + Capital gains overhang (Grinblatt and Han, 2005)										
$Ret_{i,t-4,t-1}$	0.05*** (4.68)	-0.05*** (-4.69)	-0.07*** (-5.17)	0.00 (0.35)	-0.02*** (-2.84)	0.05*** (5.32)	0.02** (2.14)	0.06*** (5.29)	0.03*** (2.70)	0.01 (1.51)
CGO	0.01 (1.44)	-0.01 (-1.43)	-0.07*** (-4.97)	0.04*** (4.25)	0.04*** (4.56)	0.00 (0.26)	0.01 (1.07)	-0.00 (-0.08)	-0.00 (-0.14)	-0.00 (-0.28)
$Ret_{i,t-2,t-1}$	0.05*** (4.93)	-0.05*** (-4.93)	-0.10*** (-7.10)	0.02* (1.89)	0.00 (0.23)	0.03*** (2.61)	0.02 (1.50)	0.06*** (5.00)	-0.00 (-0.06)	0.02 (1.60)
CGO	0.02* (1.87)	-0.02* (-1.87)	-0.06*** (-4.31)	0.03*** (3.13)	0.03*** (3.14)	0.00 (0.38)	0.01 (0.92)	-0.00 (-0.16)	0.01 (0.97)	-0.00 (-0.50)
Panel B: Winner and loser stocks separately + Gain and loss overhang (An, 2016)										
$Ret_{Loser,i,t-4,t-1}$	0.09*** (3.14)	-0.09*** (-3.12)	-0.16*** (-4.96)	0.04 (1.40)	-0.00 (-0.05)	0.09*** (3.40)	0.05 (1.60)	0.10*** (3.58)	0.07** (2.45)	0.04 (1.31)
$Ret_{Winner,i,t-4,t-1}$	0.02 (1.46)	-0.02 (-1.48)	0.00 (0.19)	-0.02* (-1.86)	-0.04** (-2.57)	0.02 (1.42)	0.01 (0.76)	0.03* (1.90)	0.02 (1.13)	-0.00 (-0.40)
Loss overhang	0.01 (0.77)	-0.01 (-0.77)	-0.04*** (-3.32)	0.03*** (2.93)	0.04*** (3.85)	-0.01 (-1.27)	0.00 (0.57)	-0.01 (-1.12)	-0.01 (-0.77)	-0.01 (-1.17)
Gain overhang	0.01 (1.51)	-0.01 (-1.53)	-0.07*** (-6.00)	0.03*** (3.85)	0.02** (2.13)	0.02** (2.05)	0.00 (0.62)	0.03** (2.43)	0.00 (0.13)	0.01 (1.11)
$Ret_{Loser,i,t-2,t-1}$	0.13*** (3.95)	-0.13*** (-3.94)	-0.24*** (-8.08)	0.05** (2.13)	0.02 (1.10)	0.06*** (2.88)	0.02 (0.71)	0.08*** (4.56)	-0.01 (-0.45)	0.03 (1.10)
$Ret_{Winner,i,t-2,t-1}$	-0.00 (-0.27)	0.00 (0.26)	-0.01 (-0.37)	-0.00 (-0.17)	-0.01 (-0.36)	0.01 (0.33)	0.01 (0.68)	0.04** (2.23)	-0.00 (-0.25)	0.01 (0.40)
Loss overhang	0.00 (0.50)	-0.00 (-0.50)	-0.03** (-2.37)	0.02** (2.27)	0.03*** (2.85)	-0.01 (-0.93)	0.00 (0.66)	-0.01 (-1.09)	0.00 (0.37)	-0.01 (-1.07)
Gain overhang	0.02** (2.35)	-0.02** (-2.37)	-0.05*** (-5.54)	0.02** (2.56)	0.00 (0.27)	0.03*** (2.68)	0.01 (0.00)	0.03*** (3.00)	0.02 (1.42)	0.01 (0.86)

4. Momentum trading over time

Thus far we have established that some investor groups are either momentum or contrarian traders on average over the 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, 2015). 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.

4.1. Momentum trading and economic state variables

Several state variables have been proposed to predict momentum profits.²² For example, Chordia and Shivakumar (2002) find that the momentum strategy is profitable during expansions but not in recessions. Antoniou et al. (2013) 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. Barroso and Santa-Clara (2015) and Wang and Xu (2015) find that the realized volatility of the market and the WML portfolio predicts low momentum profits. From a risk-based perspective, these findings are puzzling though, because a momentum strategy generates high returns following good times and low returns following bad ones.

