Limits of Arbitrage under the Microscope: Evidence from detailed Hedge Fund Transaction Data

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Abstract

We exploit detailed transaction and position data for a sample of long-short equity hedge funds to document new facts about the trading activity of sophisticated investors. We find that the initiation of both long and short positions is associated with significant abnormal returns, suggesting that the hedge funds in our sample possess investment skill. In contrast, the closing of long and short positions is followed by return continuation, implying that hedge funds close their positions too early and "leave money on the table." As we demonstrate with a simple model, this behaviour can be explained by hedge funds being (risk) capital constrained and facing position monitoring costs. Consistent with our model, we document that the return continuation following closing orders is more pronounced when these constraints become more binding (e.g., after negative fund returns or increases in volatility).

JEL classification: G11, G12, G14, G15

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Fundamental arbitrage, defined as the process of acquiring an information advantage through fundamental research and trading on it, plays a critical role for market efficiency as it helps to align individual stock prices with their (ever elusive) "fair" values.[1] In this paper, we analyze proprietary transaction data for a sample of discretionary long-short equity hedge funds to shed light on this important activity. Indeed, these type of hedge funds routinely undertake independent long and short investments ("directional bets"), making them the archetype of a fundamental arbitrageur. Exploiting the richness of our data, we uncover new facts pertaining to the *initiation and closure* of *long and short* arbitrage positions, and discuss how these findings relate to the broader research on informed trading, short selling, and the limits of arbitrage. We view our paper as providing first-hand micro evidence for the importance of several channels highlighted in these literatures.

Our data comprises the *entire trading history as well as daily position updates* for 21 long-short hedge funds over a ten-year period. This level of detail allows us to conduct a microscopic analysis of hedge funds' trading activity. In particular, we are able to distinguish buy transactions that initiate a long position ("long buys") from buys that close an existing short position ("short buys"). Similarly, we distinguish sells that initiate a short position ("short sells") from sells that close an existing long position ("long sells"). We begin our investigation with an examination of the profitability of these different trades. Focusing on the initiation and closure of trading positions, we find that long buys and short sells—i.e., trades that open new long and short positions—are, respectively, followed by significantly positive and negative benchmark-adjusted returns with an absolute magnitude of about 1.5% (2%) over the next 125 (250) trading days. This proves that the hedge funds in our sample possess investment skill.

In stark contrast, we find that closing trades are not informed. To the contrary, long sells and short buys tend to be followed, respectively, by positive and negative returns; that is, returns in the opposite direction of the closing trade. When we design a trading strategy that goes long in stocks in which hedge funds just closed a long position (long sells) and shorts stocks from closed short positions (short buys) we obtain a significant alpha of about 1% over the next six months (125 trading days). This implies that the hedge funds in our sample close their positions too early in the sense that they "leave money on the table."

[1] What we call fundamental arbitrage in this paper is not riskfree and thus represents a statistical arbitrage in the sense that it gives rise to positive expected profits (on a risk-adjusted basis). This makes fundamental arbitrage different from classical relative-value arbitrage; i.e., the process of exploiting price differences between assets or portfolios that provide identical payoffs in the future. As it violates "the law of one price," arbitrage opportunities of this kind lead to a riskless profit and thus provide a striking failure of market efficiency, perhaps explaining why they have received more attention in the academic literature. Yet, eliminating short-term price discrepancies is not the same as having more informative prices (see Brunnermeier (2005), and Weller (2016)) and fundamental arbitrage should be especially important toward the latter goal.

To understand this finding, we draw on a simple trading model (presented in the appendix) in which a hedge fund decides whether and how much to invest in mispriced stocks. We embed three important—and as we believe realistic—features into the model: First, the hedge fund is assumed to face a risk constraint, which prevents it from taking too large a position in any mispriced stock. Second, the hedge fund incurs a monitoring cost for each open position in its portfolio. The first assumption mirrors standard practice in the hedge fund industry (see, for instance, Pedersen (2015)) and should thus be uncontroversial. The second assumption can be interpreted loosely as a fixed transaction, monitoring or attention cost for maintaining the position and checking whether a previous trading signal has not lost its allure. Such a cost naturally leads the investor to focus on a limited number of open positions, consistent with what we empirically observe for the long-short equity hedge funds in our sample.[2] Finally, we assume that new investment opportunities (stock mispricings) emerge each period and partially decay over time. This is again consistent with what we find in the data as we show that roughly 75% (=1.5%/2%) of the alpha is earned within the first six months after the initiation of a stock position.

In a recent interview, Lee Ainslee III. of Maverick Capital Management, reports:

> "[The] approach of exiting a position when it is no longer as compelling as other opportunities means that we often are selling stocks that we still believe offer meaningful upside. However, if that investment is no longer one of our most compelling, then we redeploy that capital into a stock that is." — quoted from Pedersen (2015)

Our model is designed to capture this intuition. Indeed, we show that, under the abovementioned assumptions, the hedge fund's optimal trading rule involves early position closures: as the expected profitability of an investment decays, other trading opportunities become more attractive. This triggers a reallocation of the limited risk capital and monitoring capacity into these more promising opportunities, explaining why we find that hedge funds close positions that continue to generate alpha going forward. We then use the model to derive a number of additional predictions: First, at any point in time, the profits from newly opened positions should exceed the profits that hedge funds forego by closing existing ones. Second, the return continuation following position closures should be more pronounced—meaning that the hedge fund leaves more money on the table—when the fund (1) simultaneously opens a lot of new positions (that require capital), (2) has suffered from poor past performance, and (3) when the risk constraint becomes more binding due to a surge in fund return volatility.

We test and confirm these predictions in the data. We begin by comparing returns after opening and closing orders within the same month. We find that, over the 60 trading days following the order, newly initiated long (short) positions yield an alpha that is 0.5% larger (smaller) than the alpha following closed long (short) positions. Thus, we document that, within the same month, hedge funds generate more alpha with their

[2] For instance, the average hedge fund in our sample has less than 80 open positions at any time.

opening trades than they forego by closing their positions prematurely, proving that hedge funds recycle their limited risk capital into more profitable trading opportunities.

Next, we conduct a number of sample splits for the trading strategy built around hedge funds' closing trades—i.e., going long (short) in stocks from closed long (short) positions. This strategy can be thought of as measuring how much alpha hedge funds forego by closing early. First, we examine whether this strategy is more profitable when hedge funds have higher opportunity costs due to facing more trading opportunities. To proxy for the change in their trading opportunities, we look at whether hedge funds increase or decrease the number of open portfolio positions. We find that the strategy yields a highly significant excess return of 2.2% over the next half year after an increase in the number of positions, while we observe only a return of 0.8% after a decrease in the number of open positions. Second, we conduct a similar sample split based on whether the fund had a positive or a negative return over the prior week. The idea of this test is that negative returns reduce the available (risk) capital of the fund, forcing it to close down some existing stock positions. Indeed, we find that trading against closing orders following a negative fund return yields an excess return of 2.5% over the next half year, while trading against closing orders following a positive fund return only delivers 0.7%. Third, we split the sample based on whether the fund experienced an increase in volatility. Since we posit that hedge funds operate under a risk constraint, we expect such an increase in volatility to result in additional position closures. Consistent with this intuition, we find that trading against closing orders following an increase in fund volatility yields an excess return of 2.0% over the next half year, while it gives only 0.9% after a decrease in fund volatility.

Taken together, these findings suggest that early position closures—which are associated with foregone risk-adjusted returns—occur in response to binding (risk) capital and monitoring constraints, rather than being due to hedge funds' ignorance and/or investment biases. To the best of our knowledge, the results thus offer some of the first micro-level evidence for several themes commonly discussed in the limits of arbitrage literature—in particular, those strands that emphasize the importance of (risk) capital, funding and/or leverage constraints (see, e.g., Shleifer and Vishny (1997), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009)).

As mentioned before, one of the key advantages of our data is that we are able to cleanly identify the complete set of long and short positions of long-short equity hedge funds. This allows us to study the performance differences between the closing and opening of positions and also relate them to the past returns of the fund. Moreover, we argue that long-short equity hedge funds constitute an ideal laboratory to examine the limits to *fundamental* arbitrage: First, long-short equity hedge funds take *directional* bets on individual stocks rather than engaging in relative value arbitrage. Thus, the long and short positions are not part of a combined trading strategy as in, for example, merger arbitrage, allowing us to directly examine the profits of individual positions. Second, discretionary long-short equity hedge funds spend a lot of effort and money on research to distill an information advantage from public and private data sources (Pedersen (2015)). In other words, they closely resemble the textbook case of informed arbitrageurs trying to trade on fundamental mispricing.

While the availability of complete trading records and portfolio holdings are clear advantages of our data, we acknowledge that the relatively small number of hedge funds (21) raises some questions about the selection and representativeness of our sample. We try to allay such concerns to the best of our ability. First, we note that the funds in our sample represent a variety of different sizes and, like many long-short equity funds, invest in equity markets worldwide. On many dimensions, we have no reasons to believe that the funds in our sample are markedly different from a typical long-short equity hedge fund. Second, as we explain in the robustness section, the nature of our data make it unlikely that common sample problems—such as survivorship bias or back-filling bias—should be of major concern for us. Finally, we emphasize that all the results are rationalized with the help of our stylized trading model. Thus, to the degree that our model—and in particular the assumptions on risk limits and position monitoring costs—capture features that are common in the hedge fund industry, one would expect our results to be generalizable to the broader population.

In conclusion, our results make for a rich description of the anatomy of hedge fund trading. They show that long-short equity hedge funds in our sample are skilled but constrained investors: While their opening trades are clearly profitable (both on the long and short side), they do not hold on to their positions until the alpha is fully exploited. Rather, they close their positions prematurely in order to recycle their capital and/or accommodate tightened risk constraints. Thus, the hedge funds in our data behave like constrained arbitrageurs as they are portrayed in the limits of arbitrage literature. By trading on their positive and negative information, they reduce mispricings and contribute to market efficiency. At the same time, their constraints expose them to external pressures (stemming from, e.g., portfolio losses or risk management considerations) that can force them to close their arbitrage positions. While we do not document this here, it is clear that this behavior can have grave consequences for price stability and market efficiency. For instance, when many funds are forced to close their positions at the same time, their very behavior can render mispricings more severe and leave market prices destabilized. More generally, our results show how mispricings can persist in the market despite the presence of informed arbitrageurs.

Our paper contributes to several strands of research. First and foremost, we speak to the literature on hedge funds—and in particular on their trading and performance. Many papers examine hedge fund skill using databases on self-reported hedge fund returns, but are hampered by different biases of these databases (see, e.g., Agarwal, Mullally, and Naik (2015) for a survey). More recent papers try to examine hedge fund skill using quarterly 13F filings data and reach mixed conclusions: While Cao et al. (2016) find that hedge fund holdings predict future returns, Griffin and Xu (2009) find no such predictive power. Grinblatt et al. (2017)

document long-term predictability for a subset of contrarian hedge funds. Jank and Smajlbegovic (2015) use data from hedge funds' mandatory disclosure of large short positions and find evidence for predictability. We add to the debate on hedge fund performance by examining trading skill using detailed trading and position records for *both* long and short positions of the same funds. Furthermore, our data has the advantage of covering *all* equity positions of the hedge funds in the sample. We find strong evidence of hedge fund outperformance for up to one year after the opening of positions. This shows that long-short equity funds in our sample possess the skill to identify mispriced stocks, thereby complementing previous work that emphasize hedge funds' role as liquidity providers (Aragon and Strahan (2012), Ben-David, Franzoni and Moussawi (2012), Jylhä, Rinne and Suominen (2014), Franzoni and Plazzi (2015), Jame (2016)). Finally, our work is closely related to Choi, Pearson and Sandy (2016), who study hedge fund short positions gleaned from merging institutional transaction data from ANcerno with quarterly holdings from 13F. They find that the position openings by hedge funds in their sample do *not* predict long-term returns. Instead, they find that their short positions are profitable only over the short-term (up to 5 trading days), suggesting that these funds make the bulk of their profits from liquidity provision. Our data is arguably more comprehensive[3] and, more importantly, seems to cover the trading activity for a *different class* of hedge funds—long-short equity—as our results for long-term predictability are markedly different.

