Are shorts just negative longs?
Evidence from detailed hedge fund portfolio data

Bastian von Beschwitz*
Federal Reserve Board

Sandro Lunghi**
Inalytics

October 27, 2016

Abstract

Using detailed data on the trades and portfolio holdings of long-short equity hedge funds, we examine the differences between trades related to long and short positions. We find that long buys and short sells are informed, but that long sells and short buys are uninformed. In fact, it is possible to generate significant alphas by taking the opposite trades to long sells and short buys implying that hedge funds close their positions too early and "leave money on the table". Furthermore, while hedge funds trade on momentum when establishing both long and short positions, follow-up orders exhibit momentum for shorts and are contrarian for longs. We argue this comes from hedge funds' desires to keep their position sizes stable.

JEL classification: G11, G12, G14, G15

Keywords: Hedge funds, Short selling, Profitability, Momentum

* Bastian von Beschwitz, Federal Reserve Board, International Finance Division, 20th Street and Constitution Avenue N.W., Washington, D.C. 20551, USA, tel. +1 202 475 6330, e-mail: bastian.vonbeschwitz@gmail.com (corresponding author).
** Sandro Lunghi, Inalytics, 9th Floor, Corinthian House, 17 Lansdowne Road, Croydon CR0 2BX, UK, tel. +44 (0)20 3675 2904, e-mail: alunghi@inalytics.com

We thank Chris Collins and Laura Kane for excellent research assistance and Inalytics Ltd. for providing the data. We thank Adam Reed and seminar participants at McGill and the Federal Reserve Board for helpful comments. The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

Introduction

Short selling is extremely common, making up over a quarter of trading volume in U.S. equity markets (Diether, Lee, and Werner (2009)). Short selling is also very contentious. In the popular press it is often blamed for stock market declines and destabilizing markets. In contrast, many academics argue that short selling improves market efficiency ((e.g. Bris, Goetzmann, and Zhu (2007)) and prevents bubbles by allowing market participants to trade on negative information (Miller 1977).

We contribute to this debate by studying short selling from a particular angle: we examine how it differs from long investments. At a stylized level, short and long investments are very similar. Both include a buy and a sell transaction. For the short position the sell opens the position and the buy closes it, while the reverse is true for a long position. Thus, shorts are essentially just negative longs. Indeed this is how they are modeled in most theoretical papers. However, in practice short selling is more difficult. For example, short sellers need to borrow the shares they sell at fees that usually are only 10-20bp per year, but can be as high as several percentage points (Engelberg, Reed, and Ringgenberg (2015)). Furthermore, different to long positions, short positions become larger as the short seller is losing money (because the stock appreciates in value).

We ask whether these differences lead trading on short positions to be fundamentally different from the trading on long positions. In particular, we are interested in two questions. First, are short trades based on different information, in particular more negative information? Second, are short trades more likely to exhibit momentum?

If short trades contain more negative information this would underline how short selling helps to prevent overvaluation. Indeed, it is not clear that short selling is necessary to prevent overvaluation, because long investors can also trade on negative information by selling the stocks they already own (Diamond and Verrechia (1987)). However, because the amount of stocks a long investors can sell is limited to the amount they already own, they may have a lower incentive to exert effort to obtain negative information. If this is the case, short sells would be more informative than long sells, providing evidence that short selling is needed to incorporate negative information into prices.

In contrast, finding evidence that short trades exhibit more momentum, would support arguments that short selling increases volatility and potentially destabilizes markets. In fact, momentum trading can lead to reinforcing spirals, where a drop in price leads to more short selling, which causes prices to fall further.

When comparing long and short trading, it is important to control for the characteristics of the traders, because short sellers are usually more sophisticated than long investors. We can control for this issue by comparing long and short trades of the *same* traders. We are able to do this by using a unique proprietary dataset provided by Inalytics Ltd., which contains the complete trading and portfolio history of 21 long-short

equity hedge funds at a daily level from 2005 to 2015. Our data is much more detailed than anything used before. In fact, most prior studies on short selling only use aggregate data and cannot identify individual short sellers. Exceptions are papers using data on large short positions in Europe (Jones, Reed, and Waller (2015) and Jank, Roling, Smajlbegovic (2016)) and Japan (Boehmer, Duong, and Huszar (2015)), but these authors only observe a fraction of the short positions and do not observe the corresponding long positions. Similarly, papers using only trading data on hedge funds (e.g. Franzoni and Plazzi (2013), Jame (2016)) cannot distinguish between long and short positions, but can only determine the direction of the trade.

Long-short equity hedge funds constitute an ideal laboratory to examine the difference between long and short trading, because they undertake *independent* discretionary long and short investments. Thus, the long and short positions are not part of a combined trading strategy such as merger arbitrage. In addition, long-short equity hedge funds usually buy long positions on margin (Pedersen (2015)), which makes them very similar to short positions. In both cases only a fraction of the value of the position must be provided to the broker as collateral, but additional collateral must be provided if the position loses in value.

The hedge funds in our sample sometimes break up an order into several trades to limit their market impact. To avoid double counting, we group trades in the same stock and direction that happen within 2 days from each other into a single order. We generally distinguish three types of orders: *Initial orders* are orders that initiate a position, i.e. the first buy order for a long position or the first sell order for a short position. *Follow-up orders* are trades in stocks that neither initiate nor close a position. These can be buys and sells for both long and short portfolios. Finally, *closing orders* are the orders that close a position, i.e. the last buy order for a short position or the last sell order for a long position. We find that initial and closing orders are much larger than follow-up orders. We compare the size of orders to the maximum size that a position takes. On average, initial orders set up 77% of the maximum position and closing orders close 78% of the maximum positions. In contrast, follow-up orders are much smaller making up only 16% of the maximum position on average. When studying informativeness of orders, we exclude follow-up orders and focus only on initial and closing orders.

We measure profitability with risk-adjusted stock returns following the orders. We employ three different risk adjustments: excess returns with respect to the fund-specified benchmark, risk-adjusted returns following the methodology of Daniel, Grinblatt, Titman, and Wermers (1997), hereafter DGTW, and alphas using the four-factor model of Carhart (1997). DGTW returns and alphas are computed on a regional level including 5 geographic regions (North America, Europe, Asia-Pacific, Japan, and Emerging Markets).

We compare the informativeness of long and short orders by examining the profitability of orders. We test the following hypotheses:

Null hypothesis: *Buys are followed by positive returns and sells are followed by negative returns. Returns are independent on whether the trades are related to long and short positions.*

Initiation hypothesis: Short sells are followed by more negative returns than long sells and long buys are followed by more positive returns than short buys.

Our null hypothesis assumes the same profitability for buy and sell orders independent of whether they are long or short trades. In other words, only the trade matters, but the position held is irrelevant. Under this hypothesis, the same amount of negative information reaches the market through long and through short trades. For example, this hypothesis may be appropriate if most of the profitability comes from providing liquidity. Several papers argue that hedge funds are active in providing liquidity (e.g. Franzoni and Plazzi (2013), Jame (2016), Jylhä, Rinne and Suominen (2014)). In contrast, the initiation hypothesis predicts that the initiation of positions are more informed than the closing of positions. Therefore, sells are more profitable for short positions and buys are more profitable for long positions. Confirmation of this hypothesis would suggest that short sells contain more negative information than short buys.

We distinguish between the two hypotheses by running two separate regressions for buy and sell orders. We regress risk-adjusted returns following the last day of the order on a dummy variable equal to one if the order was related to a short portfolio. We find that long buys are followed by more positive returns than short buys and that short sells are followed by more positive returns than long sells. The differences are economically large at 1-1.6% in risk-adjusted returns over the 3 months following the order. They are also statistically significant at the 1% level. The differences are of similar magnitude independent of the risk adjustment used (excess returns, DGTW returns or alphas).

This finding clearly supports the *initiation hypothesis* and shows that the initiation of positions are much more profitable than the closing of positions. This underlines how important it is to distinguish whether buy or sell orders are related to a long or a short position, something that is only possible with portfolio data such as the one used in this study.

After having established that the initiation of positions is much more profitable than the closing of positions, we focus in more detail on the profitability of the closing of positions. In particular, we contrast the following three hypotheses:

Profitable closing hypothesis: *The closing of short positions is followed by more* ***positive*** *returns than the closing of long positions.*

Null hypothesis: There is no difference in returns following the closing of long or short positions.

<u>Premature closing hypothesis</u>: *The closing of short positions is followed by more* ***negative*** *returns than the closing of long positions.*

The profitable closing hypothesis is based on the idea that while less profitable than the initiation of positions, the closing of positions is still profitable. Under this hypothesis, funds would buyback a short position before a stock appreciates and sell a long position before a stock depreciates. This hypothesis is also consistent with results of Boehmer, Duong, and Huszar (2015), who find that the closure of short positions is followed by positive returns. Under this hypothesis, some negative information would still reach markets through long sells. In contrast, the null hypothesis simply predicts no return predictability from the closing of positions, implying that they are uninformed. Finally, the premature closing hypothesis predicts that hedge funds close their positions "too early" and long positions continue to experience positive returns even after being closed, while short positions continue to experience negative returns. This hypothesis is not necessarily behavioral. In fact, funding-constrained hedge funds may choose to close a position that retains some positive expected returns if they have other trading opportunities with higher expected returns.

To distinguish between the three hypotheses, we examine only our sample of closing orders and regress returns following the orders on whether the closing trade was related to a short or a long portfolio. We find that returns following the closing orders of a short positions have significantly more *negative* risk-adjusted returns. The size of the effect is economically important at 1.7% excess returns over the following 6 months (about 1% in terms of DGTW returns and 4-factor alphas).

This result provides clear support for the *premature closing hypothesis*. It shows that hedge funds are leaving substantial money on the table by closing their positions too early. They could earn an additional 1-1.7% return by keeping their positions open an additional 6 months. Put differently, it is possible to earn significant alpha by trading against the closing trades of hedge funds. This finding also suggests that long sells are not based on negative information. It shows the importance of short sells to get negative private information incorporated into prices.

In the second part of the paper, we examine the degree to which long-short equity hedge funds engage in momentum or contrarian trading in their long and short positions. We begin by examining initiating positions. We find that hedge funds engage in momentum trading both when establishing their long positions as well as when establishing their short positions. In aggregate, a given initiation of a position is 3.2 percentage points more likely to be a buy (and thus a long position) if the stock's DGTW return in the prior 6 months was 20% higher (roughly one standard deviation). This difference is also statistically significant.