²² For a survey, see Jegadeesh and Titman (2011).

In our analysis, we study trading by all private investors (contrarian traders) and their counterparts, institutional and foreign investors (momentum traders), over time. We focus on momentum trading by all non-private investors (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 follows. For each quarter, 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. For each quarter and portfolio, we compute the stocks' average change in ownership for non-household investors and its difference between the winner and loser portfolio. This sorting procedure produces a proxy for momentum trading (MT_{W-L}) for each quarter. Correspondingly, the average change in stock ownership within the winner portfolio (MT_W) and loser portfolio (MT_L) represent momentum trading for each of the legs of the strategy. A positive (negative) demand differential between the winner and loser portfolio indicates momentum (contrarian) trading. Fig. 3 displays the results of this exercise.

Two key findings emerge from Fig. 3(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 financial crisis 2007–2009 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 A.3, Panel B of the Internet Appendix), but it increased above 1.5 during the market downturn associated with the financial crisis 2007–2009.

Fig. 3(b) and (c) display the ownership changes in the winner and loser portfolios, respectively, 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 financial crisis can be attributed entirely to the sale of losers. Thus, there was excessive selling of losers by foreign and institutional investors during the market downturn, which was followed by the momentum crash in 2009, when losers suddenly outperformed winners (Daniel and Moskowitz, 2016). 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 (*GDP growth*); two economic sentiment indices provided by the Centre for European Economic Research (Zentrum für Europäische Wirtschaftsforschung, ZEW), Mannheim (*Sentiment_{ZEW}*), and the Ifo Institute for Economic Research, Munich (*Sentiment_{Ifo}*), both based on surveys of future economic expectations; the past 12-month market return (*Ret_{MKT}*); and the realized volatility of the market return (*Vola_{MKT}*) and the WML portfolio (*Vola_{WML}*), as well as implied market volatility measured by the VDAX (*Implied vola_{MKT}*), the VIX-equivalent measure for the German stock market. For the regressions we employ momentum trading measures based on the past two and four quarters, respectively. The regression results are in Table 5.

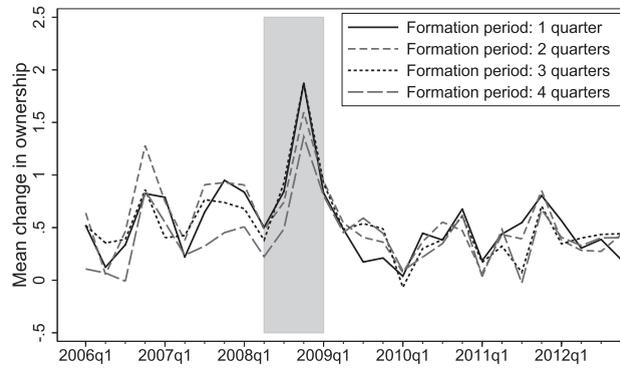
The observations from Fig. 3 are confirmed by considering the contemporaneous relation between our momentum trading measure and the state variables. Panel A shows how momentum trading (i.e., the demand differential between the winner and loser portfolio) relates to the state variables. It relates negatively to GDP growth, the two economic sentiment variables, and the market return. Furthermore, momentum trading is positively associated with the volatility measures. 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 discernible 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. In particular, when examining the trading in the loser portfolio, the regression coefficients of GDP growth, economic sentiment, and market return are positive, whereas they are negative for the volatility measures. In other words, momentum traders reduce their ownership share in past losers especially in bad economic states. The vast majority of coefficients for the time series regression of momentum trading in the winner portfolio are insignificant.²³

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 (2015) and Daniel and Moskowitz (2016) 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 (2015), 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.²⁴

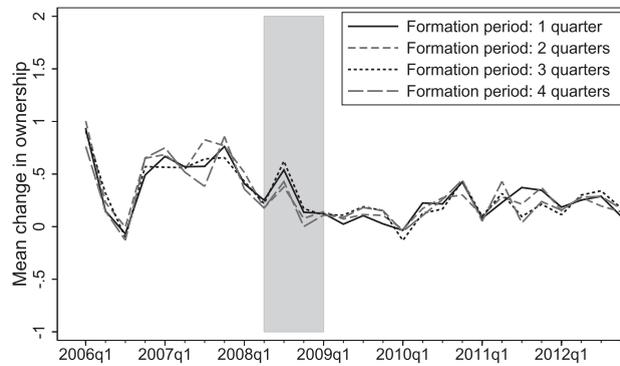
²³ When the momentum trading measure forms over a horizon of four quarters, some state variables relate statistically significantly to momentum trading in the winner portfolio, but when compared with the trading in the loser portfolio, the explained variation is small.