Second, we contribute to the literature on short selling. 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 selling or the change in short interest. We add to these papers by examining the profitability of both the *opening* and *closing* of short positions. We find negative returns after short sells, but no positive returns after short buys—suggesting that only the opening trades for new short positions are informed. The only other paper examining returns following the closing of short positions is Boehmer, Duong, and Huszar (2015). Their results differ from ours in that they show evidence of positive return predictability for closing trades. However, their analysis is based on the mandatory disclosure of very large position closures and may thus be influenced by price impact and signaling effects.

Third, we contribute to the literature on informed trading and the limits of arbitrage. Using transaction data for a sample of active mutual funds from the same data provider, Di Mascio, Lines and Naik (2016) provide an in-depth analysis on the opening of long arbitrage positions. Like us, they find abnormal returns of about 1.5% following the opening of a long position (but over a longer horizon of 18 months). They further document that the mutual funds gradually build up their positions over a horizon of up to 6 months, consistent

[3] We have access to daily as opposed to quarterly position updates and ANcerno only seems to cover a subset of the stock trades undertaken by hedge funds contained in that sample (see, e.g., Di Mascio, Lines, and Naik (2016)).

with them trying to strategically limit their price impact. While we find less of this behaviour in our sample,[4] we complement their study by including short sales and by focusing on and explaining the returns following position closures. We thereby link with the (mostly theoretical) literature on the limits of arbitrage that emphasizes different channels as to why arbitrageurs may be forced to close their positions too early (Shleifer and Vishny (1997), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Acharya and Viswanathan (2011)).[5] Existing empirical work in this area is mostly at the macro-level and explores, for example, how financial market dislocations respond to aggregate funding shocks (Nagel (2011); Pasquariello (2014)). Another strand studies hedge funds' deleveraging behavior in the wake of the 2007-09 Financial Crisis (Ang, Gorovyy and van Inwegen (2011); Khandani and Lo (2011); Aragon and Strahan (2012); Ben-David, Franzoni and Moussawi (2012)). We contribute to this literature by providing evidence for the limits of arbitrage at the *transaction*-level. Our study thereby offers a unique glimpse into the process by which hedge funds "recycle" their limited arbitrage capital—i.e., how and when they close existing positions and redeploy their capital.

The remainder of this paper is organized as follows. Section I describes the simple trading model we have in mind and lays out its testable predictions. Section II describes the data and provides summary statistics. Section III focuses on the profitability of the opening and closing of long and short positions. In Section IV, we relate post-closure returns to several proxies of hedge funds' shadow cost of capital. Section V provides robustness checks. Section VI concludes with a discussion of the broader implications of our findings for market efficiency and the limits of arbitrage.

I. Hypotheses

We think of the long-short equity hedge funds in our data as fundamental arbitrageurs. Rather than holding a diversified portfolio to earn the risk premium, they collect and analyze public and private data to form an assessment about the fundamental value of a specific target company and establish a long (short) position when they find the company's stock to be sufficiently under- (over-)valued. The starting point of our empirical investigation is therefore to see whether the long and short stock positions opened by hedge funds in our sample deliver risk-adjusted returns (alpha). Prior research on hedge fund performance and managerial skill are hampered by data constraints and reach mixed conclusions (see, for instance, the survey by Agarwal, Mullally, and Naik (2015)). Given that our data, while covering only 21 funds, is the most detailed hedge fund transaction and position data so far studied in the academic literature, our performance analysis constitutes a valuable contribution in its own right.

[4] On average, opening orders in our sample already make up about 77% of the maximum position size that we observe for the position.

[5] See Gromb and Vayanos (2010) for a survey of this literature.

Next, we investigate how and when hedge funds close their positions. If hedge funds were unconstrained, we would expect them to hold on to their positions until all the alpha is reaped, implying that post-closure risk-adjusted returns should be zero. In practice, however, we expect hedge funds to be capital and/or attention constrained: while they can take leverage, their ability to do so depends on banks willingness to provide it, and the fundamental research required to identify and monitor mispriced stocks should be time and effort intensive, implying that long-short equity hedge funds focus on a limited number of open positions (directional bets). Being cognizant of their constraints, we expect hedge funds to allocate their limited resources on the basis of a cost-benefit analysis. Each period, they will decide how many positions to maintain, which ones to open and which ones to close. An important implication is that, when constraints are binding, the hedge fund may decide to close an arbitrage position before its alpha is fully exploited. Thus, if our sample hedge funds are indeed capital or attention constrained as we posit, we expect the returns of long (short) positions to remain positive (negative) even after these positions have been closed. These post-closure returns should, however, be smaller than the returns following newly opened positions—for otherwise the hedge fund would have been better off holding on to the old position.

To guide our intuition as to when early position closures should occur, we develop and solve a simple trading model in which a hedge fund faces a risk constraint, incurs position monitoring costs, and new stock mispricings pop up every period but gradually decay over time. In Appendix B, we describe our model in detail and derive the hedge fund's optimal trading rule. Here, we summarize its key intuitions and the resulting empirical predictions.

Our modeling assumptions are supposed to reflect realistic features of the trading environment for long-short equity hedge funds: The risk constraint is meant to capture, in a simplified way, common risk management practices such as risk parity investment (see Pedersen (2005)). A straightforward implication of this constraint is that position sizes are bounded and inversely related to the volatility of the underlying stock.[6] The position monitoring cost is a placeholder for any type of fixed cost that is associated with holding a stock position. For instance, it can represent a fixed transaction cost or a fixed attention cost for monitoring a given position (the hedge fund may want to check, for example, whether the trading signal, which induced the opening of the position, is still valid after the arrival of new information). Without this assumption, the hedge fund would always smoothly scale back position sizes all the way to zero until the alpha is fully exploited. Thus, there would be no early position closures. With a fixed monitoring cost, early position closures do occur as it is not economical to hold on to a position below a certain minimum position size. A natural implication of this

[6] The precise nature of the risk constraint is not important. For example, we obtain similar predictions if we replace it by a leverage constraint as modeled in Gromb and Vayanos (2002). The only important thing is that, since both long and short positions consume from the overall risk budget (or margin capital), the hedge fund is prevented from leveraging up his positions without limit.

assumption is that wealthier funds have more open positions—a prediction for which we find strong support in the data.[7]

Our model identifies three potential reasons for why a hedge fund may close a position before its alpha is fully exploited: First, because the fund only maintains a limited number of open positions, it may close some positions when better investment opportunities arise. Second, as the hedge fund's wealth decreases, the monitoring of existing positions becomes more expensive relative to downscaled position sizes, to which it responds by reducing the total number of open positions. Third, as the hedge fund's stock positions become more volatile, it is forced to downscale its positions in order to satisfy the risk limit constraint. This again increases the monitoring costs *per dollar invested* and thus leads to a reduction in the number of total positions. Hence, the model predicts that the closure of long (short) positions should be followed by more positive (negative) returns when the hedge fund (1) simultaneously opens new positions (as a proxy for having many new investment opportunities), (2) has had a poor past performance, and (3) when the funds' stock positions become more volatile.

In the next section, we introduce our data before proceeding to our empirical tests of these predictions.

II. Data and Variable Construction

A. Analytics data

Our data on long-short equity hedge funds is provided by Inalytics Ltd. and this is the first time it is used in an academic collaboration. A different subset of the Inalytics database, for long only equity funds, has been previously studied in Di Mascio, Lines and Naik (2016). Inalytics provides portfolio monitoring services for institutional asset owners as well as investment and process management consulting for asset and hedge fund managers. When an institutional client investor, like a plan sponsor, makes an allocation to a hedge fund, this hedge fund provides its' trading and portfolio data to Inalytics so that they can monitor the fund's performance on behalf of their client.

Our data contain *complete* trading and portfolio information for the equity holdings of 21 hedge funds. For each fund, we are thus able to track both their long and short portfolios. Specifically, we have access to two datasets: The first is a transaction-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. The second dataset is a stock-day level dataset of each funds' portfolio holdings. This dataset contains

[7] When we split hedge funds into above and below median in terms of total portfolio value, we find that small and large funds have, respectively, 61 and 94 open stock positions, on average.

stock identifiers, the number of shares held, and the price of the stock at the end of the day. All prices are 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 A.3). Hedge funds often 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.

B. Summary statistics

Our sample period runs from 2005 to 2015. However, each individual fund 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 open positions in the data. Orders move more proportional to the number of funds. From 2008 Q1 onward we have around 20 orders per day, 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 further 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 (Pedersen (2005)). The funds conduct on average 6 orders per day. Compared to an average of 74 positions this corresponds to a new order for a given stock position every 12 trading days. The daily fund turnover (trading volume over total portfolio holdings) is on average 5.4% (median 2.8%). Our funds have fairly different sizes. The 10^{th} percentile fund holds 0.12 billion USD in assets, while the 90^{th} percentile fund holds 6 billion USD. The median fund holds 0.4 billion USD. The investment areas of the funds vary as shown 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. Hence, European stocks are somewhat overrepresented in our sample (they make up 29% of stocks held, compared to making up 17% of world market capitalization in Worldscope).

[Insert Table 1 about here.]

In Panel B, we display summary statistics by position. A position lasts from its opening—i.e., the first buy for long positions or the first sell for short positions—to its close—i.e., the moment when the stock holding goes back 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 over the lifetime of the fund. Our data contains about 16,000 positions; 6.9% of them are already open when the fund enters the database, while 11% are still open 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: on average position are open for 104 trading days (about half a year), although the median is only 35 trading days (about 2 months). Over the lifetime of a position, 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 at the order-level. We distinguish between three types of orders: Opening 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 opening and closing orders are much larger than the follow-up orders in: when standardized by the maximum size of a given position, opening and closing orders on average make up around 77% of this maximum position size (median 100), while the follow-up orders make up only 15.8% (median 8.7%). This suggests that the important investment decisions are the openings and closures of positions. We therefore focus on these two types of orders in our main analyses. Follow-up orders are small and thus more likely to be based on liquidity or rebalancing motives rather than on information. Still, follow-up orders make up 69% of all orders in our sample. We thus check in the robustness section that the inclusion of these orders leads to similar results. 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.

C. Datastream and Worldscope data

Because the hedge funds in our sample trade stocks internationally, we require 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. For stocks that appear in our transaction and holdings data but are not covered in Datastream we add stock return information provided by Inalytics (this affects approx. 14% of our stocks). We show in Appendix C.4 that our results are robust if we only use return data from Datastream. We use three methodologies to risk-adjust returns: (1) excess returns computed with respect to the fund-specified benchmark, (2) risk-adjusted returns computed following the methodology of Daniel, Grinblatt, Titman, and Wermers (1997), hereafter DGTW, and (3) alphas estimated using the four-factor model of Carhart (1997). The details of the risk-adjustments are explained in Appendix A.3; here we provide only a brief summary description.

Excess returns are computed as returns minus the return of the fund-specified benchmark. Since this risk-adjustment depends on the fund, excess returns for the same stock may differ across funds. The benchmarks can even vary within the same investment area. For example, some Europe-focused funds benchmark against the MSCI Europe, while others benchmark against the FTSE Europe. However, benchmarks are the same for both long and short positions of the same fund and they do not change over time.

As a second methodology, we compute DGTW returns on a regional level. We categorize stock markets 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 A.2. Within each region, we sort stocks into quintiles by market capitalization, market-to-book ratio and past-12 month returns, thus forming 625 portfolios (125 per region). We compute DGTW returns as stock returns minus the returns of the respective benchmark portfolio. Given prior evidence suggesting that local factors are better able in pricing risk (Griffin (2002)), our approach to compute portfolios on a regional level provides for a reasonable compromise between a desirable granularity and the need to sufficiently populate 125 portfolios.

As a third methodology, we implement a regional version of the Carhart (1997) 4-factor model, which includes 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 the best results are obtained by daily regressions over 1 year horizons and after shrinking the estimated betas. Finally, we compute alphas on the daily level as:

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

Finally, we note that all our return measures are winsorized at the 1% level on both sides.