Next, we ask whether short and long positions differ in their momentum trading in follow-up orders. We propose the following two competing hypotheses:

*<u>Rebalancing Hypothesis:</u> Short positions exhibit **more** momentum trading than long positions for follow-up orders.*

*<u>Risk Management Hypothesis:</u> Short positions exhibit **less** momentum trading than long positions for follow-up orders.*

The *rebalancing hypothesis* is motivated by the idea that funds may target to maintain a certain level of dollar investment in a position. In this case, they would reduce their positions after a positive return and increase their position after a negative return. Such behavior would lead to contrarian trading for long positions (sells following positive returns) and momentum trading for short positions (buys following positive returns). In contrast, the *risk management hypothesis* is based on the idea that hedge funds want to reduce their (usually levered) positions during times of higher volatility. As negative returns are usually followed by higher volatility, this would mean decreasing a position following a negative return. Such behavior would lead to momentum trading for long positions (sells following negative returns) and contrarian trading for short positions (buys following negative returns).

To distinguish between the two hypothesis, we conduct both an order-level and a holding-level analysis. In the order level analysis, we include only follow-up orders and regress a dummy variable whether the order is a buy on the returns in the 60 and 125 trading days prior to the order. We conduct this analysis separately for long and short positions. We find a positive association between past returns and buys for short positions, but a negative association for long positions. We also find that this difference is statistically significant, when we run the same regression on a combined sample and include an interaction between prior returns and the short position dummy variable as the explanatory variable of interested. The effect is also economically significant: a 20% higher 60-day return (approximately a standard deviation) increases the probability of a buy by 4% for short positions relative to long positions. Next, we conduct the same regression on the daily holding level. We create the variable *Direction* that is equal to 1 for buys, -1 for sells and 0 for no trades. Regressing *Direction* on past returns, we can confirm the results from above: there is momentum trading in short positions, but contrarian trading in long positions. Furthermore, we show that this effect comes from both buy and sell orders.

These results confirm that for follow-up orders short positions exhibit more momentum trading than long positions, which confirms the rebalancing hypothesis. Funds reduce their positions after positive returns to keep the dollar exposure to the stock more constant. This leads to buying after positive returns in short positions (momentum trading) and selling after positive returns in short positions (contrarian trading).

To summarize, we find that there are substantial differences between long and short positions of the same long-short equity hedge funds. Examining how short trading differs from long trading that can inform

the debate on whether short selling is beneficial for financial markets. On the positive side, we find that only short positions trade on negative information, while long positions trade exclusively on positive information. This finding suggests that short selling is important to get negative information into prices and can help to prevent overvaluation in stocks. On the negative side, short positions exhibit more momentum trading than long positions, which implies that short selling may increase volatility in the market and potentially destabilize asset prices.

Our paper contributes to four strands of literature. The first is the literature on the profitability of short sales. Several papers find that short selling predicts future returns (e.g. Desai, Thiagarajan, and Balachandran (2002), Boehmer, Jones, and Zhang (2008), Diether, Lee, and Werner (2009), Asquith, Pathak, and Ritter (2005), Engelberg, Reed, and Ringgenberg (2012)). However these papers usually focus only on short buying or the change in short interest. We add to these papers by examining the profitability of the closing of short positions. In contrast to short sells, we show that short buys do not profitably predict future returns. The only other paper examining returns following the closing of short positions is Boehmer, Duong, and Huszar (2015). Their results differ from ours and indicate somewhat positive return predictability for closing trades. However, their analysis is based on very large positions that had to be publicly disclosed. Thus, their results are more likely biased by the price impact of the trade and the signaling effects from the disclosure. Furthermore, our results can show that unprofitable closing trades are not unique to short positions, but also occur for long positions.

The second is the literature on short selling and momentum. While Diether, Lee, and Werner (2009) find that short sellers are contrarian at the 5-day horizon, several papers find evidence that short sellers are momentum traders at the 1-month (Savor and Gamboa-Cavazos (2011)) and 12-month horizon (Curtis and Fargher (2014)). However, all of these results are based on aggregate short sell trading or short interest data that do not allow to identify individual positions. We add to this literature by showing momentum trading of short sellers for both initiating positions and follow-up trades. More importantly, we show that short sellers exhibit more momentum trading than long investors for follow-up trades due to the rebalancing effect.

The third is the literature on the skill of hedge funds. Many papers examine hedge fund skill using databases on hedge fund returns and trying to control for the different biases of these databases (see Agarwal, Mullally, and Naik (2015) for a survey of the literature). More recent papers that examine hedge fund skill using quarterly data of their equity positions from 13F filings find mixed results. While Cao et al. (2016) find that hedge fund holdings predict future returns, Griffin and Xu (2009) find no predictive power of hedge fund holdings. Jank and Smajlbegovic (2015) use data from the disclosure of large short positions of hedge funds and find predictability. We add to this literature by examining trading skill using detailed trading records for *both* long and short positions of the *same* funds. We find evidence of hedge fund skill in the opening of

positions, but not in the closing of positions. Furthermore, since our data is not public, there is no risk that the disclosure of the position is driving the stock returns.

Fourth, our paper is related to studies examining hedge funds tendency to engage in contrarian vs. momentum trading. Using hedge fund trading data, Jame (2016) finds that hedge funds that provide liquidity (measured as trading contrarian) exhibit outperformance. Similarly, Jylhä, Rinne and Suominen (2014) find that hedge fund returns are positively correlated with a long-short contrarian trading strategy, suggesting that they are on average contrarian. In contrast, Jank and Smajlbegovic (2015) find that hedge funds trade on momentum in their short positions. We add to this literature by showing that long-short equity hedge funds exhibit more momentum in their long than in their short positions due to the rebalancing effect.

1. Data and Variable Construction

In this paper, we use unique proprietary data on trades and portfolio holdings of hedge funds provided by Inalytics Ltd. We merge these data with international stock market data from Datastream and balance sheet data from Worldscope (both products of Thompson Reuters).

1.1 Inalytics data

Our data on long-short equity hedge funds is provided by Inalytics and this is the first time it has been used in an academic collaboration. A subset of the Inalytics database, long only equity, has been previously used in Di Mascio, Lines and Naik (2016). Inalytics analyses patterns of investment decisions to interrogate the robustness of various investment processes. The output is portfolio monitoring for institutional asset owners and investment consultants and process improvement for asset and hedge fund managers. When an institutional investor, like a plan sponsor, makes an allocation to a hedge fund that hedge fund will provide its trading and portfolio data to enable Inalytics to monitor their performance for the end client.

The Inalytics data we use contain complete trading and portfolio information for the equity holdings of 21 hedge funds. For each fund we obtain information on the short and the long portfolio. For each portfolio we have two datasets: The first is a trade-level dataset containing all trades. Variables in this dataset include stock identifiers (ISIN, SEDOL, and CUSIP), the date of the trade, the number of shares traded, and the execution price (expressed in the base currency of the fund and in the local currency of the stock). The second is a day-stock-level dataset of each funds' portfolio holdings. This dataset contains stock identifiers, the number of shares held, and the price of the stock at the end of the day (expressed in the base currency of the fund and in the local currency of the stock).

We use a merged dataset that combines the holdings and trading data (details on merging these two datasets can be found in Appendix 3). Several funds split their orders into several trades that are executed on

different days to reduce the market impact of their orders. To avoid double counting, we follow Di Mascio, Lines, and Naik (2016) and aggregate the trades belonging to one investment decision into orders. We assume that trades belong to one order if they trade the same stock in the same direction and the distance between two trades of the order is two days or less. Seventy-three percent of the orders consist of only one trade.

1.2 Summary statistics for Inalytics data

Our sample period is quite long and runs from 2005 to 2015. However, the coverage for each individual funds covers only a fraction of this sample period. Figure 1 gives an overview about how the number of funds, positions and orders changes over the sample period. From 2005 to 2007, the sample is fairly small with only 1-6 funds. From late 2008 to mid-2013, we have 8 to 9 funds in the sample. In 2013, the number of funds jumps to 17. However, the early funds have more positions, so from 2008 Q1 to the end of the sample period we always have at least 500 positions in the data. Orders move more proportional to the number of funds. From 2008 Q1 to the end we have around 20 orders per day in the sample, but towards the end of the sample period that number jumps to over 100 orders per day. We include our full sample period in our tests to preserve statistical power and ensure that no specific time period is driving our results.

In Table 1, Panel A, we display summary statistics by fund. Funds hold on average 50 long positions and 24 short positions (median values are 36 and 19). The fewer number of short positions is also reflected by the fact that short positions make up about 30% by USD value. Having a larger long than short portfolio is seen as typical for long-short equity hedge funds. The funds conduct on average 5 orders per day. Compared to an average of 74 positions this corresponds to a new order for a stock every 15 trading days. The daily USD trading volume of a fund divided by its holdings is on average 5.4% (median 2.8%). Our funds have fairly difference sizes. The 10th percentile fund holds 0.12 billion USD in assets, while the 90th percentile fund holds 6 billion USD. The median fund holds 0.4 billion USD. Also the investment areas of the funds differ. We present them in Figure 2. We have 7 Europe-focused funds, 3 US, 3 UK and 2 Australia-focused funds, as well as 6 funds that invest world-wide. Due to that, European stocks are somewhat heavier weighted in the stocks that the funds hold. In Table 1, Panel B, we show that funds most heavily hold stocks from Europe (29%) and North America (31%). Despite this, 19% of stocks are from emerging markets.

In Panel B, we display summary statistics by position. A position lasts from its initiation, i.e. the first buy for long positions or the first sell for short positions to its close, i.e. the moment the holding of the stock is reduced to zero. After being closed, a new position can be established in the same stock. However, this does not happen very often: on average there are only 2 positions in a given stock. Our data contains about 16,000 positions; 6.9% of them are open at the start, i.e. they existed already when the fund entered the database, while 11% are open at the end, i.e. they are still active when the fund leaves the database. Due to this censoring, the length of positions will be biased downwards. The investment horizon of the funds seems

to be fairly long. The average length of a position is 104 trading days (about half a year), but the median is only 35 trading days (about 2 months). In this time, funds conduct on average 6 orders (median 3) and change the direction of trading on average 2.5 times (median 1).

Next, we examine summary statistics on the order-level. We distinguish between three types of orders: Initial orders that initiate the position, closing orders that close the position and follow-up orders that change the size of the position in between. We display summary statistics for each type of order separately in Panels C to E. The initial and closing orders are much larger (mean of 10.8 million USD) than the orders in between (mean of 7.4 million USD). The difference is even starker if we standardize the size of the order relative to the largest size that the position reaches. On average initial and closing orders make up around 77% of the maximum size of the position (median 100), while the follow-up orders make up only 15.8% (median 8.7%). This suggests that the important investment decisions are the initiation and closing of positions. The orders in between are small and thus likely based more on liquidity motives than on information. Still, the follow-up orders make up 70% of all orders in our sample. Hedge funds don't split orders into separate trades very often: the average number of trades per order is only about 1.6 and the median is 1 for each order type.

1.3 Datastream and Worldscope data

Because of the international nature of our hedge fund data, we also need international stock market and balance sheet data. We use the datasets most commonly used in the international context: Datastream for stock returns and Worldscope for balance sheet data. We use this data mainly to compute risk-adjusted returns to benchmark the performance of different funds and orders. We use three methodologies to risk-adjust returns: we compute excess returns with respect to the fund-specified benchmark, we compute risk-adjusted returns following the methodology of Daniel, Grinblatt, Titman, and Wermers (1997), hereafter DGTW, and we compute alphas using the four-factor model of Carhart (1997). The details of the risk-adjustments are explained in Appendix 3, but we will touch here on the main aspects of the methodology.