²⁴ In additional tests we show that the observed pattern documented in this subsection is not driven by particular industries. Table A.6 in the Internet Appendix shows that the results hold within the six largest industries. Each of the other industry groups account for less than 5% of the overall sample and do not provide sufficient variation to construct winner and loser portfolios. Overall, the findings for the different industries are qualitatively similar to the aggregate pattern.

(a) Winner-Loser portfolio



(b) Winner portfolio



(c) Loser portfolio

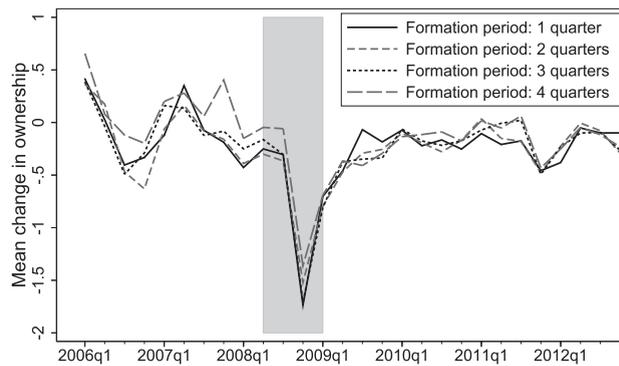


Fig. 3. Momentum trading over time. This figure displays the degree of momentum trading in the stock market by foreign and institutional investors. At each point in time, we calculate the cross-sectional average change in ownership by non-households in the winner and loser portfolios, with portfolio cutoffs at the 30th and 70th percentiles of past returns. Past returns are measured over formation horizons of one to four quarters. Fig. 3(a) shows the difference in ownership change between the winner and loser portfolio; Fig. 3(b) and (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 5

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 real GDP growth (*GDP growth*); two economic sentiment indices provided by the Centre for European Economic Research (Zentrum für Europäische Wirtschaftsforschung, ZEW), Mannheim (*Sentiment_{ZEW}*), and the Ifo Institute for Economic Research, Munich (*Sentiment_{Ifo}*), both based on surveys of future economic expectations; the past 12-month market return (*Ret_{MKT}*); and the realized volatility of the market return (*Vol_{MKT}*) and the WML portfolio (*Vol_{WML}*), as well as implied market volatility measured by the VDAX (*Implied vol_{MKT}*), the VIX-equivalent measure for the German stock market. The results for the momentum trading measure are reported for horizons of 2 and 4 quarters. For each regression, we report the slope coefficient, its t-value (in parentheses), and its R². *, **, 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)	Implied volatility (VDAX)	Realized volatility (WML)
Panel A: Momentum trading (Winner - Loser)							
Horizon: 2 quarters							
<i>MT_{W-L}</i>	-13.11** (-2.45)	-0.51*** (-2.93)	-1.11** (-2.70)	-0.66** (-2.63)	1.61** (2.73)	1.25 (1.59)	1.54** (2.62)
R ² (in%)	18.8	24.8	21.9	21.0	22.2	8.9	20.9
Horizon: 4 quarters							
<i>MT_{W-L}</i>	-13.87*** (-3.35)	-0.24 (-1.50)	-1.09*** (-3.37)	-0.61*** (-3.00)	1.46*** (3.04)	1.15* (1.77)	1.56*** (3.41)
R ² (in%)	30.1	7.9	30.4	25.7	26.2	10.7	30.9
Panel B: Momentum trading in the winner portfolio							
Horizon: 2 quarters							
<i>MT_W</i>	5.02 (1.16)	-0.07 (-0.49)	0.56 (1.68)	0.26 (1.28)	-0.72 (-1.49)	-1.10* (-1.91)	-0.77 (-1.64)
R ² (in%)	4.9	0.9	9.8	5.9	7.9	12.3	9.4
Horizon: 4 quarters							
<i>MT_W</i>	3.86 (0.93)	-0.04 (-0.28)	0.54* (1.73)	0.25 (1.31)	-0.99** (-2.30)	-1.26** (-2.38)	-0.85* (-1.95)
R ² (in%)	3.2	0.3	10.3	6.2	16.9	17.9	12.8
Panel C: Momentum trading in the loser portfolio							
Horizon: 2 quarters							
<i>MT_L</i>	18.13*** (3.95)	0.43** (2.47)	1.66*** (5.25)	0.93*** (4.42)	-2.32*** (-4.96)	-2.36*** (-3.56)	-2.31*** (-5.03)
R ² (in%)	37.6	19.0	51.5	42.9	48.6	32.7	49.3
Horizon: 4 quarters							
<i>MT_L</i>	17.72*** (3.65)	0.20 (1.02)	1.63*** (4.77)	0.87*** (3.78)	-2.45*** (-5.19)	-2.42*** (-3.54)	-2.41*** (-5.18)
R ² (in%)	33.8	3.8	46.7	35.4	50.9	32.5	50.8