III. Profitability Results

A. Profitability of opening and closing trades

We display gross fund profitability computed from holdings by year in Figure 3. In Panel A, we display the actual profitability of the fund. Because most funds have more long than short positions, this profitability co-moves a lot with the market. The worst year is 2008 when equity markets crashed worldwide in the wake of the Lehman bankruptcy. In 2009, equity markets recovered and our sample hedge funds see their best year. To get a better idea of the fund’s stock-picking skill, we display profitability based on equal-weighting the long and short portfolios in Panel B. Now 2009 appears to be the worst year, consistent with this year being known as a bad year for hedge funds because of the so called momentum crash (Daniel and Moskowitz (2013)). With the exception of 2009, the funds always exhibit positive returns that are fairly stable in the 2-8% range. This seems to suggest that the funds in our sample exhibit skill.

We now examine hedge funds' trading skill in more detail by studying the post-trade returns for the stocks they buy and sell. We start with a simple graphical analysis presented in Figure 4. 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 either open or close a position (that is, we exclude follow-up orders). We further separate between orders that are related to long or short positions.

Figure 4 reveals clear evidence of informed trading for the opening of positions: in the 250 days following the initiation of a long (short) position, cumulative excess returns are around 2% (-2%). Moreover, on both the long and the short side, a large fraction of these returns is realized in the first 125 trading days (6 months) following the opening order, after which the return drift appears to be more muted. In other words, the post-trade alphas (per unit of time) for initiated positions decay over time: they are highest immediately after the position is established and then gradually shrink as time progresses.[8]

In contrast, the closing of long and short positions does not seem 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 about 1%. 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.

Next, we investigate the statistical significance of these findings. In Table 2, we focus on position openings and run a regression of risk-adjusted returns following the order on *D(Short)*, a dummy variable equal to one if the order initiates a short position (and zero if it initiates a long position). We examine all three measures of risk-adjusted returns for holding periods of 60 and 125 trading days (approximately 3 and 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 within order returns. We include fund fixed effects to control for any differences in post-trade profitability across funds that could correlate with their propensity to enter a short position. We also include month fixed effects to ensure that our results are not driven by a particular time period. Finally, we cluster standard errors two-way by stock and last date of order. Clustering by stock accounts for correlation due to overlapping returns and clustering by date accounts for correlation in the cross-section of stock returns.

[Insert Table 2 about here.]

[8] This finding is consistent with the evidence provided in Di Mascio, Lines and Naik (2016) who document a similar convexity in the cumulative abnormal returns following the opening of long positions for the long-only mutual funds in their sample.

Given our specification, the coefficient estimate for the *D(Short)* dummy can be interpreted as the return difference between long and short positions that have been opened in the same month. The results, presented in Table 2, show that this return difference is economically and statistically significant. For instance, for excess returns, long positions outperform short positions by about 1.8% over 60 days and 2.5% over 125 days. For DGTW returns and alphas the effect is slightly smaller at about 1.6% over 60 days and 2% over 125 days. These results are all statistically significant at the 1% level. In short, hedge funds' position openings are clearly profitable, suggesting that the fund managers in our sample possess investment skill.

In Table 3, we repeat our analysis for closing orders. We again find a negative coefficient for the *D(Short)* dummy, albeit with a smaller economic magnitude. For excess returns, the return difference between closed long and closed short positions equals 0.7% over 60 days and 1.5% over 125 days. For DGTW returns and alphas the effect is again slightly smaller. Over the 125 days horizon, the return difference is statistically significant for all measures of risk-adjusted returns. These results suggest that the hedge funds in our sample close their positions too early in the sense that these positions would have earned significant risk-adjusted returns going forward. However, such early position closures don't have to be suboptimal. Indeed, we argue below that they can be explained by the presence of (risk) capital constraints and position monitoring costs faced by the hedge funds in our sample.

[Insert Table 3 about here.]

These results have important implications for our understanding of the informativeness of different types of trades. Indeed, they suggest that at least for the long-short equity hedge funds in our sample, only trades that open new stock positions are informative, whereas those that close a position are not only uninformative but rather predict returns in the opposite direction of the closing trade. Our analysis thus shows that, in order to study the informativeness of individual buy and sell trades, it is important to determine whether these trades open or close a stock position, which is only possible with access to portfolio data such as we use here. Without this distinction, long buys and short buys as well as short sells and long sells are lumped together, causing a potential downward bias when assessing the profitability of these trades.

B. Opening a new stock position vs. holding-on to an old one

We have established that both the opening and the closure of a long (short) position is followed by positive (negative) returns. As argued in the hypotheses section, a natural explanation for this is the presence of a risk capital (or margin capital) constraint: a constrained hedge fund may want to close an existing stock position even though it still offers some alpha in order to free-up capital that can be invested into new, more promising, trading opportunities. Of course, this argument only makes sense when these new investments indeed deliver higher returns than those that are foregone by closing existing positions. A casual inspection of Figure 4 suggests that this is indeed the case: newly established positions earn most of their alpha in the first weeks/months after the opening trade. After some time, alphas peter out and so it could to be more attractive to open a new position.

We now test for this prediction more rigorously in a regression setting. Because this analysis combines opening and closing trades (which often take place close to each other), we have enough variation to include fund×month fixed effects. This approach allows us to compare openings and closures undertaken by the same fund at roughly the same point in time—and where it is thus likely that the closure provided the capital for the new position opening. The key variable of interest is *D(Opening)*, a dummy variable that takes the value one when the order opens a (long or short) position and zero when it closes the position (follow-up orders are again excluded from this analysis).

Table 4 shows the results. In Panel A, we focus on long positions only. The significantly positive coefficient for the *D(Opening)* dummy implies that newly initiated long positions are indeed more profitable than the previous long positions that are closed within the same month by about 0.5-0.7% depending on the risk-adjustment and the holding horizon. For short positions (Panel B), the coefficient flips sign, meaning that initiated short positions are followed by more negative returns than closed short positions (although it is not always significant). In Panel C, we examine both long and short positions jointly. To be able to combine long and short positions, we use signed returns instead of returns as the dependent variable. Signed returns are defined as returns for long positions and minus one times the returns for short positions. We find about 0.5-0.7% higher signed returns following the opening of positions. Because combining short and long positions improves statistical power, these tests are all highly statistically significant. This finding shows that hedge funds are on average right when they reallocate their capital into new stock positions.

[Insert Table 4 about here.]

In summary, the results of this section show that the hedge funds in our sample possess investment skill but face constraints: they open stock positions that generate alpha, but close them before this alpha is fully exploited so that they are able to recycle their capital into new investment opportunities. In the next section, we investigate position closures in greater detail.

IV. Explaining Post-Closure Returns

In Appendix B, we show with the help of a stylized trading model that early position closures can be explained by funds being subject to risk capital constraints and position monitoring costs. In this section, we wish to provide further support for this mechanism by testing three distinct predictions from our model.

The first prediction states that existing stock positions should be closed earlier at times when more new trading opportunities emerge, which manifests itself in many newly opened positions. A larger number of early position closures in turn implies that hedge funds "leave more money on the table"—i.e., the return difference between closed long and closed short positions should increase. In Table 5, we test this prediction by splitting the sample of closing orders by whether the hedge fund increased or decreased the number of open positions over the previous 5 days (Panel A) or over the previous 10 days (Panel B). We then repeat our regression analysis from Table 3 for these different subsamples. Table 5 shows the results for a holding period of 125 trading days.[9] The results broadly confirm our prediction: whereas the excess return difference between closed long and short positions after increases in the number of open positions over the previous 5 days is 2.2%, it is only 0.8% and insignificant after decreases in the number of open positions over the previous 5 days. The results for DGTW returns and 4-Factor Alpha are similar with 1.7% vs. 0.5%, and 1.7% vs. 0.3%. Furthermore, the results are robust to using the change over the previous 10 trading days instead of the previous 5 trading days (Table 5, Panel B). In summary, our results suggest that early position closures appear to be more common when hedge funds simultaneously seize new trading opportunities.

[Insert Table 5 about here.]

The second prediction concerns the relation between past portfolio profits and subsequent position closures. In the model, the hedge fund's optimal number of open positions is pinned down, among other things, by the fund's equity wealth (or total net asset value) relative to the position monitoring cost. Intuitively, this fixed cost makes it uneconomical to hold positions below a certain minimum position size. As such, wealthier funds naturally hold a larger number of open positions, and when a given fund suffers portfolio losses it may respond by closing existing positions. We thus check whether the returns from the post-closure investment strategy from Table 3 are more pronounced after times in which the fund has experienced negative portfolio returns. The results, shown in Table 6, support this prediction. When we split closing orders by prior fund returns over the previous five trading days, the excess return difference between closed long and short positions is 2.5% in the subsample with negative prior fund returns and only 0.7% in the subsample of positive prior fund returns. For the other risk-adjusted return measures, the difference is smaller but goes in the same direction. When we split the sample based on fund returns over the previous 10 trading days, we again obtain similar results. These findings suggest that trading losses force funds to close some of their positions earlier, leaving more money on the table.

[Insert Table 6 about here.]

[9] The results for 60 days go in the same direction but are economically weaker.

The third prediction follows from the risk constraint: when the volatility of stock returns goes up, hedge funds have to curb their position sizes in order to satisfy their risk constraint. Because of the fixed position monitoring cost, this may again cause the premature closure of some outstanding stock positions. We therefore conduct a sample split by the change in fund return volatility compared to the previous month.[10] When volatility goes up, the volatility constraint becomes tighter and the fund may be forced to reduce the number of open positions, leading to early position closures. In contrast, when volatility decreases, there is less need for early position closures. Table 7 confirms this prediction. Focusing on excess returns over a 125-days horizon, we see that the return difference between closed long and short positions amounts to a statistically significant 2% at times when fund volatility goes up, while it is less than 1% and insignificant when volatility goes down. For DGTW returns (but not for 4-factor alphas), we find a similar difference between the two subsamples.

[Insert Table 7 about here.]

Overall, the findings in this section are consistent with a model in which hedge funds close their positions due to risk capital constraints and position monitoring costs. In other words, the hedge funds in our sample resemble constrained arbitrageurs as they are portrayed in the limits to arbitrage literature.

V. Selection Concerns and Robustness Checks

A) Potential data biases and selection concerns

Our data sample is quite small in that it covers only 21 long-short equity hedge funds. In our view, this drawback should be easily outweighed by the unprecedented level of detail that this data provides. Indeed, to the best of our knowledge, our data constitutes the first *complete* account of the stock trading activity for a sample of hedge funds studied in the academic literature to date.[11] In this section, we discuss potential data and selection biases that one could be concerned about.

[10] We compute monthly fund return volatilities as the standard deviation of daily fund returns. We set volatility to missing when we have fewer than 15 non-missing daily return observations for a given month. We then calculate monthly fund return volatility changes.

[11] The data that comes closest to ours in its level of detail is obtained via a fuzzy name-matching approach between the hedge fund trades contained in the ANcerno institutional transaction data and their quarterly equity holdings reported in 13F filings. However, funds covered by ANcerno only make available a subset of their transaction records and identifying long and short positions—a crucial element of our study—from quarterly holdings is bound to be noisy. Finally, while our data is on long-short equity hedge funds (for which we document clear evidence of stock-picking ability), the hedge funds covered in ANcerno appear to belong to a different class of hedge funds as they make most of their profits from liquidity provision and their trades do not predict long-term alpha (Franzoni and Plazzi (2015), Jame (2016), Choi, Pearson and Sandy (2016)).

We begin by noting that several sample biases that have been identified in the literature should not be of major concern here. For instance, since hedge funds that engage with Inalytics provide their transaction data in real time, there should be little incentives for window dressing and back-filling bias should be limited. Moreover, since our data also covers funds that have already been terminated, survivorship bias should not be an issue.