Excess returns are computed as returns minus the return of the fund-specified benchmark. This means that the risk-adjustment depends on the fund, i.e. the excess return of the same stock may be positive for one fund but negative for another fund. The benchmarks can even be different within the same investment area, for example some Europe-focused funds benchmark against the MSCI Europe, while others benchmark against the FTSE Europe. However, the benchmarks are always the same for both long and short positions of the same fund and they do not change for the same fund over time.

As a second methodology, we compute DGTW returns on a regional level. We split the world into 5 regions (Japan, North America, Europe, Asia-Pacific and Emerging Markets) following Karolyi and Wu (2014). The assignment of countries into regions is displayed in Appendix 2. Within each region, we sort

stocks into quintiles by market capitalization, market-to-book ratio and past 12 months returns, thus forming 625 portfolios (125 per region). We compute DGTW returns as stock returns minus the returns of the respective portfolio. We choose to compute portfolios on a regional level, because it is more granular than using the same portfolios for the whole world and prior evidence suggests that local factors are better in pricing risk (Griffin (2002)). At the same time, it is less cumbersome to compute factors at the regional rather than the country level and for many countries we have too few stocks to populate 125 portfolios.

As a third methodology, we implement a regional version of the Carhart (1997) 4-factor model. For each of our 5 regions we compute a market factor, a High minus Low Book to Market Factor (HML), a Small minus Big (SMB) factor and a Momentum (MOM) factor of winners minus losers. For each stock, we compute betas with respect to these factors using daily regressions over the prior 12 months. We then shrink these betas to their cross-sectional average following Vasicek (1973). This implementation follows the suggestions of Levi and Welch (2016), who find that for predicting betas, daily regressions are more accurate than monthly regressions, 1 year horizons are better than longer horizons and it is important to shrink the betas. Finally, we compute alphas on the daily level as:

$$Four\ factor\ alpha_{c,t} = r_{c,t} - \beta_c * \left(r_{m,t} - r_{f,t}\right) - \beta_{HML} * HML_t - \beta_{SMB} * SMB_t - \beta_{MOM} * MOM_t$$

More details on the construction of the risk-adjustment is presented in Appendix 3.

2. Results

2.1 Are initiation of positions more profitable than closing of positions?

In this section we examine whether buys and sells have the same profitability independent of whether they belong to short or long portfolios (*null hypothesis*) or whether buys are more profitable for long positions and sells are more profitable for short positions (*initiation hypothesis*).

We do this by splitting the sample into buys and sells and regressing risk-adjusted returns following the order on *D(Short)*, a dummy variable equal to one if the order is undertaken for a short position (and zero if it is undertaken for a long position). We only include orders that initiate or close a position. We examine all three measures of risk-adjusted returns in the 60 or 125 trading days (approximately 3 or 6 months) following the order. We measure returns from the date following the last date of the order, i.e. we do not account for with-in order returns. We cluster standard errors two-way by stock and last date of order. Clustering by stock controls for correlation due to overlapping returns (for example if two trades happen in the same stock in the same month) and clustering by date controls for correlation in the cross-section of stock returns.

We present the results for buys in Panel A of Table 2. The coefficient of *D(Short)* is significantly negative, showing that long buys are followed by more positive returns than long sells. The difference is 1.6% in excess returns over 60 days and 2.3% over 125 days. For DGTW returns and alphas the effect is slightly smaller at 1.1% over 60 days and 1.5% over 125 days. This finding suggests that buys are more profitable for long than for short positions.

Next, we present the results for sells in Panel B. Once again *D(Short)* is significantly negative, suggesting that short sells are followed by more negative returns than short buys. The magnitudes are comparable to the result of buys with short sells having 0.8-1.3% more negative returns in the first 3 months and 1.4-2.2% more negative returns in the first 6 months following the order.

Our results clearly support the *initiation hypothesis* that trades are more predictive of future returns when they initiate rather than close a position. Long-short equity hedge funds seem to be trading mainly on positive information in long positions, while they trade on negative information in short positions. This finding suggests that it is very important to split buy and sell orders into long-buys and short-buys as well as long-sells and short-sells. Such distinctions cannot be made using simple trading data such as the Ancerno dataset, which shows the importance of having access to portfolio data.

2.2 Do hedge funds close positions too early?

After having established that the initiation of positions is much more profitable than the closing of positions, we focus in more detail on the profitability of the closing of positions. In particular, we want to know if returns after the closing of short positions are more positive (*profitable closing hypothesis*) or more negative (premature closing hypothesis) relative to the closing of long positions.

We start with a very simple graphical analysis presented in Figure 3. We show cumulative returns in excess of the fund-specified benchmark in the 250 trading days (approximately 1 year) following an order. We include only orders that initiate and or close a position, i.e. we exclude follow-up orders. We also split orders by whether they are related to a long or a short position.

We see clear evidence of informed trading in the initiation of positions: in the 250 days following the initiation of a long position cumulative excess returns are 1.5%. Most of this return is realized in the first the 125 trading days (6 months) following the order, staying relatively constant from there on. Similarly, in the 250 days following the initiation of a short position cumulative excess returns are -2%. Most of this negative return is realized in the first 180 trading days (9 months), staying flat afterwards.

In contrast, the closing of long positions seems not to be informed. Long sells are not followed by negative returns, but rather by positive returns. In the 250 days following the closing of a long position

cumulative excess returns are 0.5%. Similarly, short buys are followed by negative excess returns (-1% after 250 days). In both cases, most of the cumulative return is realized in the first 125 trading days following the order

These graphical results are consistent with the *premature closing hypothesis*, suggesting that hedge funds close their positions too early leaving money on the table. But are these results statistically significant and robust to other forms of risk-adjustments? Is it possible to create a profitable trading strategy trading against hedge funds when they close their positions?

To examine these questions, we plot the difference between the returns following the closure of long positions and the returns following the closure of short positions in Figure 4. These returns correspond to a strategy that goes long in stocks with closed long positions and short in stocks with closed short positions. Put differently, it takes the opposite side of the trade as the hedge funds do when closing their position.

We see that this strategy continues to accumulate positive risk-adjusted returns for about 125 trading days (6 months) following the closure of positions. This suggests that the funds close their positions too early. Holding positions open an additional 6 months would earn an additional excess return of 1.7% for short and long positions combined (about 1% in terms of DGTW returns and alphas).

In Table 3, we confirm that this difference is significantly different from zero. We regress risk-adjusted returns in the 60 and 125 trading days (3 months or 6 months) after the last day of the order closing the position on an dummy variable equal to one for closed short positions (and zero for closed long positions). Confirming the result from the figure, closed short positions are followed by 6-month excess returns that are 1.7% lower (1% for DGTW returns and alphas). This difference is statistically significant. For the shorter horizon of 3 months, the difference is only significant for excess returns.

Taken together, these results show that returns continue to trend up after the closing of long positions and down after the closing short positions, supporting the *premature closing hypothesis*. This suggests that hedge funds could make more money on a specific position if they would hold on to it for an additional 6 months. However, this does not mean that hedge funds are acting irrationally. Indeed, if they are funding constrained, hedge funds might rationally decide to close a position that still expects positive excess returns to invest in another position with higher expected excess returns. We cannot evaluate whether they close too early, because it depends on their other trading opportunities, on the market impact that they have and on their preferences for diversification.

2.3 Momentum trading

There is a long literature in finance suggesting that stock returns exhibit momentum, i.e. winning stocks continue to appreciate while losing stocks continue to depreciate (e.g. Jegadeesh and Titman (1993)). The literature has different results on how much hedge funds follow momentum strategies (see discussion in introduction). In this section we examine whether the long-short equity hedge funds in our sample engage in momentum trading and whether their tendency to do so is different for long and for short positions.

2.3.1 Momentum when initiating orders

We start by examining whether hedge funds trade on momentum when establishing their positions. We start with a very simple analysis in Figure 5, where we display DGTW returns and 4-factor alphas in the 250 trading days before the initiation of short and long positions. The graph signals clear signs of momentum trading: stocks experienced risk-adjusted returns of 2.5% in the 250 days before the initiation of long positions and negative 0.5% in the 250 days prior to short positions. For short positions, this return is even more negative (close to -1%) if we look back only 125 days. Interestingly, returns in the 40 days before the orders do not differ between long and short positions. This suggests, that funds base their momentum trading mainly on the period from t-6 to t-2 months prior to the order. Furthermore, we see momentum trading for both long and short positions, but it seems stronger for long positions.

Next, we study whether we also find evidence of momentum trading using regressions. We run our analysis on the order-level focusing only on orders that initiate a position. We are interested whether the past return of the stock predicts whether the fund establishes a long or a short position. Therefore, we regress *D(Buy)*, a dummy variable indicating whether the order is a buy or a sell on measures of past returns. Because the graph indicated most momentum with respect to the past 6-months, we look at returns for 60 and 125 trading days prior to the order. To control for any desires of a fund to expand its long or short portfolios, general market moves and fund specific characteristics, we include fund-date fixed effects. Because of these high dimensional fixed effects, logit or probit estimation would be biased (Chamberlain (1980), Neyman and Scott (1948)). As is commonly done (e.g. Khwaja and Mian (2008)), we use a linear probability model (OLS) instead.

We present the results in Table 4. For both the 60 and 125 days horizon and for both simple and risk-adjusted returns we find a correlation between past returns and the probability of establishing a long position. This result is significant at least at the 5% level. The result is also economically significant: a 20% higher DGTW return in the prior 125 days (about one standard deviation) increases the probability of the order being a buy by 3.1%. To conclude, the regression analysis confirms that hedge funds engage in momentum trading when establishing their positions.

2.3.2 Momentum for follow-up orders

Next, we examine whether our long-short equity hedge funds also engage in momentum trading on follow-up orders. Especially, we are interested whether funds exhibit different momentum trading behavior for long and short positions. Such differences could occur due to two reasons that lead to opposing predictions.