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 the trading of loser stocks is not just a proxy for the state variables introduced in prior studies, we control for each of them. The coefficient for our variable remains unchanged or even becomes slightly stronger in columns (3)–(9). With the caveat of a relatively short sample period, our results 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. This predictability relation holds even after controlling for previously used state variables, which subsume both level and uncertainty measures.

These results can best be understood in the setting of [Hong and Stein \(1999\)](#), which includes two types of investors: “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.

5. 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 investors. 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](#)). We find some evidence in accordance with this notion, especially for the trading in winner stocks. However, unrealized losses do not seem to be the only driver of private investors’ demand for past loser stocks.

Although the momentum strategy is highly profitable on average, it crashed in 2009, when past losers suddenly outperformed past 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 past losers in 2008 preceded the strong reversal in momentum profits in 2009, which is in support of a “crowded trading” explanation for the momentum crash.

Appendix A. Data appendix

Ownership data from the Securities Holdings Statistics 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.²⁵ We broadly follow this classification. For domestic investors, we group 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 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.”

²⁵ 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).

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, *DEADB1-DEADB6* for securities that are no longer traded. After dropping duplicates and securities that have not been traded since 2005:Q4, 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.

Construction of capital gain and loss overhang

We follow [An \(2016\)](#) in constructing the gain and loss overhang variables. For each stock we compute the aggregate unrealized gains and losses at the end of each quarter using the percentage deviation of past prices from current prices weighted by a function of trading volume. Similar to [Grinblatt and Han \(2005\)](#) and in contrast to [An \(2016\)](#), we rely on weekly instead of daily prices to avoid calculations that involve a large number of daily observations with zero trading volume.

The gain overhang is computed as follows:

$$\begin{aligned} \text{Gain overhang}_{i,t} &= \sum_{n=1}^{\infty} \omega_{i,t-n} \text{gain}_{i,t-n} \\ \text{gain}_{i,t-n} &= \frac{P_{i,t} - P_{i,t-n}}{P_{i,t}} \times \mathbb{1}_{P_{i,t} \geq P_{i,t-n}} \\ \omega_{i,t-n} &= \frac{1}{k} V_{i,t-n} \prod_{i=1}^{n-1} [1 - V_{i,t-n+i}], \end{aligned} \quad (\text{A.1})$$

where $V_{i,t-n}$ and $P_{i,t-n}$ are the turnover ratio and price of stock i in (at the end of) week $t - n$. Note that in calculating the gain overhang, we set the gain to zero for weeks in which the current price is lower than the past purchase price. The weight $\omega_{i,t-n}$ is a proxy for the fraction of stocks purchased at $t - n$ but not sold until t . For each quarter, we employ three years of past data and normalize the weights accordingly by $k = \sum V_{i,t-n} \sum \prod_{i=1}^{n-1} [1 - V_{i,t-n+i}]$.

For the loss overhang, we use a similar procedure:

$$\begin{aligned} \text{Loss overhang}_{i,t} &= \sum_{n=1}^{\infty} \omega_{i,t-n} \text{loss}_{i,t-n} \\ \text{loss}_{i,t-n} &= \frac{P_{i,t} - P_{i,t-n}}{P_{i,t}} \times \mathbb{1}_{P_{i,t} < P_{i,t-n}} \\ \omega_{i,t-n} &= \frac{1}{k} V_{i,t-n} \prod_{i=1}^{n-1} [1 - V_{i,t-n+i}], \end{aligned} \quad (\text{A.2})$$

where we set the loss to zero for weeks in which the current price is larger than the past purchase price.

Finally, we compute the capital gains overhang (CGO) of [Grinblatt and Han \(2005\)](#) as the sum of gain and loss overhang:

$$\text{CGO}_{i,t} = \text{Gain overhang}_{i,t} + \text{Loss overhang}_{i,t}. \quad (\text{A.3})$$

Appendix B. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.finmar.2018.08.003>.

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