One important remaining concern with our data is self-selection into the sample. Here, the biggest worry is that successful hedge funds strategically engage with Inalytics in order to advertise their trading success—implying that the documented trade profitability would be biased upward. To address this concern, we study the return series of funds in our sample to detect any signs of fund selection. The idea is that, since we cannot observe fund returns prior to them entering our sample, we can at least examine whether funds with poor returns are more likely to drop out of the sample. Figure 5 shows compounded fund return indexes for all hedge funds in our sample. These return indexes are obtained by compounding the daily (position-weighted) average portfolio returns over time, starting with a normalized value of one. If selection based on past performance were a major concern, we would expect funds that drop out of sample before the end of the sample period (December 2015) to exhibit subpar returns. If anything, the opposite seems to be true. For instance, the top-5 funds in terms of the compounded return index all leave the sample prematurely, whereas the worst performing fund stays in. This finding is potentially consistent with a selection effect running in the opposite direction: institutional clients may demand from a poorly-performing hedge fund to submit its trades to Inalytics for monitoring and verification purposes. In this case, the trade profitability documented above can be understood as a lower bound estimate of the average trade profitability for the class of long-short equity hedge funds. Given the data constraints, we prefer not to take a clear stance on whether such a selection effect is present or not. We only emphasize that our evidence is inconsistent with a type of strategic self-selection that could lead to an upward bias of our estimates.

Finally, we argue that any remaining selection concerns should only affect the inference about the representativeness of the average trade performance that we document. We believe, however, that they should not invalidate our micro evidence in support of the limits to arbitrage channels. Indeed, these channels should apply to every arbitrageur that faces some sort of risk-capital or margin-capital constraint. Thus, any selection concerns notwithstanding, the fact that we have detailed trading data for a sample of informed traders is sufficient for testing these channels.

B) Can rebalancing explain our results?

We have interpreted the premature position closures by our sample hedge funds as being due to their risk capital constraints and position monitoring costs. One may wonder whether there could be an alternative explanation based on portfolio rebalancing, where hedge funds try to maintain a certain risk exposure for each individual stock position. Indeed, for long positions, rebalancing has the potential to explain why hedge funds reduce their positions before alphas are fully exploited. To see this, consider a hedge fund with a long position in a stock whose price is expected to go up over time. As the stock price starts increasing, the position size grows and, being concerned about the risk exposure to a single stock, the hedge fund may want to rebalance the position by selling some stocks. Such rebalancing trades appear to leave additional money on the table.[12]

We point out, however, that this rebalancing story cannot explain why we find return continuation after position *closures*. This is because rebalancing trades by definition never close a position entirely, but only reduce it to the desired size. In other words, position closing decisions should be independent of rebalancing considerations.

To see this empirically, we present in Table 8 results from a sample split of post-closure returns by the underlying stock's return over the prior 10 trading days. Rebalancing trades that close a position should be more likely to occur after a positive return because positive returns increase the size of a position. Thus, if the alpha following closing orders was explained by rebalancing, we would expect a larger alpha if the closing happens after a positive stock return. The regression setup in Table 8 is identical to our earlier sample splits in Tables 5 to 7, except that we now split by the prior stock return rather than by some fund characteristic. We find very similar returns following closing orders after positive and negative stock returns. If anything, hedge funds seem to leave slightly more money on the table when they close positions after negative stock returns, which is the exact opposite of what we would expect if closing orders were due to rebalancing. This finding confirms our argument that portfolio rebalancing cannot explain early position closures.

[Insert Table 8 about here.]

C) Are follow-up orders profitable?

In our main analysis, we focus on studying the profitability of opening and closing orders. This means that we exclude follow-up orders, even though they make up about 69% of all orders in our sample. Apart from ruling out rebalancing-based explanations (see above), this choice is motivated by the intuition that, out of all trading orders, opening orders should be the most informed (as they capture the point in time when a hedge fund started acting on its trading signal), whereas closing orders should in principle be the least informed (as an unconstrained hedge fund will only close after fully exploiting its trading signal).

[12] Note, however, that for short positions the logic is reversed: since short positions shrink in (absolute) size as the stock price decreases, rebalancing trades take the form of sells that tend to be followed by negative stock returns (assuming the hedge fund's opening of the short position was informed).

Follow-up orders, in contrast, can occur for a multitude of reasons, making the relation between the direction of follow-up orders and subsequent returns highly ambiguous. For instance, hedge funds may gradually build-up their arbitrage positions so as to minimize their price impact, in which case their follow-up orders would appear to be informed (see Kyle (1985), Foster and Viswanathan (1996), Di Mascio, Lines and Naik (2016)). Alternatively, follow-up orders can result from hedge funds' portfolio rebalancing motives, in which case they may look uninformed. While a detailed investigation of the motives behind follow-up orders is outside of the scope of this paper, we nevertheless want to study whether follow-up orders, on balance, appear to be informed; that is, whether position-increasing orders are followed by higher returns than position-decreasing ones.

To this end, we focus on the sample of follow-up orders and regress post-order returns on a dummy variable indicating whether the order increased or decreased the position. The results are shown in Table 9. In essence, our test is the analogue of Table 4 where we studied whether position openings outperform position closures.

In columns 1 and 2, we only include follow up orders related to long positions. If follow-up orders were to contain additional information, we would expect more positive returns after follow-up buys (which increase the long position). We find a positive coefficient, but it is very small and not statistically significant. Similarly, in columns 3 and 4, we find more negative returns following orders that increase short positions (follow-up sells) but the magnitude remains small and insignificant. Finally, in columns 5 and 6, we combine long and short positions and use signed returns as the dependent variable. Once again the coefficients are very close to zero and insignificant.

[Insert Table 9 about here.]

These results suggest that hedge funds' follow-up trades are not informed, because post-trade returns are independent of the direction of the follow-up order. In other words, in contrast to opening and closing trades, the capital freed from decreasing some existing positions is not more profitably employed by increasing other existing positions. In conclusion, follow-up trades appear to be caused by different underlying reasons and do not obey to the same return patterns as opening and closing decisions. This justifies why we focus on opening and closing orders for our analysis of the limits of fundamental arbitrage.

VI. Conclusion

The question to which extent rational arbitrageurs remove mispricings and thus promote efficient prices is of crucial importance in asset pricing. Many arbitrageurs (and academics) focus on relative-value arbitrage; i.e., the process of exploiting relative price differences between two assets with comparable payoffs. However, a group of assets can be priced correctly relative to each other, while still being jointly mispriced when all assets are far away from their fundamental value. Thus, relative-value arbitrage in and of itself is not sufficient to ensure that prices reflect fundamental values. Similarly, while relative-value arbitrageurs arguably make prices more efficient (in the sense that they faster incorporate public information), they don't necessarily make prices more informative (in the sense that prices summarize a higher absolute level of information).[13] In financial markets, this important void is filled by what we call *fundamental arbitrageurs*—traders that produce new and synthesize existing information in order to trade on deviations of asset prices from their fundamental values. Long-short equity hedge funds are presumably the most important group of investors belonging to this category. They spend substantial resources to gain an informational advantage and then take directional (long or short) bets in relatively small number of stocks about which they have strong convictions.

In this paper, we exploit proprietary trading data for a sample of such long-short equity hedge funds to offer a microscopic analysis of their arbitrage activity. We first establish that positions opened by these funds predict risk-adjusted returns over a horizon of up to one year, suggesting that their trades are informed. We then make the surprising observation that their closing trades are not only uninformed, but rather predict returns in the opposite direction of the closing trade. This implies that our sample hedge funds close positions that would have otherwise earned risk-adjusted returns going forward. In other words, they leave money on the table.

We then show that this behavior can be rationalized with the help of a simple trading model in which hedge funds are subject to a risk constraint and position monitoring costs and in which trading opportunities exhibit alpha decay. Under these assumptions, funds may rationally decide to close positions that are still expected to generate profits (1) in order to invest their limited capital in even more profitable trading opportunities or (2) in response to tightened capital of volatility constraints. We document supporting evidence for these predictions in the data.

Our findings have profound implications for our understanding of the limits to (fundamental) arbitrage. Indeed, we believe that we are the first to provide micro-level evidence on how rational arbitrageurs decide to abandon a profitable trading opportunity due to their risk capital and/or position monitoring constraints. As the trading opportunity is not fully exploited, mispricing persists. Thus, despite the presence of informed and rational arbitrageurs, market prices remain inefficient.

[13] See Brunnermeier (2005) and Weller (2016) on this point.

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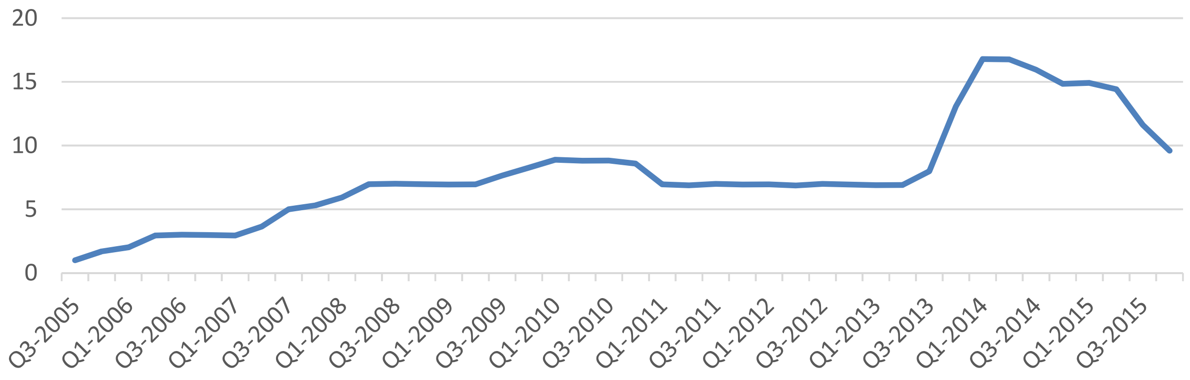
Figure 1: Coverage over sample period

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

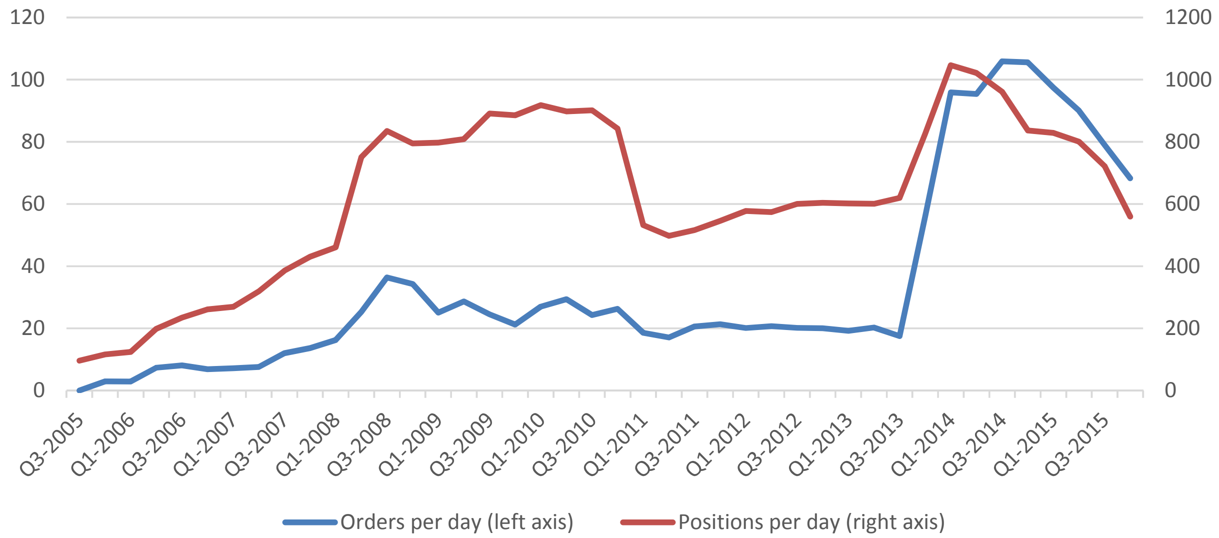
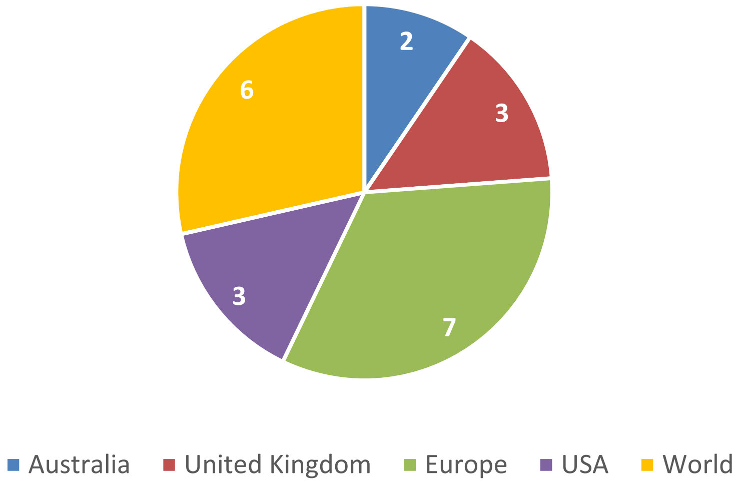


Figure 2: Investment areas of funds

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 A.2.