First, funds may target to maintain a certain level of dollar investment in a position and may conduct rebalancing trades to keep this level constant. In this case, they would reduce their position after a stock increases in value and increase their position after a stock decreases in value. Such behavior would lead to contrarian trading for long positions and momentum trading for short positions. The reason for this is that to reduce a short position after a stock price increase, the fund needs to buy back the stock, while he needs to sell the stock to close a long position. Thus we formulate the following hypothesis:

Rebalancing Hypothesis: *Short positions exhibit* ***more*** *momentum trading than long positions for follow-up orders.*

Second, there is an argument that predicts an effect going in the opposite direction. Hedge funds need to provide collateral for both short and long positions, because they usually purchase long positions on margin. If positions move against them, they may be forced to close out of profitable positions. Thus they need to manage their capital and may want to reduce positions when the market becomes more volatile. It is an established empirical fact that volatility increases are correlated with negative returns. Thus, hedge funds may have an incentive to reduce their position following a negative return, which would lead to momentum trading for long positions and contrarian trading for short positions. Thus we formulate the following hypothesis:

Risk Management Hypothesis: *Short positions exhibit* ***less*** *momentum trading than long positions for follow-up orders.*

We now examine which of these two effects is stronger in the data. We start by conducting an order level analysis similar to the one conducted in section 2.2.1:

$$D(Buy) = \alpha_{f,d} + \beta * Ret_{t-60,t-1} + \gamma * Controls + \varepsilon$$

Where *D(Buy)* is a dummy variable equal to one for a buy and $\alpha_{f,d}$ are fund-date fixed effects. We add *Position Tenure*, which is the logarithm of the number of days the position is open to control for the fact that funds are more likely to close a position that has been open for a long time. However, different to the prior analysis, we exclude initiating orders from the sample. Follow-up orders can be buy and sell orders for both the long and the short portfolio. This allows us to run the analysis separately for long and short positions allowing us to distinguish whether longs or shorts exhibit more momentum trading.

We present the results in Table 5. For the short position sample we exhibit clear momentum behavior that is statistically significant. After a 20% increase in the prior 125 day return, a short position trade is 1.2% more likely to be a buy rather than a sell. In contrast, for long positions we observe the opposite behavior: a trade is less likely to be a buy following positive returns (however this effect is only statistically significant for the prior 60 day return).

Next we see whether the difference between short and long momentum trading is statistically significant. For this purpose, we use the full sample of follow-up orders and run the following regression:

$$D(Buy) = \alpha_{f,p,d} + \beta_1 * D(Short) * Ret_{t-60,t-1} + \beta_2 * Ret_{t-60,t-1} + \gamma * D(Short) * Controls + \gamma * Controls + \varepsilon$$

where $\alpha_{f,p,d}$ are fund-portfolio-date fixed effects, i.e. we use different fixed effects for the short and the long portfolio. The coefficient of interest is β_1. It measures the difference in momentum behavior between long and short portfolios. It is significantly positive showing that for short positions a positive return is more likely to be followed with a buy order than for long positions. The effect is also economically significant: a 20% higher 60-day return (approximately a standard deviation) increases the probability of a buy by 4% for short positions relative to long positions. These results confirm that for follow-up orders short positions exhibit more momentum trading than long positions, which confirms the rebalancing hypothesis. Funds reduce their positions after positive returns to keep the dollar exposure to the stock more constant. This leads to buying after positive returns in short positions (momentum trading) and selling after positive returns in short positions (contrarian trading).

So far we have only examined situations where there is an order. However, on many days there are no new orders in a stock. To address this issue, we extend our analysis to include all days in which a stock is held. For each date, we construct the variable *Direction*, which is equal to 1 for days with a buy, 0 for no trade and -1 for days with a sell. Because we use all days, we base this classification on trades rather than orders. Therefore the trade on the second day of a buy order gets also a 1 rather than a 0. We exclude the trade initiating and closing the position. Then we conduct the same analysis as above with *Direction* as the dependent variable. We confirm the results from above: there is momentum trading in the short positions, but contrarian trading in the long positions. This time, the evidence for contrarian trading in the long positions is significant at the 1% level for both 60 and 125 day prior returns.

Next, we want to see whether our results are driven mainly by buys or by sells. For this purpose, we create the variables D(Buy)-Holding and D(Sell)-Holding, which are equal to one for a buy (sell) and zero otherwise. We use both of these variables as dependent variables in our interaction specification. The results suggest that both buys and sells contribute to more momentum behavior for short positions. More positive returns predict both more buys and more sells for shorts relative to longs.

3. Robustness Checks

3.1 Examining all orders

When examining the profitability following buy and sell orders in sections 2.1 we only include orders that open or close a position in our sample. In this robustness check, we extend the analysis to include all orders. If anything, we would expect the inclusion of all orders to increase the differences between long and short orders, because now a position remains following long sells and short buys. We confirm in Table 6 Panel A and B that this is the case. Excess returns in the 125 day following an order are 2.7% higher for long buys than for short buys when including all trades. This difference is larger than the 2.3% difference when comparing only long buys that open positions to short buys that close positions. Similarly, for sells we find a larger difference of 2.8% when including all sells compared to 2.2% when including only sells opening or closing a position.

In Panel C, we expand our analysis for the closing of short positions to a larger sample. While we only include closing orders in our original analysis in Table 3, we now also include orders that reduce the position (i.e. all long sells and short buys). Once again this increases our results. While we found 1.6% higher excess returns in the 6 months following the closing of long positions compared to the closing of short positions, this result increases to 2.5% when including also orders that reduce the size of the position.

Taken together, this robustness check confirms that our results are not driven by the fact that we focus exclusively on initial or closing orders, but that the effects actually get larger when we also include follow-up orders.

4. Conclusion

In this paper, we use detailed daily data on the trades and portfolio holdings of international long-short equity hedge funds to examine the differences between the trading on long and short positions. We are especially interested in two aspects: whether trades related to long and short positions use different types of information and whether they differ in the degree to which they exhibit momentum trading.

On the first issue, we find that long buys and short sells are informed, but that long sells and short buys are uninformed. In other words, we find that trades initiating a position are profitable, while trades closing a position are not profitable. More than that, sells that close a long position are followed by more *positive* returns than buys that close a short position. This finding implies that hedge funds close too early and leave money on the table. This finding is consistent with funding-constrained hedge funds closing positions that remain profitable to invest their resources in other more profitable positions. Furthermore, this finding shows

that only short sells contain negative information, while long investments seem only based on positive information.

On the second issue, we find that momentum trading differs between long and short positions. While both long and short positions exhibit momentum when initiating a position, only short positions exhibit momentum in follow-up trades that modify the size of the position. In contrast, follow up trades for long positions exhibit contrarian behavior. This finding is consistent with a rebalancing effect, where hedge funds reduce positions after positive returns to keep their dollar exposure to the stock constant.

Our findings have important implications for the debate on whether short selling is beneficial for markets. Our first finding suggests that short selling is important to incorporate negative private information into prices. Thus, without the ability to short sell, traders may not have enough incentives to spend the effort to acquire negative information. If negative information is not incorporated into prices, this can lead to overvaluation and potential market crashes. In contrast, our second finding suggests a potential downside to short selling. Because short sellers engage more in momentum trading, their trades are more likely to increase volatility in the market. A vicious circle is possible, where a fall in price causes more short sells that make prices fall further.

References

Agarwal, Vikas, Kevin A. Mullally, and Narayan Y. Naik, 2015, Hedge Funds: A Survey of the Academic Literature, *Foundations and Trends in Finance*, forthcoming.

Asquith, P., Pathak, P. A., and Ritter, J. R., 2005, Short interest, institutional ownership, and stock returns. *Journal of Financial Economics* 78, 24-276.

Boehmer, Ekkehart, Truong X. Duong, and Zsuzsa R. Huszár, 2015, Short covering trades, *Working Paper*.

Boehmer, Ekkehart, Charles M. Jones, and Xiaoyan Zhang, 2008, Which Shorts Are Informed?, *Journal of Finance* 63, 491-527.

Boehmer, Ekkehart, Charles M. Jones, and Xiaoyan Zhang, 2008, Shackling the short sellers: the 2008 shorting ban, *Review of Financial Studies* 26, 1363-1400.

Bris, Arturo, William N. Goetzmann, and Ning Zhu, 2007, Efficiency and the Bear: Short Sales and Markets Around the World, *The Journal of Finance* 62, 1029-1079.

Cao, Charles, Yong Chen, William N. Goetzmann, and Bing Liang, 2013, The role of hedge funds in the security price formation process, *Working paper*.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, *The Journal of Finance* 52, 57-82.

Chamberlain, Gary, 1980, Analysis of Covariance with Qualitative Data, *The Review of Economic Studies 47*, pp. 225-238.

Curtis, Asher, and Neil L. Fargher, 2014, Does Short Selling Amplify Price Declines or Align Stocks with Their Fundamental Values?, *Management Science* 60, 2324-2340.

Daniel, Kent, Mark Grinblatt, Sheridan Titman and Russ Wermers, 1997, Measuring Mutual Fund Performance with Characteristic-Based Benchmarks, *Journal of Finance 52*, 1035-1058.

Desai, H., Ramesh, K., Thiagarajan, S. R., Balachandran, B. V., 2002. Investigation of the information role of short interest in the NASDAQ Market. *Journal of Finance* 57, 2263-2287.

Diamond, Douglas W., and Robert E. Verrrecchia, Constraints on short-selling and asset price adjustment to private information, *Journal of Financial Economics* 18, 277-311.

Diether, Karl B., Kuan-Hui Lee, and Ingrid M. Werner, 2009, Short-Sale Strategies and Return Predictability, *Review of Financial Studies* 22, 575-607.

Di Mascio, Rick, Anton Lines and Narayan Y. Naik, 2016, Alpha Decay and Strategic Trading, *Working Paper*.

Engelberg, Joseph E., Adam V. Reed, and Matthew C. Ringgenberg, 2012, How are shorts informed?: Short sellers, news, and information processing, *Journal of Financial Economics* 105, 260-278.

Engelberg, Joseph E., Adam V. Reed, and Matthew C. Ringgenberg, 2015, Short Selling Risk, *Working Paper*.

Fama, Eugene F. and Kenneth R. French, 2012, Size, Value, and Momentum in International Stock Returns, *Journal of Financial Economics* 103, 457-472.

Franzoni, Francesco and Alberto Plazzi, 2013, What Constrains Liquidity Provision? Evidence From Hedge Fund Trades, *Working Paper*.

Frazzini, Andrea and Lasse Heje Pedersen (2014). "Betting Against Beta", *Journal of Financial Economics* 111, 1–25.

Griffin, John M. and Jun Xu, 2009, How smart are the smart guys? A unique view from hedge fund stock holdings, *Review of Financial Studies* 22, 2332-2370.

Griffin, John M., 2002, Are the Fama and French Factors Global or Country Specific?, *Review of Financial Studies* 15, 783-803.

Ince, Ozgur S., and R. B. Porter, 2004, Individual Equity Return Data from Thomson Datastream: Handle with Care! *SSRN eLibrary* .

Jame, Russell, 2016, Liquidity Provision and the Cross-Section of Hedge Fund Returns, *Working Paper*.

Jank, Stephan, Christoph Roling, and Esad Smajlbegovic, 2016, Flying Under the Radar: The Effects of Short-Sale Disclosure Rules on Investor Behavior and Stock Prices, *Working Paper*.

Jank, Stephan, and Esad Smajlbegovic, 2015, Dissecting Short-Sale Performance: Evidence from Large Position Disclosures, *Working Paper*.

Jegadeesh, Narasimhan and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *The Journal of Finance* 48, 65-91.