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



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

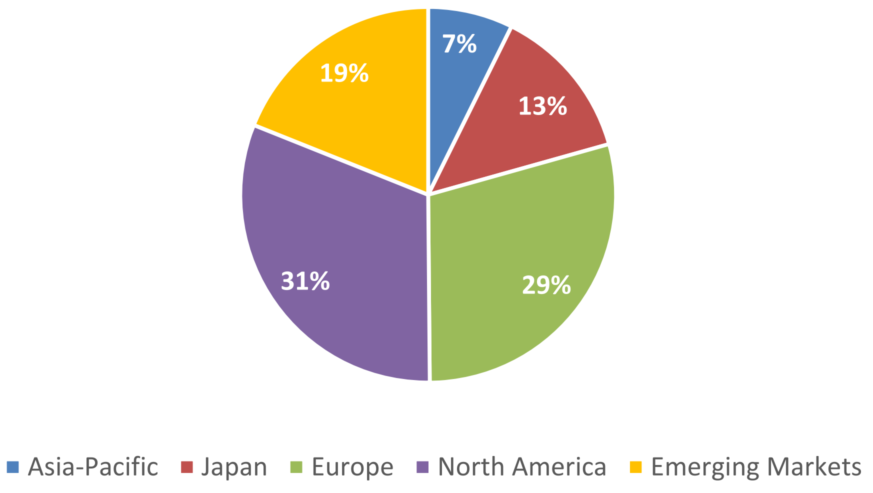
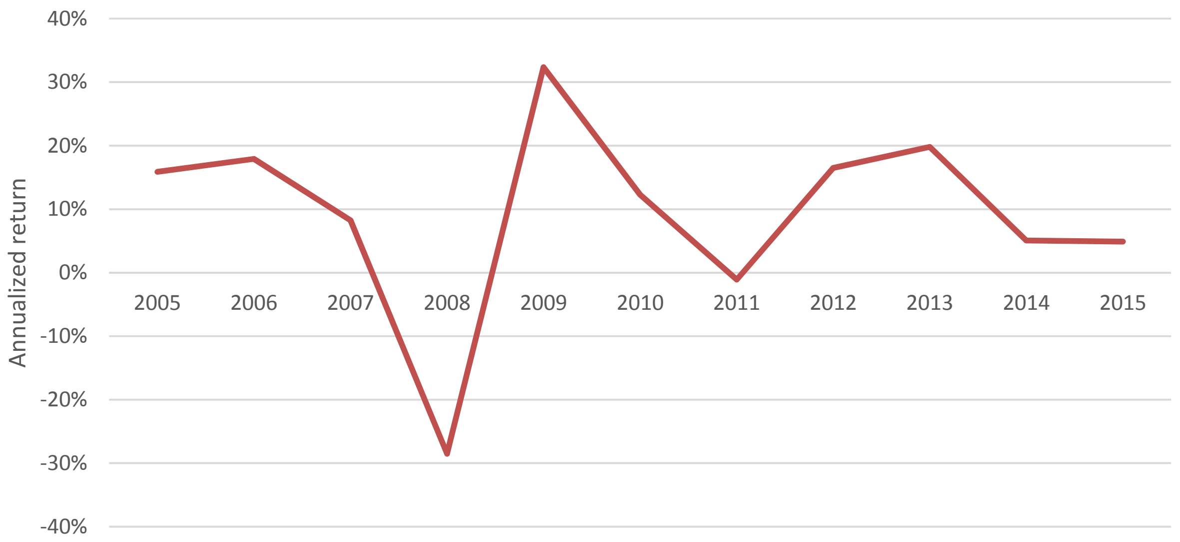


Figure 3: Fund returns

In this figure, we display fund returns by year. Fund returns are computed from holdings data at the daily level and then annualized. In Panel A, we display average holdings-weighted fund returns based on the portfolio of all long and short positions. In Panel B, we first compute fund returns on the long and short side separately and then weigh them equally.

Panel A: Fund return



Panel B: Fund return (long and short portfolio equally-weighted)

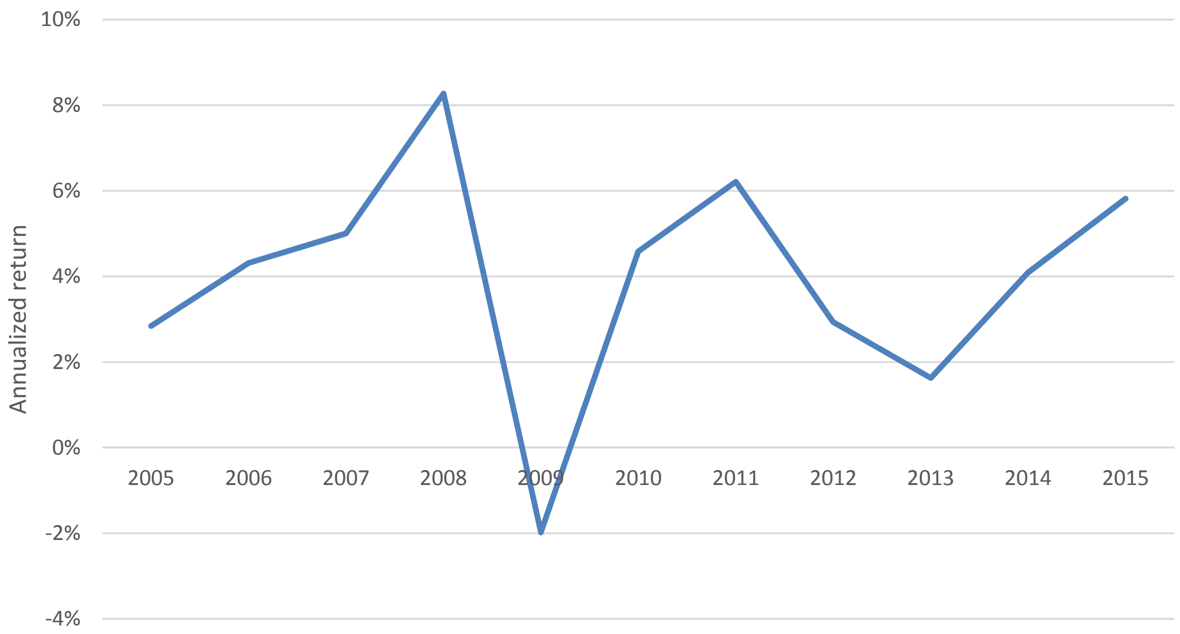


Figure 4: Excess returns following orders

This figure displays cumulative excess return indices for 250 trading days following orders that open or close a position. *Open Long Position* is the buy order establishing a long position ("long buy"). *Open Short Position* is the sell order establishing a short position ("short sale"). *Close Short Position* is the buy order closing a short position ("short buy"). *Close Long Position* is the sell order closing a long position ("long sell"). *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.

Excess returns around orders

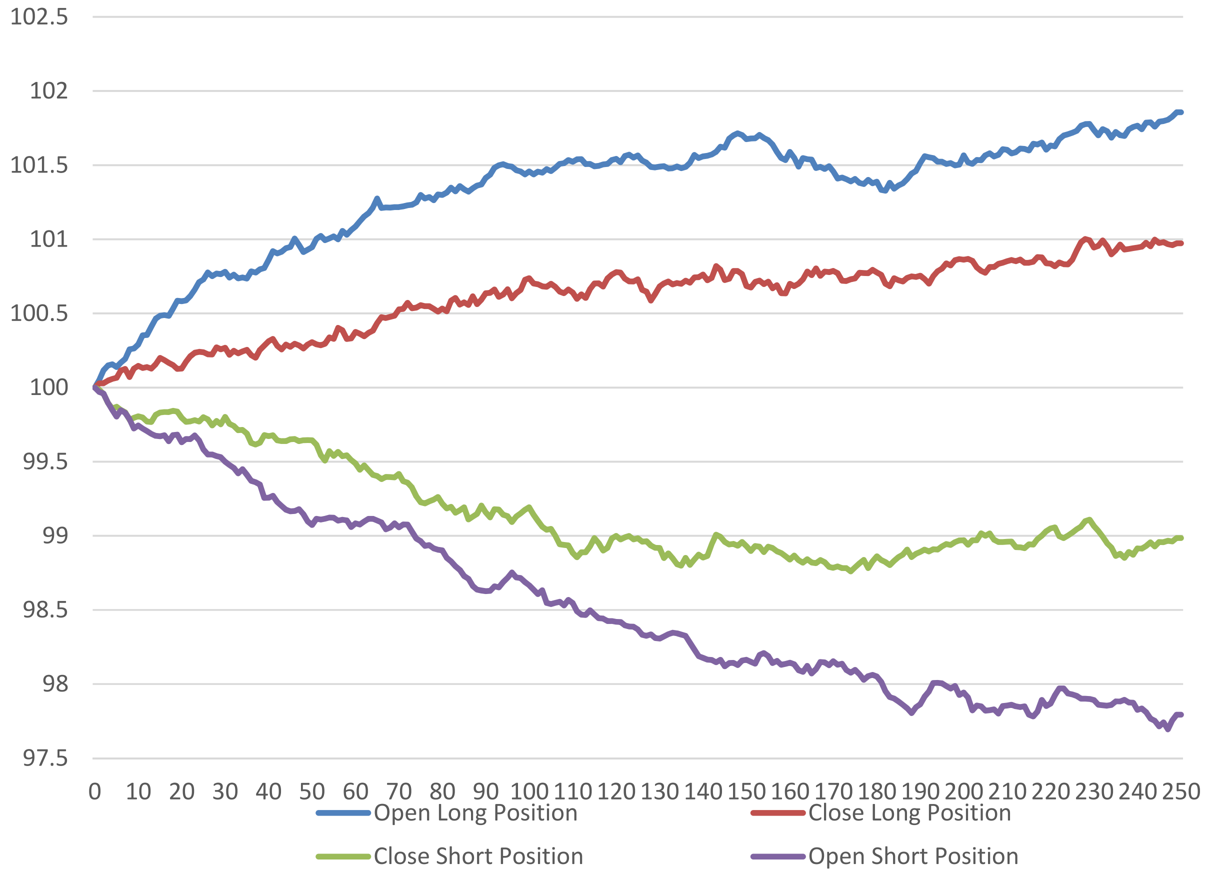


Figure 5: Compounded fund return indexes

This figure displays compounded portfolio return indexes for all hedge funds in our sample. For each fund, we first calculate daily portfolio returns as the position-weighted average return of the funds' equity positions. We then compound these daily returns over time starting from a normalized value of one.