Jones, Charles M., Adam V. Reed, William Waller, 2015, Revealing shorts: An examiniation of large short position disclosures, *Working Paper*.

Jylha, Petri, Kalle Rinne, and Matti Suominen, 2013, Do hedge funds supply or demand liquidity, *Review of Finance* 18, 1259-1298.

Karolyi, Andrew and Ying Wu, 2014, Size, Value, and Momentum in International Stock Returns: A New Partial-Segmentation Approach, *Working Paper*.

Levi, Yaron and Ivo Welch, 2016, Assessing Cost-of-Capital Inputs, *Working Paper*.

Miller, Edward M., 1977, Risk, Uncertainty, and Divergence of Opinion, *The Journal of Finance* 32, 1151-1168.

Neyman, J., and Elizabeth L. Scott, 1948, Consistent Estimates Based on Partially Consistent Observations, *Econometrica* 16, 1-32.

Pedersen, Lasse H., 2015, Efficiently Inefficient: How smart money invests & market prices are determined, *Princeton University Press*.

Puri, Manju, Jörg Rocholl, and Sascha Steffen, 2011, Global retail lending in the aftermath of the US financial crisis: Distinguishing between supply and demand effects, *Journal of Financial Economics* 100, 556-578.

Saffi, Pedro A. C., and Kari Sigurdsson, 2011, Price Efficiency and Short Selling, *Review of Financial Studies* 24, 821-852.

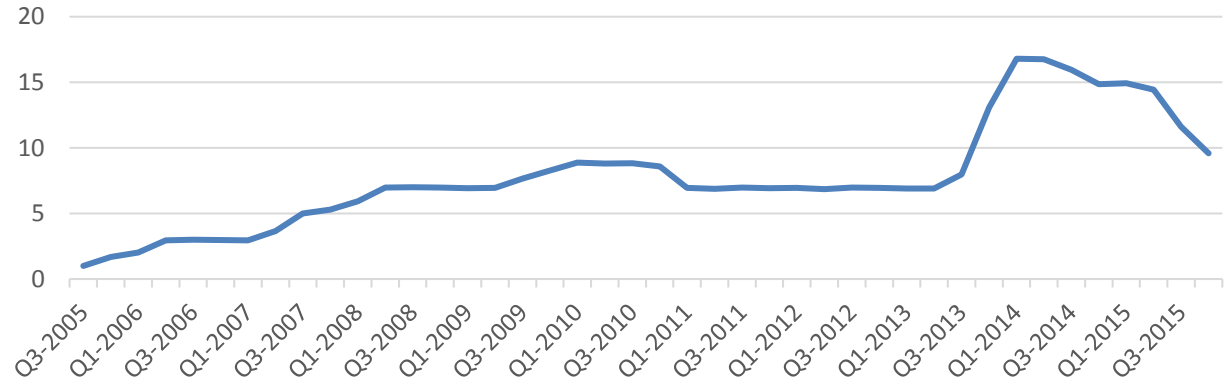
Savor, Pavel G., and Mario Gamboa-Cavazos, 2011, Holding on to Your Shorts: When Do Short Sellers Retreat?, *Working Paper*.

Vasicek, Oldrich A. (1973). “A Note On Using Cross-Sectional Information In Bayesian Estimation Of Security Betas”, *Journal of Finance* 28, 1233–1239.

Figure 1: Coverage over sample period

This figure shows the coverage over our sample period. Panel A shows the average number of funds in the sample for each quarter. Panel B shows the number of orders per day and of open positions per day averaged over the quarter.

Panel A: Number of funds in the sample



Panel B: Number of orders and positions per day

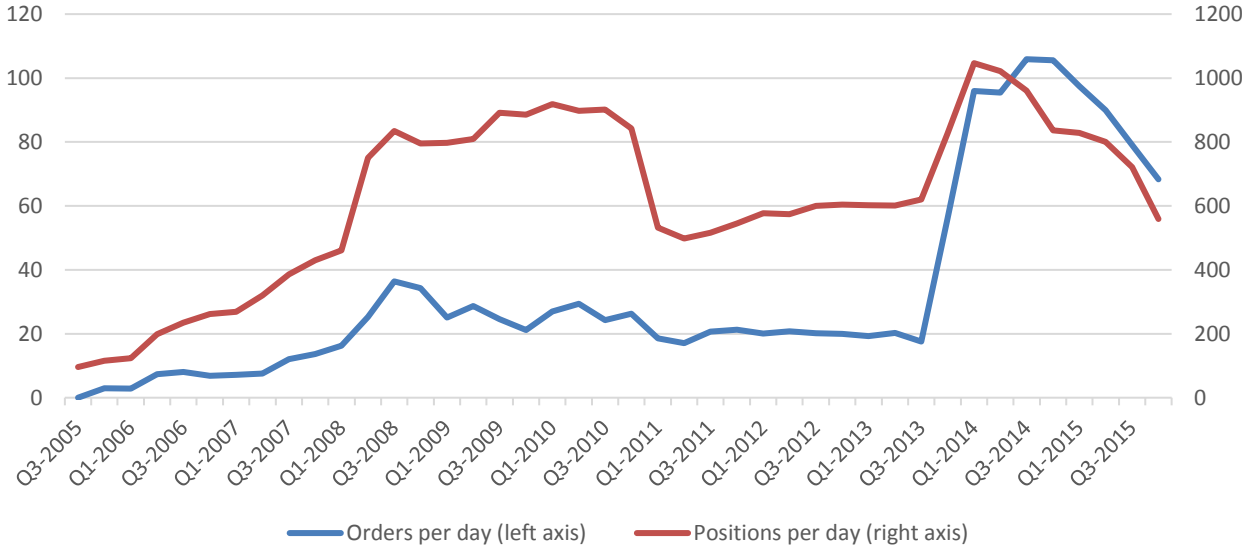
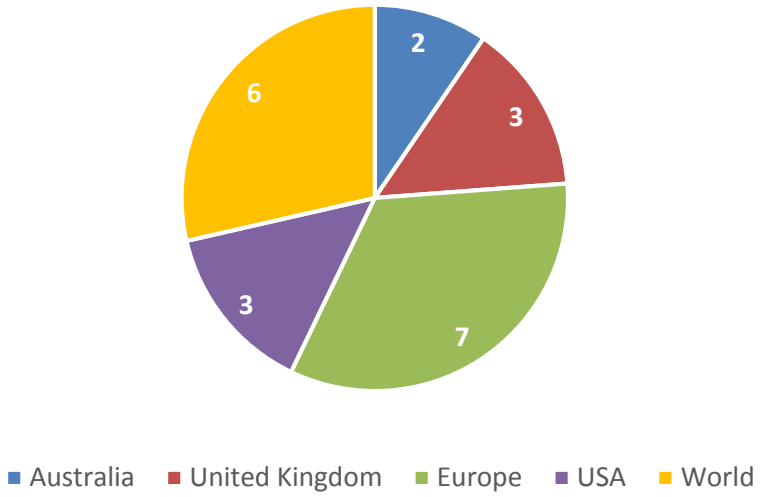


Figure 2: Investment areas of funds

Panel A shows the investment areas of our sample of funds. We base these areas on their chosen benchmark, but verify that the funds indeed invest predominantly in these regions. Panel B depicts the regions of the stocks held by the funds. We compute this average over the number of positions over the entire sample period. The definition of the regions are displayed in Appendix 2.

Panel A: Investment area of fund as specified by their benchmark



Panel B: Region of stocks held by funds (%)

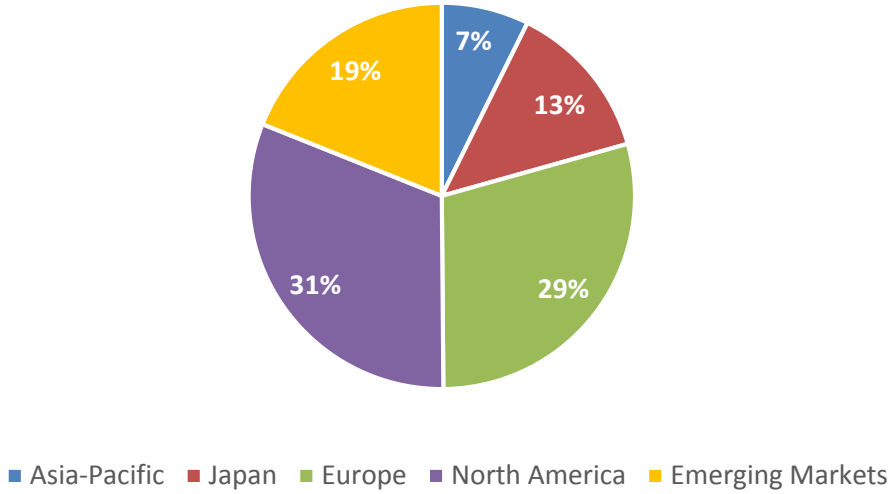


Figure 3: Excess returns following orders

This figure displays cumulative excess return indices for 250 trading days following orders that initiate or close a position. *Initiate Long Position* is the buy order establishing a long position. *Initiate Short Position* is the sell order establishing a short position. *Close Short Position* is the buy order closing a short position. *Close Long Position* is the sell order closing a long position. *Excess return* is the return of the stock minus the return of the fund-specified benchmark. The return index is set to 100 at the last day of the order. To reduce the effect of outliers, we set daily returns above 10% to 10% and below -10% to -10%.

Excess returns around orders

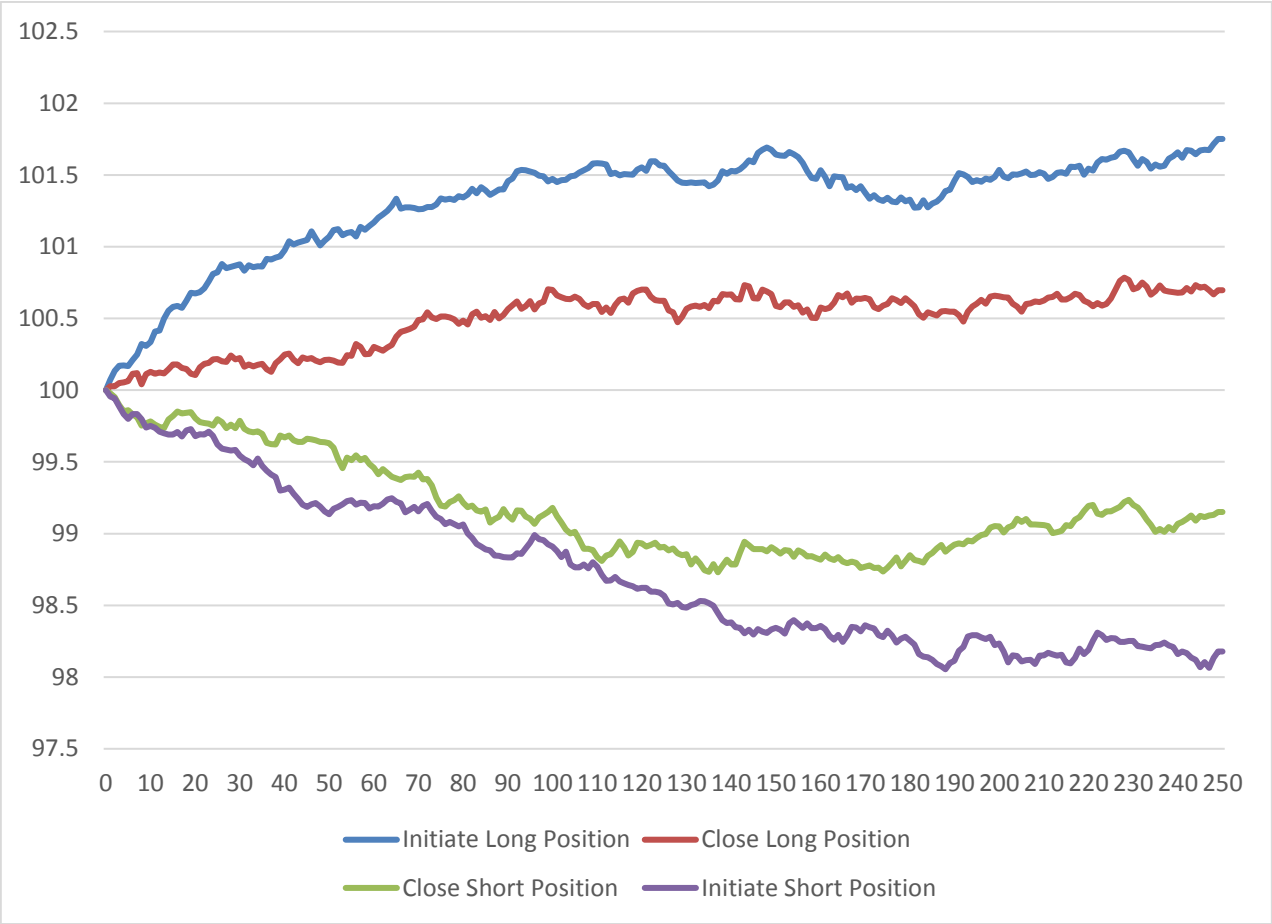


Figure 4: Excess returns following orders

This panel displays cumulative *excess returns*, *DGTW returns* and *4-factor alphas* for 250 trading days following orders that close a position. The returns are computed as the average returns following the closure of long positions minus the average returns following the closure of short positions. The return index is set to 100 at the last day of the order. To reduce the effect of outliers, we set daily returns above 10% to 10% and below -10% to -10%.

Return difference between long and short position closures

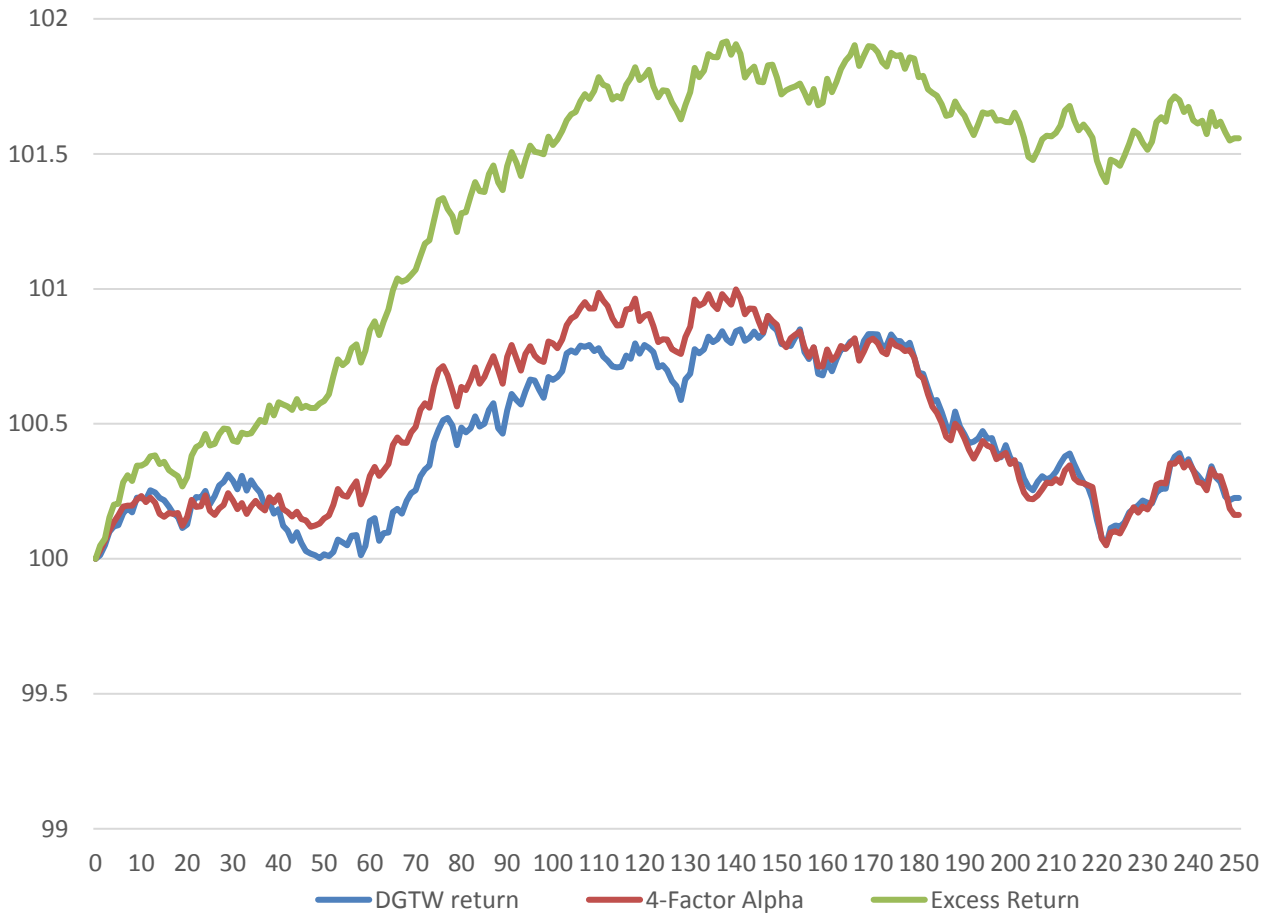


Figure 5: Excess returns before initiation of positions

This panel displays cumulative *DGTW returns* and *4-Factor Alphas* for 250 trading days before the order that initiates a position. The return index is set to 100 at the first day of the order. To reduce the effect of outliers, we set daily returns above 10% to 10% and below -10% to -10%.

Risk-adjusted returns prior to the opening of positions

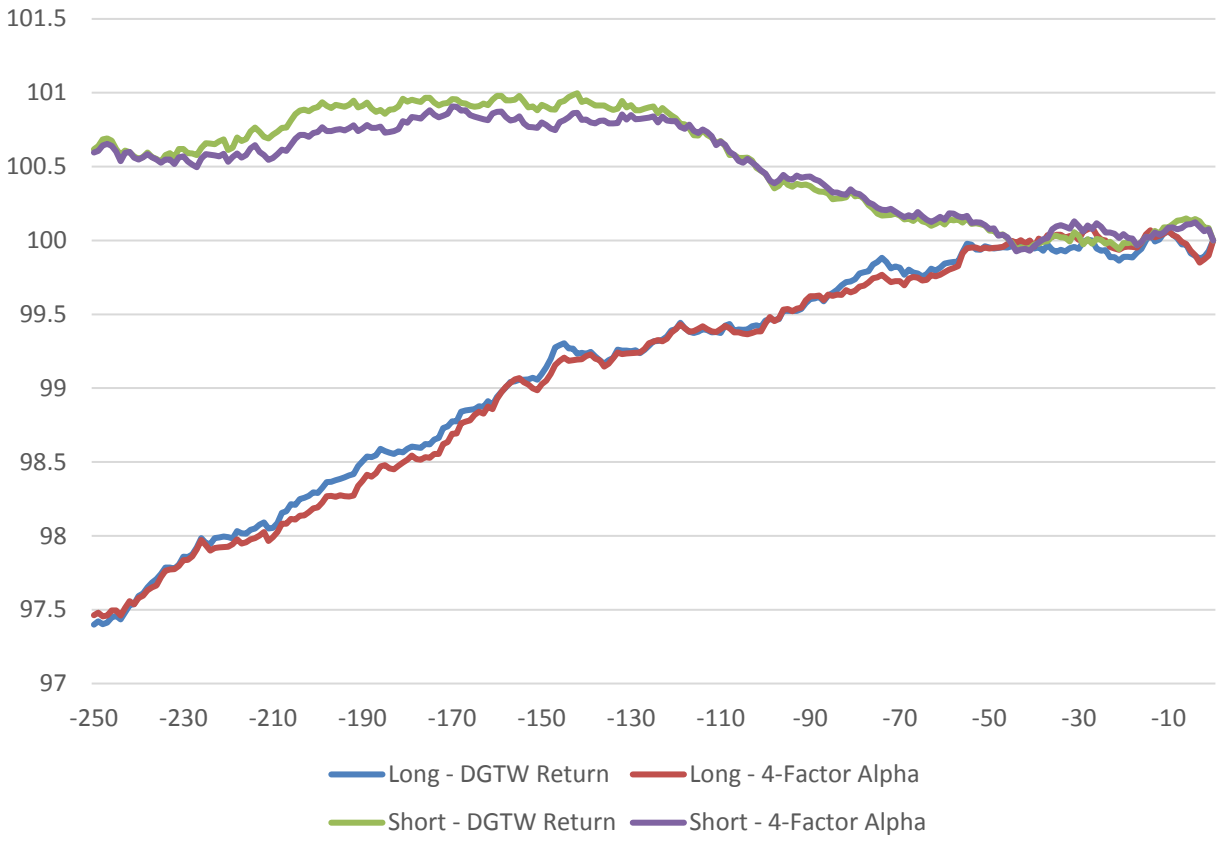


Table 1: Summary statistics

Panel A displays summary statistics by fund. *Number of Long (Short) Positions* is the average of long (short) positions held by the fund. *Short Fraction* is the average fraction that short positions constitute of the fund holdings (measured in USD). *Orders per Day* are the average number of orders initiated per day. *Trade Fraction* is the average of the funds trading volume divided by the value of its holdings. *Value of Fund* is the average value of all positions (long and short combined). *Positions per Stock* is the average number of times the fund establishes a position in the specific stock. Panel B displays summary statistics by position. A position lasts from its initiation (first buy for long positions or first sell for short positions) to its close (moment the holding of the stock is reduced to zero). *Number of Direction Changes* is the number of times the orders move from buy to sell orders or from sell to buy orders while the position is open. *Open Start* is a dummy variable equal to one if the position is open already at the time the fund enters the database. *Open End* is a dummy variable equal to one if the position is still open when the fund leaves the database. Panel C-E display summary statistics by order. We split the orders by whether they initiate a position, close a position or simply change the size of a position. *Size as fraction of largest holding* is the size of the order in terms of number of stocks traded divided by the largest size the position ever has.