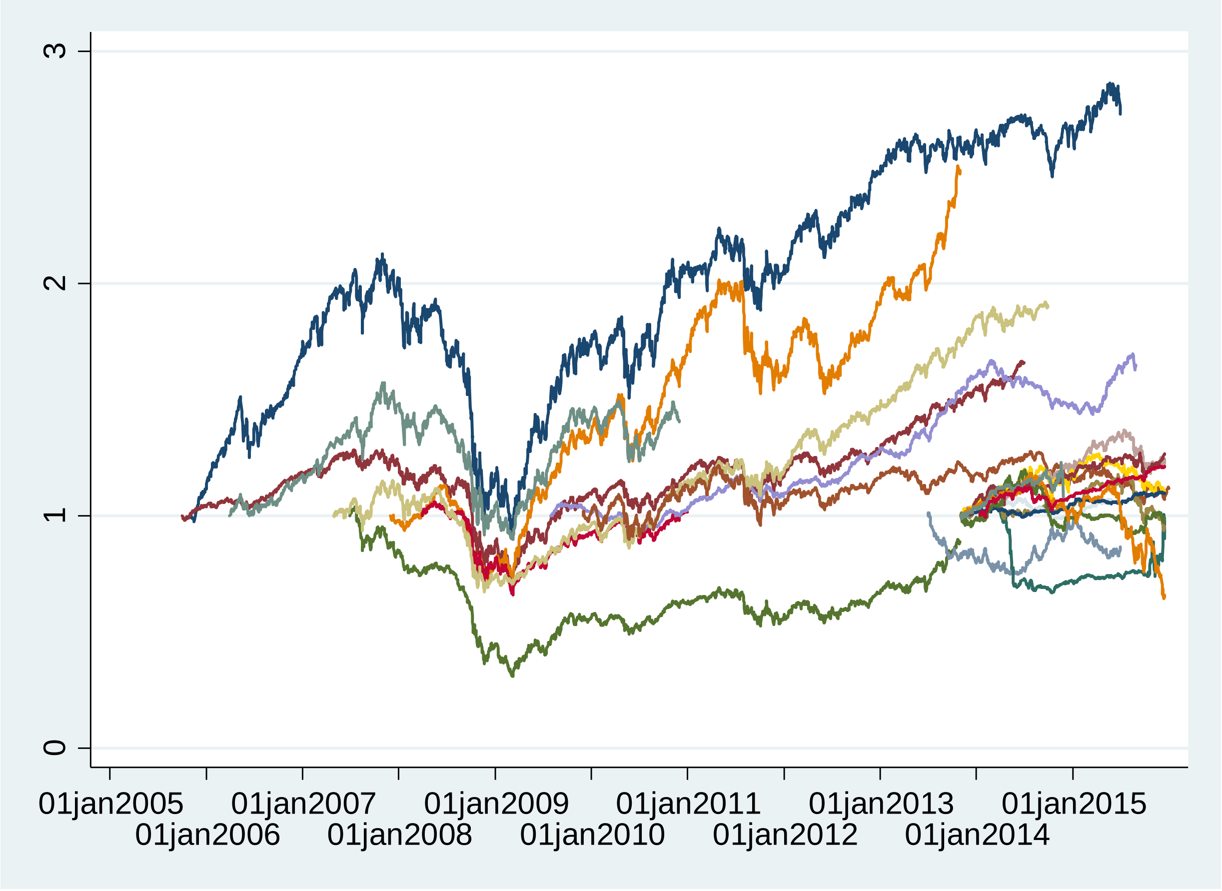


Table 1: Summary statistics

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 of short positions over total fund holdings (measured in USD). *Orders per Day* are the average number of orders executed per day. *Trade Fraction* is the average of the funds trading volume divided by the value of its holdings. *Value of Fund* is the absolute value of all positions (long and short positions added together). *Positions per Stock* is the average number of times the fund establishes a position in a given stock. Panel B displays summary statistics by position. A position lasts from its opening (first buy for long positions or first sell for short positions) to its close (i.e., the moment the holding of the stock goes back to zero). *Length* is the average number of trading days for which the position remains open. *Number of Orders* is the average number of trading orders per position. *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 open a position, close a position or simply change the size of a position. *Number of trades* is the average number of trades per order (defined as a sequence of individual trades in the same direction with a gap of no more than 2 days between them). *USD volume* is the average order volume in USD millions. *Size as fraction of largest holding* is the average size of the order relative to the maximum position size.

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 – opening orders

Variable	Mean	10th Percentile	Median	90th Percentile	Standard Deviation
Number of Trades	1.61	1	1	3	1.54
USD volume (million USD)	11.3	0.27	3.64	22.5	40.8
Size as fraction of largest holding (%)	77.3	24.8	100	100	31.0
Observations	15114				

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	1.30
USD volume (million USD)	7.66	0.085	1.70	17.1	31.5
Size as fraction of largest holding (%)	15.8	0.92	8.65	42.6	18.3
Observations	66700				

Panel E: Statistics by order – closing orders

Variable	Mean	10th Percentile	Median	90th Percentile	Standard Deviation
Number of Trades	1.64	1	1	3	1.94
USD volume (million USD)	10.9	0.23	3.30	22.2	34.4
Size as fraction of largest holding (%)	78.2	25.7	100	100	31.0
Observations	14330				

Table 2: Returns following the opening of positions

This table examines returns following the opening of positions (follow-up and closing orders are excluded). We regress average returns following the order on a dummy variable whether the order is related to a short position (and is thus a short sell). 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 A.1. We include fund fixed effects and month fixed effects (based on the month of the last day of the order). 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)	(4)	(5)	(6)
D(Short)	-1.81***	-2.46***	-1.58***	-1.90***	-1.58***	-2.06***
	(-6.39)	(-5.70)	(-5.95)	(-4.95)	(-5.68)	(-5.00)
Observations	13050	12409	11700	11214	12598	12074
Adjusted R^2	0.06	0.09	0.04	0.05	0.03	0.04
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Returns following the closing of positions

This table examines returns following the closure of positions (opening and follow-up orders are excluded). We regress average returns following the order on a dummy variable whether the order is related to a short position (and is thus a short buy). 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 A.1. We include fund fixed effects and month fixed effects (based on the month of the last day of the order). 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)	(4)	(5)	(6)
D(Short)	-0.74**	-1.46***	-0.40	-1.09***	-0.52*	-1.02**
	(-2.57)	(-3.28)	(-1.40)	(-2.63)	(-1.87)	(-2.39)
Observations	11952	11320	11027	10469	11860	11262
Adjusted R^2	0.07	0.10	0.04	0.06	0.04	0.05
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Comparing returns following opening and closing orders

This table compares returns following the opening and closing of positions (follow-up orders are excluded). We regress returns following the order on a dummy variable equal to one if the trade is an opening order. In Panel A, we only include orders related to long positions (i.e., long buys and long sells). In Panel B, we only include orders related to short positions (i.e., short sells and short buys). In Panel C, we include orders related to both long and short positions. In Panel C, the dependent variables are signed position returns (equal to the stock return for long positions and the stock return times minus one for short positions). 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 A.1. We include fund×month fixed effects (based on the month of the last day of the order). 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 Positions

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)	(4)	(5)	(6)
D(Opening)	0.55**	0.72**	0.69***	0.55**	0.46**	0.71**
	(2.54)	(2.28)	(3.83)	(2.21)	(2.28)	(2.55)
Observations	13419	12779	11980	11457	13050	12484
Adjusted R^2	0.13	0.16	0.11	0.14	0.11	0.13
Fund×Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Short Positions

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)	(4)	(5)	(6)
D(Opening)	-0.45**	-0.36	-0.63***	-0.47*	-0.52**	-0.40
	(-2.05)	(-1.22)	(-3.08)	(-1.75)	(-2.35)	(-1.42)
Observations	11583	10950	10747	10226	11408	10852
Adjusted R^2	0.14	0.16	0.11	0.12	0.11	0.10
Fund×Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Long and Short Positions

Dependent Variable:	Signed Excess Return t+1, t+60	Signed Excess Return t+1, t+125	Signed DGTW Return t+1, t+60	Signed DGTW Return t+1, t+125	Signed 4-Factor Alpha t+1, t+60	Signed 4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Opening)	0.50***	0.59**	0.69***	0.54***	0.54***	0.58***
	(3.08)	(2.38)	(4.72)	(2.58)	(3.42)	(2.66)
Observations	25002	23729	22727	21683	24458	23336
Adjusted R^2	0.02	0.03	0.02	0.02	0.02	0.02
Fund×Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Returns following the closure of positions – Split by position changes

This table examines whether returns following the closure of positions depend on changes in the number of positions of the fund (opening and follow-up orders are excluded). We run the same regression as in Table 3 but split the sample by whether the fund increased or decreased the number of open positions before the first day of the order. In Panel A, we split by change in number of positions in the 5 days prior to the order. In Panel B, we split by change in number of positions in the 10 days prior to the order. We regress average returns following the order on a dummy variable whether the order is related to a short position (and is thus a short buy). 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 A.1. We include fund fixed effects and month fixed effects (based on the month of the last day of the order). 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: Split by change in number of positions relative to 5 trading days before

Dependent Variable:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	More Positions	Less Positions	More Positions	Less Positions	More Positions	Less Positions
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-2.21***	-0.77	-1.74***	-0.54	-1.67***	-0.50
	(-3.39)	(-1.31)	(-2.93)	(-0.98)	(-2.69)	(-0.86)
Observations	5079	6228	4715	5744	5059	6191
Adjusted R^2	0.11	0.10	0.06	0.06	0.05	0.05
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Split by change in number of positions relative to 10 trading days before

Dependent Variable:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	More Positions	Less Positions	More Positions	Less Positions	More Positions	Less Positions
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.80***	-1.36**	-1.47***	-0.93*	-1.44**	-0.84
	(-2.93)	(-2.31)	(-2.65)	(-1.66)	(-2.46)	(-1.46)
Observations	5477	5830	5097	5362	5453	5797
Adjusted R^2	0.10	0.11	0.07	0.05	0.06	0.04
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Returns following the closure of positions – Split by fund returns

This table examines whether returns following the closure of positions depend on the profitability of the fund before the order (opening and closing orders are excluded). We run the same regression as in Table 3 but split the sample by whether the fund had positive or negative returns before the first day of the order. In Panel A, we split by fund return in the 5 days prior to the order. In Panel B, we split by fund return in the 10 days prior to an order. We regress average returns following the order on a dummy variable whether the order is related to a short position (and is thus a short buy). 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 A.1. We include fund fixed effects and month fixed effects (based on the month of the last day of the order). 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: Split by fund return over prior 5 trading days

Dependent Variable:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Positive Fund Return	Negative Fund Return	Positive Fund Return	Negative Fund Return	Positive Fund Return	Negative Fund Return
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-0.67	-2.47***	-0.78	-1.64**	-0.56	-1.62**
	(-1.27)	(-3.67)	(-1.54)	(-2.54)	(-1.07)	(-2.51)
Observations	6350	4970	5859	4610	6308	4954
Adjusted R^2	0.08	0.12	0.05	0.07	0.05	0.06
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Split by fund return over prior 10 trading days

Dependent Variable:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Positive Fund Return	Negative Fund Return	Positive Fund Return	Negative Fund Return	Positive Fund Return	Negative Fund Return
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-0.61	-2.49***	-0.58	-1.64***	-0.53	-1.71***
	(-1.08)	(-3.72)	(-1.15)	(-2.65)	(-0.96)	(-2.69)
Observations	6563	4757	6066	4403	6530	4732
Adjusted R^2	0.09	0.13	0.06	0.07	0.05	0.06
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Returns following the closure of positions – Split by change in fund return volatility

This table examines whether returns following the closure of positions depend on changes in fund volatility (opening and follow-up orders are excluded). We run the same regression as in Table 3 but split the sample by whether the fund experienced an increase or a decrease in its return volatility. Our measure of fund volatility is the standard deviation of daily fund returns over a month. We compare this volatility in the month of the order relative to the volatility in the prior month. We regress average returns following the order on a dummy variable whether the order is related to a short position (and is thus a short buy). 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 A.1. We include fund fixed effects and month fixed effects (based on the month of the last day of the order). 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+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Higher Volatility	Lower Volatility	Higher Volatility	Lower Volatility	Higher Volatility	Lower Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.99***	-0.96	-1.65***	-0.50	-1.36**	-0.65
	(-3.31)	(-1.59)	(-2.86)	(-0.89)	(-2.28)	(-1.11)
Observations	5814	5282	5360	4896	5791	5250
Adjusted R^2	0.10	0.13	0.08	0.07	0.07	0.05
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Returns following the closure of positions – Split by past stock return