Panel A: Averages by fund

Variable	Mean	10th Percentile	Median	90th Percentile	Standard Deviation
Number of Long Positions	49.8	16.9	36.1	74.9	43.4
Number of Short Positions	23.9	10.8	18.6	46.3	14.2
Short Fraction (%)	30.2	15.8	26.4	48.7	19.2
Orders per Day	5.81	1.54	5.60	10.5	3.58
Trade Fraction (%)	5.37	0.82	2.75	14.0	5.36
Value of Fund (billion USD)	2.05	0.12	0.35	6.41	3.63
Positions per Stock	1.96	1.37	1.90	2.70	0.61
Observations	21				

Panel B: Statistics by position

Variable	Mean	10th Percentile	Median	90th Percentile	Standard Deviation
Length (trading days)	104.4	4	35	275	188.9
Number of Orders	5.92	2	3	12	8.89
Number of Direction Changes	2.50	1	1	5	5.06
Open Start	0.069	0	0	0	0.25
Open End	0.11	0	0	1	0.32
Observations	16241				

Panel C: Statistics by order – initial orders

Variable	Mean	10th Percentile	Median	90th Percentile	Standard Deviation
Number of Trades	1.61	1	1	3	1.50
USD volume (million USD)	11.2	0.27	3.61	22.1	41.6
Size as fraction of largest holding (%)	77.1	24.7	100	100	31.0
Observations	13884				

Panel D: Statistics by order – follow-up orders

Variable	Mean	10th Percentile	Median	90th Percentile	Standard Deviation
Number of Trades	1.49	1	1	3	1.29
USD volume (million USD)	7.44	0.083	1.65	16.4	31.8
Size as fraction of largest holding (%)	15.8	0.92	8.70	42.7	18.3
Observations	62103				

Panel E: Statistics by order – closing orders

Variable	Mean	10th Percentile	Median	90th Percentile	Standard Deviation
Number of Trades	1.65	1	1	3	1.97
USD volume (million USD)	10.4	0.23	3.27	21.6	30.7
Size as fraction of largest holding (%)	77.9	25.2	100	100	31.2
Observations	13090				

Table 2: Profitability of buys and sells for long and short portfolios

This table examines whether buys and sells are more profitable for short or for long positions. We regress average returns on a dummy variable whether the trade took place for a long or a short position. Panel A displays results for only buy orders that initiate or close a position, while Panel B displays results for only sell orders that initiate or close a position. Panel C displays results for all buy orders, while Panel D displays results for all sell orders. The dependent variable is the cumulative return expressed in percent for 60 and 125 trading days following the last day of the order. *Excess return* is the return of the stock minus the return of the fund-specified benchmark. *DGTW return* is the return of the stock minus the average return of a portfolio sorted by region, size, book-to-market and momentum. *Four-factor Alpha* is the alpha according to the Carhart (1997) model estimated at the regional level. Details on variable constructions can be found in Appendix 1. All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Long buys vs. short buys

Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)			
D(Short)	-1.6023***	-2.3343***	-1.0512***	-1.4917***	-1.0817***	-1.5722***
	(-4.71)	(-4.36)	(-3.43)	(-3.51)	(-3.14)	(-3.27)
Constant	1.4123***	2.3168***	0.6364***	0.2870	0.4469*	0.3400
	(5.38)	(5.10)	(2.82)	(0.75)	(1.91)	(0.90)
Observations	12230	11670	11441	10940	11735	11339

Panel B: Long sells vs. short sells

Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)			
D(Short)	-1.2561***	-2.1914***	-0.7825**	-1.2866***	-0.9944***	-1.3512***
	(-3.50)	(-4.23)	(-2.53)	(-3.02)	(-3.09)	(-2.98)
Constant	0.6604**	1.6533***	-0.2143	-0.3267	-0.2896	-0.3482
	(2.25)	(3.26)	(-0.84)	(-0.78)	(-1.20)	(-0.88)
Observations	11994	11398	11286	10743	11595	11138

Table 3: Returns following the closure of positions

This table examines whether returns after the closing of positions differ for long and short positions. We only include orders that close a position. We regress average returns on a dummy variable equal to one if the closed position was a short position. The dependent variable is the cumulative return expressed in percent for 60 and 125 trading days following the last day of the order. *Excess return* is the return of the stock minus the return of the fund-specified benchmark. *DGTW return* is the return of the stock minus the average return of a portfolio sorted by region, size, book-to-market and momentum. *Four-factor alpha* is the alpha according to the Carhart (1997) model estimated at the regional level. Details on variable constructions can be found in Appendix 1. All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)			
D(Short)	-0.8503**	-1.6708***	-0.2005	-0.8780**	-0.3451	-0.8841*
	(-2.43)	(-3.08)	(-0.62)	(-1.97)	(-1.03)	(-1.87)
Constant	0.6604**	1.6533***	-0.2143	-0.3267	-0.2896	-0.3482
	(2.25)	(3.26)	(-0.84)	(-0.78)	(-1.20)	(-0.88)
Observations	11698	11077	11027	10469	11322	10860

Table 4: Momentum trading when initiating positions

This table examines whether hedge funds trade on momentum when establishing their positions. We conduct an order-level analysis including only orders that establish a position. The dependent variable is *D(Buy)*, which is a dummy variable equal to one for buys (i.e. initiation of a long position) and zero for sells (i.e. initiation of a short position). Independent variables are return, DGTW return, and 4-factor alpha in the 60 and 125 trading days prior to the first trade of the order. Details on variable constructions can be found in Appendix 1. All regressions include fixed effects for fund-date. All standard errors are two-way clustered by stock and first date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Dependent Variable:	D(Buy)					
	(1)	(2)	(3)	(4)	(5)	(6)
Return t-60, t-1	0.0653**					
	(2.55)					
DGTW Return t-60, t-1		0.1223***				
		(2.68)				
4-Factor Alpha t-60, t-1			0.0774***			
			(2.77)			
Return t-125, t-1				0.0900***		
				(4.47)		
DGTW Return t-125, t-1					0.1551***	
					(4.97)	
4-Factor Alpha t-125, t-1						0.0997***
						(4.24)
Observations	9092	8464	8729	9029	8394	8762
Fund-Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Momentum trading on follow-up orders

This table examines whether hedge funds trade on momentum when conducting follow-up orders. In Panel A, we conduct an order-level analysis excluding the initial order establishing a position. We regress a dummy variable indicating whether the order is a buy or a sell on prior returns and prior returns interacted with *D(Short)*. In regressions 1 and 4, we include only long positions. In regressions 2 and 5, we include only short positions and in regressions 3 and 6 we include both. In Panel B and C, we conduct a similar analysis on the daily holding level excluding the day a position gets initiated or closed. *Direction* is equal to 1 for buys, -1 for sells and 0 for no trade. *D(Buy)-Holding* is equal to 1 for buys and 0 for sells and no trade. *D(Sell)-Holding* is equal to 1 for sells and 0 for buys and no trade. *Position Tenure* is the logarithm of the number of days the position is open. All regressions include fixed effects for fund-date-portfolio, where portfolio is whether it is the funds long or short portfolio. All standard errors are two-way clustered by stock and first date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Order-level analysis

Dependent Variable:	D(Buy)					
Sample:	Long Only	Short Only	Both	Long Only	Short Only	Both
	(1)	(2)	(3)	(4)	(5)	(6)
Return t-60, t-1 * D(Short)			0.1929***			
			(4.47)			
Return t-125, t-1 * D(Short)						0.0754***
						(2.77)
Return t-60, t-1	-0.0796***	0.1133***	-0.0796***			
	(-2.83)	(3.28)	(-2.83)			
Return t-125, t-1				-0.0140	0.0614***	-0.0140
				(-0.90)	(2.94)	(-0.90)
Position Tenure	-0.0429***	0.0374***	-0.0429***	-0.0425***	0.0377***	-0.0425***
	(-13.13)	(8.00)	(-13.13)	(-13.03)	(7.99)	(-13.03)
Position Tenure * D(Short)			0.0803***			0.0802***
			(12.62)			(12.56)
Observations	33894	16676	50570	33573	16633	50206
Fund-Portfolio-Date F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Holding-level analysis

Dependent Variable:	D(Direction)					
Sample:	Long Only	Short Only	Both	Long Only	Short Only	Both
	(1)	(2)	(3)	(4)	(5)	(6)
Return t-60, t-1 * D(Short)			0.0316***			
			(6.20)			
Return t-125, t-1 * D(Short)						0.0204***
						(6.08)
Return t-60, t-1	-0.0107***	0.0209***	-0.0107***			
	(-3.36)	(5.26)	(-3.36)			
Return t-125, t-1				-0.0056***	0.0148***	-0.0056***
				(-2.87)	(5.45)	(-2.87)
Position Tenure	-0.0189***	0.0230***	-0.0189***	-0.0189***	0.0231***	-0.0189***
	(-24.88)	(20.44)	(-24.88)	(-24.85)	(20.40)	(-24.85)
Position Tenure * D(Short)			0.0419***			0.0420***
			(29.48)			(29.41)
Observations	927344	464626	1391970	921194	463467	1384661
Fund-Portfolio-Date F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Holding-level analysis

Dependent Variable:	D(Buy) - Holding		D(Sell) - Holding	
	(1)	(2)	(4)	(5)
Return t-60, t-1 * D(Short)	0.0152***		-0.0164***	
	(4.43)		(-4.79)	
Return t-125, t-1 * D(Short)		0.0107***		-0.0097***
		(4.61)		(-4.07)
Return t-60, t-1	-0.0068***		0.0039**	
	(-3.18)		(2.06)	
Return t-125, t-1		-0.0035**		0.0021*
		(-2.41)		(1.86)
Position Tenure	-0.0146***	-0.0145***	0.0043***	0.0044***
	(-21.51)	(-21.32)	(10.73)	(10.93)
Position Tenure * D(Short)	0.0201***	0.0201***	-0.0218***	-0.0219***
	(23.09)	(22.95)	(-21.47)	(-21.50)
Observations	1391970	1384661	1391970	1384661
Fund-Portfolio-Date F.E.	Yes	Yes	Yes	Yes

Table 6: Robustness Check: Tables 2 and 3 with all orders

This reruns the analyses from Tables 2 and 3, but instead of including only initial and closing orders, we include all orders. Specifically, in Panel A we compare long buys to short buys. In Panel B, we compare long sells to short sells. Finally, in Panel C, we compare Long sells to short buys. The dependent variable is the cumulative return expressed in percent for 60 and 125 trading days following the last day of the order. Details on variable constructions can be found in Appendix 1. All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Long buys vs. short buys

Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)			
D(Short)	-1.4347***	-2.6573***	-1.1266***	-1.6750***	-0.8308**	-1.3782**
	(-4.08)	(-4.40)	(-3.96)	(-3.47)	(-2.58)	(-2.48)
Constant	1.0110***	1.9354***	0.3527**	0.1426	0.0790	-0.0936
	(4.92)	(5.29)	(2.11)	(0.47)	(0.45)	(-0.30)
Observations	40064	38024	37777	35943	38713	37076

Panel B: Long sells vs. short sells

Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)			
D(Short)	-1.6449***	-2.7963***	-0.8456***	-1.5055***	-0.7411**	-1.0883**
	(-4.48)	(-4.59)	(-2.92)	(-3.11)	(-2.28)	(-1.96)
Constant	0.8170***	1.7683***	-0.0552	-0.2697	-0.3429*	-0.4930
	(3.57)	(4.36)	(-0.28)	(-0.77)	(-1.76)	(-1.40)
Observations	40115	38077	37741	35883	38806	37093

Panel C: Long sells vs. short buys

Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)			
D(Short)	-1.2407***	-2.4902***	-0.7186**	-1.2627**	-0.4090	-0.9788*
	(-3.47)	(-4.01)	(-2.41)	(-2.49)	(-1.24)	(-1.72)
Constant	0.8170***	1.7683***	-0.0552	-0.2697	-0.3429*	-0.4930
	(3.57)	(4.36)	(-0.28)	(-0.77)	(-1.76)	(-1.40)
Observations	38905	36707	36583	34578	37640	35779

Appendix 1: Variable definitions

This table displays the variable definitions for all variables used in the regressions.