This table examines whether returns following the closure of positions depend on the stocks prior return. We run the same regression as in Table 3 but split the sample by whether the stock had a positive or negative return in the 10 trading days prior to the first day of the order. We regress average returns following the order on a dummy variable whether the order is related to a short position (and is thus a short buy). 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 A.1. We include fund fixed effects and month fixed effects (based on the month of the last day of the order). 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+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Positive Stock Return	Negative Stock Return	Positive Stock Return	Negative Stock Return	Positive Stock Return	Negative Stock Return
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.08*	-1.59***	-1.03*	-1.00*	-0.93*	-1.01*
	(-1.84)	(-2.62)	(-1.88)	(-1.76)	(-1.66)	(-1.68)
Observations	5777	5509	5349	5119	5764	5487
Adjusted R^2	0.09	0.12	0.06	0.06	0.05	0.06
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Post-trade returns for follow-up orders

This table studies the post-trade returns for follow-up orders (i.e., all orders that neither open nor close a stock position). In Panel A, we show tests analogous to those reported in Tables 2 to 4. Regressions 1 and 2 are run on follow-up orders that increase an existing long or short position and thus mirror Table 2. Regressions 3 and 4 are run on follow-up orders that decrease an existing long or short position and thus mirror Table 3. Regressions 5 and 6 are run on both increasing and decreasing follow-up orders and thus mirror Table 4 Panel C. In Panel B we show tests analogous to those reported in Tables 5 to 7. Regressions 1 and 2 splits the sample of decreasing follow-up trades based on the change in number of positions in the 5 days prior to the order. Regressions 3 and 4 split the sample of decreasing follow-up trades based on whether the fund return in the 5 days prior to the order was positive. Regressions 5 and 6 split the sample of decreasing follow-up trades by whether fund volatility in the month of the order increased relative to the previous month. Details on variable constructions can be found in Appendix A.1. We include fund fixed effects and month fixed effects (based on the month of the last day of the order), except for regressions 5 and 6 in Panel A which have fund×month fixed effects instead. 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.

Sample:	Long Positions		Short Positions		Long and Short Positions	
Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125	Signed Excess Return t+1, t+60	Signed Excess Return t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Increasing)	0.02	0.23	-0.15	-0.18	0.09	0.14
	(0.15)	(0.96)	(-0.72)	(-0.63)	(0.72)	(0.71)
Observations	39364	37184	19766	18470	59130	55654
Adjusted R^2	0.12	0.15	0.16	0.18	0.04	0.06
Fund Fixed Effects	Yes	Yes	Yes	Yes	No	No
Month Fixed Effects	Yes	Yes	Yes	Yes	No	No
Fund×Month F.E.	No	No	No	No	Yes	Yes

Appendix A.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 or Analytics.
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 Analytics.
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 A.3.
4-Factor Alpha	$r_{c,t} - r_{f,t} - \beta_m * (r_{m,t} - r_{f,t}) - \beta_{HML} * HML_t - \beta_{SMB} * SMB_t - \beta_{MOM} * MOM_t$ For more details see Appendix A.3.
D(Short)	Dummy variable equal to one if the order is related to a short position (i.e., a short sell or a short buy) and zero if it is related to a long position (i.e., a long buy or a long sell).
D(Opening)	Dummy variable equal to one if the order is related to a position opening (i.e., a long buy or a short sell) and zero if the order is related to a position closure (i.e., a long sell or a short buy).
Fund return	Value-weighted average return of all positions of the fund, where the weight is the dollar value of the position.
Fund volatility	Monthly standard deviation of daily fund returns. Volatility is set to missing when we have fewer than 15 non-missing daily return observations for a given month.

Appendix A.2: Regions

This table displays the regions to which the countries are assigned. The region assignments follows Karolyi and Wu (2014). All but the EME region are identical to Fama and French (2012).

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 A.3: Additional information on dataset construction

1) Merging of datasets

We merge the trading and the holding datasets provided by Inalytics. We first merge based on ISIN. Trades that we cannot match by ISIN, we match by SEDOL and finally by CUSIP. Whenever there is a change in the number of shares held in the holdings data (and there was no stock split), 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. We therefore rely on the holdings data, i.e. we assume there is a trade whenever there is a change of holding in the holdings data. There are two exceptions to this: we adjust for some holdings that erroneously disappear and we make sure that stock splits (and stock dividends) are not identified as trades.

We treat as a mistake if a holding disappears from the data and then reappears shortly afterwards *without a trade being recorded*. In these cases we fill in the missing dates in between with the old holding 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 we identify 637 of these mistakes (compared to 150,000 trades in the full sample).

We identify stock splits in two ways: we use a dataset of corporate actions provided by Inalytics and we use Datastream data. Specifically, we assume that there is a stock split if shares outstanding in Datastream changed by at least 1% and there is a corresponding mismatch between the stock price change and the return (the Datastream return is adjusted for stock splits). We confirm the validitiy of the Datastream measure by confirming that it identifies over 95% of the stock splits from the corporate action data as stock splits. On days with a stock split we only treat holding changes as trades if they are initiating or closing trades (as these cannot come from a stock split). In total we identify 155 stock splits (compared to 150,000 trades in the full sample).

In total, we have about 150,000 (inferred) 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 match the change in the number of stocks held in the holding data. In these cases we follow Inalytics' advice and assume the holdings data to be correct. In Appendix C Table C.1, we show that our results are very similar if we only use the cases where the holdings and trade data perfectly agree.

2) Stock universe

To compute DGTW returns (and regional factors for the emerging market region, see below), 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 the Worldscope Permanent Identifier). We only keep stocks from the countries listed in Appendix A.2 (we take the country from Worldscope). We require stocks to have a positive book value, information on market capitalization in Worldscope and a stock price of at least USD 0.20.

If funds trade stocks that are outside this stock universe (e.g. because they cannot be assigned to one of the regions or have no information on book value), we still include these trades in our sample. For such trades, we can only compute excess returns and alphas (as described below) but we cannot compute DGTW returns. Our results are unchanged if we (1) exclude trades of stocks with a stock price of less than USD 1 (see Table C.2 in Appendix C) or (2) include only trades of stocks that are in the stock universe used to compute DGTW returns and factors (see Table C.3 in Appendix C).

3) Stock returns and balance sheet data

We download daily returns for stocks in our stock universe 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 stocks are delisted, Datastream continues to report zero returns for these stocks. Following Goyal (???), we remove these trailing zeros, as well as any period with consecutives zero-return days that is at least 20 trading days long. 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.

For stocks in the Inalytics data that are not covered in Datastream, we receive stock return information from Inalytics. Because we don't have balance sheet information for these stocks, we cannot compute DGTW returns (but we can compute excess returns and alphas). Of about 1.7 million stock-days in which a position is open, we have 1.43 million (84%) observations with return data on Datastream. By filling in the Inalytics return data we can increase this coverage to 1.66 million stock-days with returns (98%).

4) Excess returns

Excess returns are defined as the stock return minus the return of the fund-specific benchmark index. The benchmark indexes are the benchmark returns against which hedge funds mark their own performance (for which they are then compensated). They are self-reported by the funds and do not change over the lifetime of a fund in our sample. Benchmark returns are provided to us by Analytics.

5) Four-Factor alphas

To compute alphas, we use daily factor returns of the Carhart (1997) model for each of our 5 regions (see Appendix A.2). We use daily factors for America, Asia-Pacific, Europe, and Japan provided on Kenneth French's website.[14] Because he does not provide factors for the emerging market region, we compute the emerging market factors ourselves following the instructions given on his website.[15] 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 the EME region (the stock universe construction is described above). To construct the SMB and HML factors, we sort stocks in the 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 (cumulative) market capitalization for the region, and small stocks are those in the bottom 10% (Fama and French (2012) use this method because for North America it roughly corresponds to the NYSE median used in Fama French (1993)). The B/M breakpoints for a region are the 30th and 70th percentiles of B/M for the big stocks of the region (according to Fama and French (2012) big stocks are more reliable for identifying these breakpoints). 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, we compute value weighted returns for each day and then compute the momentum factor as:

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

[14] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. In our description of the construction of factor-adjusted returns below, we directly quote from the instructions on this website.

[15] To confirm our methodology, we also compute factors for the other regions and compare them with those provided by Kenneth French. We find them to be very similar and, consequently, our results are virtually identical when we use these self-constructed factors throughout.

For each stock and each month, we then compute the beta with respect to those factors from a daily regression over the past year. For stocks that cannot be assigned to a region (either because country information is missing or the country is not included in any regions), we compute alphas relative to the global factors provided by Kenneth French. 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 non-missing return data.

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

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), we shrink the betas toward their cross sectional mean by computing:

$$\beta_{j,t}^{shrunk} = 0.7 * \beta_{j,t} + 0.3 * \bar{\beta}_{j,t}$$

for $j \in \{m, HML, SMB, MOM\}$ and $\bar{\beta}_{j,t}$ is the equal-weighted average $\beta_{j,t}$ estimated in the region to which stock c belongs. Finally, we use shrunk betas to compute daily alphas as follows:

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

6) 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 A.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 benchmark portfolio.

7) Return winsorization

Since the international stock return data contains large outliers, we winsorize all our return measures at the 1% level on both sides.

Appendix B: A simple hedge fund trading model

1) General setup

Time is discrete. In a given period t, a hedge fund has W_t units of capital and faces different investment opportunities: it can invest in a riskless asset with a net return of $r_f = 0$ or into N risky stocks that are all assumed to be uncorrelated with each other (and over time). Any stock i is either fairly priced or mispriced. If it is fairly priced, then its return from one period to the next is given by $r_{it} = \varepsilon_{it}$ where ε_{it} is a zero-mean noise term with variance σ_t^2 (constant for all i).[16] If stock i is mispriced, then its return is given by $r_{it} = \Delta_{it} + \varepsilon_{it}$ where $\Delta_{it} > 0$ ($\Delta_{it} < 0$) captures the underpricing (overpricing). To capture the empirical reality that such trading opportunities disappear over time, we assume that the mispricing Δ_{it} decays over subsequent periods. That is, if the mispricing of stock i occurs in period t and lasts for τ periods, then we have $|\Delta_{it}| > |\Delta_{it+1}| > \cdots > |\Delta_{it+\tau}| = 0$. The hedge fund is assumed to know which stocks are mispriced and by how much.

The stock return component ε_{it} represents fluctuations in the stock's fair value driven by public news. There are two ways to think about the mispricing in this setup: First, it could be that, occasionally, a stock price movement ε_{it} occurs that is not justified by fundamentals. After such an occurrence, the hedge fund learns about this mispricing and expects it to revert over time.[17] Second, it could be that the hedge fund obtained private information that some future dividend is going to be higher/lower than expected, and the hedge fund expects this information to leak to the market over time.[18]

We assume that the hedge fund maximizes expected returns (i) after accounting for a *position-monitoring* cost and (ii) subject to not exceeding a volatility limit $\bar{\sigma}$. Let $\boldsymbol{w}_t = (w_{1t} \quad \cdots \quad w_{Nt})'$ denote the vector of portfolio weights of the N risky stocks, w_{ft} be the portfolio weight of the riskfree asset, and $E(\boldsymbol{r}_t) = (E(r_{1t}) \quad \cdots \quad E(r_{Nt}))'$ be the vector of expected stock returns (where $E(r_{it}) = \Delta_{it}$ if stock i is mispriced and zero otherwise). Furthermore, let $\mathbb{I}_{w_{it} \neq 0}$ be a dummy variable that takes the value one if the portfolio weight of stock i is strictly positive and zero otherwise. Let $\mathbb{I}_{\boldsymbol{w}_t}$ be the N-dimensional vector of these dummy variables.