Variable Name	Definition
Excess Return	$Stock\ Return - \ Benchmark\ Return$
Stock Return	Return in USD from Datastream.
Benchmark Return	USD return of the benchmark specified by the fund. The benchmark is specific for the fund, but is the same for both long and short positions of the fund. Data is provided by Inalytics.
DGTW Return	$Stock\ Return - \ Return\ of\ portfolio\ of\ similar\ stocks$ Similar stocks are stocks in the same quintile of market capitalization, book-to-market ratio and 12 month momentum within the same region. For more details see Appendix 3.
4-Factor Alpha	$r_{c,t} - \beta_c * (r_{m,t} - r_{f,t}) - \beta_{HML} * HML_t - \beta_{SMB} * SMB_t - \beta_{MOM} * MOM_t$ For more details see Appendix 3.
D(Short)	Dummy variable equal to one if the order related to a short position and zero if it is related to a long position.
D(Buy)	Dummy variable equal to one if the order is a buy order and zero if the order is a sell order.
D(Buy) - Holding	Dummy variable equal to one if the day contained a buy trade and zero if there was no trade or a sell trade. Notice that this variable is constructed based on trades rather than orders, so the variable is equal to 1 on the day of the second trade of a buy order.
D(Sell) - Holding	Dummy variable equal to one if the day contained a sell trade and zero if there was no trade or a buy trade. Notice that this variable is constructed based on trades rather than orders, so the variable is equal to 1 on the day of the second trade of a sell order.
Direction	Variable equal to one if the day contained a buy trade, minus one if it contained a sell trade and zero if there was no trade. Notice that this variable is constructed based on trades rather than orders, so the variable is equal to 1 on the day of the second trade of a buy order.
Position Tenure	$\log(Number\ of\ days\ the\ position\ is\ open)$

Appendix 2: Regions

This table displays the regions to which the countries are assigned. The region assignments follows Karolyi and Wu (2014)

Panel A: Region assignments

Country Name	Region
Japan	Japan
Canada	North America
United States	North America
Australia	Asia-Pacific
New Zealand	Asia-Pacific
Singapore	Asia-Pacific
Hong Kong	Asia-Pacific
Austria	Europe
Belgium	Europe
Denmark	Europe
Finland	Europe
France	Europe
Germany	Europe
Greece	Europe
Ireland	Europe
Italy	Europe
Netherlands	Europe
Norway	Europe
Portugal	Europe
Spain	Europe
Sweden	Europe
Switzerland	Europe
United Kingdom	Europe
Argentina	EME
Brazil	EME
Chile	EME
China	EME
Colombia	EME
Czech Republic	EME
Hungary	EME
India	EME
Indonesia	EME
Israel	EME
Korea (South)	EME
Malaysia	EME
Mexico	EME
Pakistan	EME
Peru	EME
Philippines	EME
Poland	EME
Russian Federation	EME
South Africa	EME
Taiwan	EME
Thailand	EME
Turkey	EME
Venezuela	EME

Appendix 3: Additional Information on Dataset Construction

Merging of datasets

We merge the trading and the holding dataset provided by Inalytics. We first merge based on ISIN. Trades that we cannot match by ISIN, we match by SEDOL and finally by CUSIP. Theoretically, whenever there is a change in the number of shares held in the holdings data, we would expect to see a corresponding trade in the trade data. In fact, there are some errors in the data and the trade and holding data do not match perfectly. According to Inalytics, the holding data are more accurate. Therefore, we rely on the holdings data, i.e. we assume there is a trade whenever there is a change of holding in the holdings data. The only exception is if a holding disappears from the data and then reappears shortly afterwards. In these cases we fill in the missing dates in between with the old quantity. Reappearing shortly afterwards means within 22 trading days (one month) or within 70 trading days (one quarter) if the position reappears with the exact same number of stocks. In total this fill in affects only about 3400 stock-days in the holding data (compared to about 1.7 million stock-days in the full sample).

In total, we have about 150,000 trades according to the holdings data. For about 90% of these trades, we have a corresponding trade in the trading data. However, for only about 83% of these trades does the number of stocks traded according to the trading data matche the change in the number of stocks held in the holding data. We assume the holdings data to be correct, but still use the trading price from the trading data even if the number of stocks traded does not match. Still, we do not have a trade price if we do not have a matching trade in the trade data. In addition, we set unrealistic trade prices to missing. We determine if a trade price is realistic by comparing it to the closing prices around the trade. If the trade price is more than 5% outside of the bound between these two prices, we set it to missing. This correction affects about 2000 trades. In this paper, we only use trade prices to compute summary statistics.

Stock Universe

To compute DGTW returns and regional factors, we need a universe of stocks. We construct this stock universe by matching Worldscope and Datastream data. We only keep stocks that are covered in both databases. We only keep one stock per company (we identify companies using Worldscope Permanent Identifier). We also only keep stocks from the countries listed in Appendix 2 (we take the country from Worldscope). We require stock to have a positive book value, information on market capitalization in Worldscope and a stock price of at least USD 0.20.

Stock Returns and Balance Sheet Data

We download daily returns for stocks in our stock universe and in the Inalytics data from Datastream using ISINs (and then using SEDOLs if we do not find a match using ISINs). We download returns in local currency

and convert them to USD using the exchange rates on Datastream. Using local currency returns minimizes the errors due to rounding for stocks with low stock prices. When computing returns for the DGTW portfolios and Carhart (1997) factor, we remove returns in the top and bottom 0.25% by region following the instructions on the website of Kenneth French.

We take market capitalization in USD directly from Worldscope (code 07210) and compute book-to-market directly from Worlscope as the inverse of the price-to-book ratio (code 09304). We use annual Worldscope data.

Four-Factor alphas

To compute alphas, we construct daily four-factors of the Carhart (1997) model for each of our 5 regions (see Appendix 2) following the instructions on the website of Kenneth French[1]. We use the U.S. one month T-bill rate as the risk free rate and all returns are in U.S. dollars. We compute market returns as value-weight average returns for our stock universe in each region (the stock universe construction is describe above). To construct the SMB and HML factors, we sort stocks in a region into two market cap and three book-to-market equity (B/M) groups at the end of each June. Big stocks are those in the top 90% of market cap for the region, and small stocks are those in the bottom 10%. The B/M breakpoints for a region are the 30th and 70th percentiles of B/M for the big stocks of the region. For the 6 portfolios thus formed, we compute value weighted returns for each day and then compute the factors as:

$$SMB = \frac{1}{3} * (Small\ Value + Small\ Neutral + Small\ Growth) - \frac{1}{3} * (Big\ Value + Big\ Neutral + Big\ Growth)$$

$$HML = \frac{1}{2} * (Small\ Value + Big\ Value) - \frac{1}{2} * (Small\ Growth + Big\ Growth)$$

The 2x3 sorts on size and lagged momentum to construct MOM are formed monthly. For portfolios formed at the end of month t–1, the lagged momentum return is a stock's cumulative return for month t–12 to month t–2. The momentum breakpoints for a region are the 30th and 70th percentiles of the lagged momentum returns of the big stocks of the region. For the 6 portfolios thus formed, I compute value weighted returns for each day and then compute the momentum factor as:

$$MOM = \frac{1}{2} * (Small\ High + Big\ High) - \frac{1}{2} * (Small\ Low + Big\ Low)$$

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. I quote directly from these instructions in the description below. At the time of the construction of these factors, daily factors were not yet available on Ken French's website.

For each stock and each month, we then compute the beta with respect to those factors from a daily regression over the past year. We remove returns from the regression that are in the top and bottom 0.25% by region. Furthermore, we only keep betas that are based on at least 50 days of data.

$$r_{c,t} = \alpha + \beta_m * \left(r_{m,t} - r_{f,t}\right) + \beta_{HML} * HML + \beta_{SMB} * SMB + \beta_{MOM} * MOM$$

Where $r_{c,t}$ is the daily company return, $r_{m,t}$ is the daily market return and $r_{f,t}$ is the daily risk free rate.

Following Frazzini and Pedersen (2014), I shrink the betas to their cross sectional mean by computing:

$$\beta_{c,t}^{shrunk} = 0.7 * \beta_{c,t} + 0.3 * \beta_{region,t}$$

Then we use these shrunk betas to compute daily alphas as follows:

$$Four\ factor\ alpha_{c,t} = r_{c,t} - \beta_c * \left(r_{m,t} - r_{f,t}\right) - \beta_{HML} * HML_t - \beta_{SMB} * SMB_t - \beta_{MOM} * MOM_t$$

We compute alphas for all stocks in our region even if these stocks do not match the criteria to be included in the stock universe.

DGTW returns

To compute DGTW returns, we split the stocks in our universe (the stock universe construction is describe above) into 625 portfolios. First, we split the universe into the 5 geographic region (see Appendix 2). Second, each year, within each region we sort stocks into 5 portfolios by market capitalization. Third, within each of these 25 size-region portfolios we sort stocks by book-to-market. Fourth, within each of these 125 regio-size-book to market porftolios, we sort stocks into 5 portfolios by returns over months t-12 to t-2. While splits for market cap and market-to-book happen once a year, splits by past return are executed every month.

Then we compute the average return within each of the 625 portfolio as the average USD return in the portfolio weighted by market cap. Finally, we compute DGTW returns as stock return minus the return of the respective portfolio. We only compute a DGTW return if the stock was part of the portfolio.