Formally, the hedge fund's objective in period t is given by:

$$\max_{\boldsymbol{w}_t, w_{ft}, N_{Pt}} \quad W_t[1 + \boldsymbol{w}_t' E(\boldsymbol{r}_{t+1})] - cN_{Pt} \qquad \text{subject to}$$

$$\boldsymbol{w}_t' \mathbf{1}_N + w_{ft} = 1 \qquad (1)$$

$$\boldsymbol{w}_t' \boldsymbol{w}_t \sigma_t^2 \leq \bar{\sigma}^2 \qquad (2)$$

$$\mathbb{I}_{\boldsymbol{w}_t}' \mathbf{1}_N = N_{Pt} \qquad (3)$$

---

[16] Because all stocks are uncorrelated, there is no systematic risk in the economy and hence the risk premium is zero. Thus, the riskfree asset can be viewed as an investment in the perfectly-diversified market portfolio. Note that the assumption of a zero risk premium is without loss of generality: we obtain the same predictions if we assume that the hedge fund chases mispricings as a source of α; i.e., any return in excess of the market risk premium.

[17] Thus, in the example where the hedge fund becomes aware of the mispricing at the beginning of period t and expects it to last for τ periods, the return of stock i in period *t-1* was given by $\varepsilon_{it-1} = \prod_{\pi=0}^{\tau-1}(1 + \Delta_{t+\pi})^{-1} - 1$ and was not justified by fundamental news.

[18] For instance, the hedge fund could have learnt that the dividend in period *t+ τ-1* is higher than expected by an amount which would justify a compounded return of $\prod_{\pi=0}^{\tau-1}(1 + \Delta_{t+\pi}) - 1$.

where $\mathbf{1}_N$ denotes the N-dimensional unit vector, N_{Pt} denotes the total number of open stock positions (i.e., positions with $w_{it} \neq 0$), and $c > 0$ is the monitoring cost *per* open position. Constraint (1) describes the standard *portfolio additivity* condition that portfolio weights have to sum to one. Constraint (2) ensures that the volatility of the entire portfolio is less or equal to $\bar{\sigma}$. This *risk limit* constraint is supposed to reflect risk management practices common among hedge funds (such as risk-parity investment). Constraint (3) says that the number of stock positions with non-zero portfolio weights equals N_{Pt}, which then causes total position monitoring costs of cN_{Pt}. This *position monitoring cost* is supposed to reflect the fact that the monitoring and management of directional equity bets requires a significant amount of limited attention (which can be relaxed by acquiring additional attention capacity at the cost c). As a result of this assumption, the hedge fund may choose to invest in fewer than the total number of mispriced stocks. Empirically, it is well-known that discretionary long-short hedge funds—in contrast to most institutional investors that seek well-diversified portfolios—choose to hold a fairly limited number of open positions.

It is important to understand that without the risk limit constraint, the hedge fund's trading strategy and hence its profits would become unbounded. Indeed, by short-selling any overpriced stock (or the riskfree asset) and levering-up its positions in underpriced stocks, the hedge fund could increase profits without violating the portfolio additivity constraint. However, since such a strategy also increases the portfolio's risk, the risk limit constraint prevents this case from occurring. This argument makes clear that the optimal trading rule must be such that the risk limit is exactly binding (as long as there is at least one mispriced stock).

In our simple setup, the hedge fund is myopic in that it maximizes its expected wealth one period ahead: $E(W_{t+1}) = W_t\big(1 + E(r_{Pt+1})\big) - cN_{Pt}$, where $r_{Pt+1} \equiv \boldsymbol{w}_t'\boldsymbol{r}_{t+1}$. This is obviously equivalent to maximizing expected future wealth for an indeterminate final period $T \gg t$. Finally, note that the hedge fund's optimization problem does not consider any transaction costs (other than the per-position monitoring costs). This choice is only for parsimony and we don't expect transaction costs to affect any of the predictions derived below.

2) Solution for a specific example

We now impose a specific structure on the nature of stock mispricings that will allow for an explicit, simple solution. We are convinced that the resulting predictions also obtain under a more general structure.

Specifically, we now assume that stock mispricings have the same magnitude and last for two periods. That is, in the period of occurrence, the mispricing is given by Δ $(-\Delta)$. In the following period, the mispricing reduces to $|\Delta(1-\delta)|$ with $0 < \delta < 1$ being the rate of alpha decay. After two periods, the mispricing is assumed to have disappeared. We further assume that every period t, a random number M_t of new stocks becomes mispriced (some positive, some negative). The number of mispriced stocks is small relative to the total number of stocks, $M_t \ll N$. It follows that in any period t, there are M_t "newly mispriced stocks" with an expected alpha of $|\Delta|$, M_{t-1} "previously mispriced stocks" with an alpha of $|\Delta(1-\delta)|$, and M_{t-2} stocks that just stopped being mispriced. Finally, we assume (without loss of generality) that $\bar{\sigma}^2 = \kappa_t \sigma_t^2$ for some $\kappa_t > 0$.

Recall that the hedge fund maximizes the expected return by choosing (i) in how many mispriced stocks to invest in and (ii) how much to invest in those stocks subject to not exceeding the volatility limit. For these choices, the hedge fund trades off the diversification benefits of investing into many mispriced stocks with the costs of monitoring a large number of open positions.

Let N_{At} be the hedge fund's choice of how many of the M_t newly mispriced stocks to invest in. Since newly mispriced stocks have the same maximum (absolute) mispricing, same volatility, and are uncorrelated with each other, the hedge fund will want to invest with equal (absolute) weights w_{At} into these N_{At} stocks.[19] Similarly, let N_{Bt} be the number of previously mispriced stocks that the hedge fund chooses to invest in. Because they have the same level of (partially decayed) mispricing, the hedge fund will again want to invest with equal (absolute) weights w_{Bt} into these N_{Bt} stocks.

Given these definitions, $N_{Pt} = N_{At} + N_{Bt}$ and the hedge fund's optimization problem can be written as

$$\max_{w_{At}, w_{Bt}, N_{At}, N_{Bt}} \quad W_t[N_{At}w_{At} + N_{Bt}w_{Bt}(1-\delta)]\Delta - c(N_{At} + N_{Bt}) \quad \text{s.t.} \;\; N_{At}w_{At}^2 + N_{Bt}w_{Bt}^2 = \kappa \,.$$

It is easy to see that it will be suboptimal for the fund to choose $N_{At} < M_t$ while having $N_{Bt} > 0$. This is because all mispriced stocks have the same risk and the same monitoring costs, but newly mispriced stocks offer strictly higher returns. As such, the hedge fund will always want to prioritize investments into newly mispriced stocks (i.e., $N_{Bt} > 0$ only if $N_{At} = M_t$).

Proposition (Optimal Trading Rule):
Let $\bar{M}_{1t} \equiv \kappa_t \left(\frac{W_t\Delta}{2c}\right)^2 (1-\delta)^4 - M_{t-1}(1-\delta)^2$, $\bar{M}_{2t} \equiv \kappa_t \left(\frac{W_t\Delta}{2c}\right)^2 (1-\delta)^4$, *and* $\bar{M}_{3t} \equiv \kappa_t \left(\frac{W_t\Delta}{2c}\right)^2$. *The hedge fund's optimization problem has a unique solution which takes the following form:*

- *For* $M_t \geq \bar{M}_{3t}$, *the hedge fund only invests into some of the newly mispriced stocks. We have*

$$w_{At} = \frac{2c}{W_t\Delta}, w_{Bt} = 0, N_{At} = \kappa_t \left(\frac{W_t\Delta}{2c}\right)^2, \textit{and } N_{Bt} = 0 \,.$$

- *For* $\bar{M}_{2t} \leq M_t < \bar{M}_{3t}$, *the hedge fund only invests into all newly mispriced stocks. We have*

$$w_{At} = \sqrt{\frac{\kappa_t}{M_t}}, w_{Bt} = 0, N_{At} = M_t, \textit{and } N_{Bt} = 0 \,.$$

- *For* $\bar{M}_{1t} \leq M_t < \bar{M}_{2t}$, *the hedge fund invests into all newly mispriced stocks and some of the previously mispriced stocks. We have*

$$w_{At} = \frac{2c}{W_t\Delta(1-\delta)^2}, w_{Bt} = \frac{2c}{W_t\Delta(1-\delta)}, N_{At} = M_t, \textit{and } N_{Bt} = \kappa_t\left(\frac{W_t\Delta(1-\delta)}{2c}\right)^2 - \frac{M_t}{(1-\delta)^2} \,.$$

- *For* $M_t < \bar{M}_{1t}$, *the hedge fund invests into all newly mispriced stocks and all previously mispriced stocks. We have*

$$w_{At} = \sqrt{\frac{\kappa_t}{M_t + M_{t-1}(1-\delta)^2}}, w_{Bt} = \sqrt{\frac{\kappa_t(1-\delta)^2}{M_t + M_{t-1}(1-\delta)^2}}, N_{At} = M_t, \textit{and } N_{Bt} = M_{t-1} \,.$$

[19] To see this, note that having equal weights as opposed to any others yields the same expected return, but minimizes the total variance of these investments.

Proof: We start with assuming that the hedge fund only invests into newly mispriced stocks. That is $N_{At} \leq M_t$, and $N_{Bt} = w_{Bt} = 0$. In this case, the Lagrangian of the fund's optimization problem becomes

$$\mathcal{L}(w_{At}, N_{At}, \lambda) \equiv W_t N_{At} w_{At} \Delta - c N_{At} - \lambda (N_{At} w_{At}^2 - \kappa_t) ,$$

where the Lagrange-multiplier λ needs to be positive. Solving the system of equations resulting from the first-order-conditions yields the unique solution

$$w_{At} = \frac{2c}{W_t \Delta}, N_{At} = \kappa_t \left(\frac{W_t \Delta}{2c}\right)^2 , \text{and } \lambda = \frac{W_t \Delta^2}{4c} > 0 .$$

By assumption, $N_{At} \leq M_t$ and so this solution is only valid for $M_t \geq \kappa_t \left(\frac{W_t \Delta}{2c}\right)^2 \equiv \bar{M}_{3t}$.

Next, we consider the case where the hedge fund invests into all newly mispriced stocks, $N_{At} = M_t$,, and chooses how many previously mispriced stocks to invest in. The Lagrangian is

$$\mathcal{L}(w_{At}, w_{Bt}, N_{Bt}, \lambda) \equiv W_t [M_t w_{At} + N_{Bt} w_{Bt} (1 - \delta)] \Delta - c(M_t + N_{Bt}) - \lambda (M_t w_{At}^2 + N_{Bt} w_{Bt}^2 - \kappa_t) .$$

Solving the system of first-order-conditions again yields a unique solution with $\lambda > 0$:

$$w_{At} = \frac{2c}{W_t \Delta (1 - \delta)^2}, w_{Bt} = \frac{2c}{W_t \Delta (1 - \delta)}, N_{At} = M_t, N_{Bt} = \kappa_t \left(\frac{W_t \Delta (1 - \delta)}{2c}\right)^2 - \frac{M_t}{(1 - \delta)^2},$$
$$\text{and } \lambda = \frac{W_t \Delta^2 (1 - \delta)^2}{4c} > 0 .$$

Clearly, we must have $0 < N_{Bt} \leq M_{t-1}$. These conditions imply that the solution is only valid in the range $\bar{M}_{1t} \equiv \kappa_t \left(\frac{W_t \Delta}{2c}\right)^2 (1 - \delta)^4 - M_{t-1}(1 - \delta)^2 \leq M_t < \kappa_t \left(\frac{W_t \Delta}{2c}\right)^2 (1 - \delta)^4 \equiv \bar{M}_{2t}$.

Since $\bar{M}_{2t} < \bar{M}_{3t}$, there is a range for M_t in which neither solution applies. This means that, for $\bar{M}_{2t} \leq M_t < \bar{M}_{3t}$, there exists neither an interior solution for N_{At} nor for N_{Bt}. We are thus left with a corner solution in which the hedge fund invests only in newly mispriced stocks but not in previously mispriced ones, $N_{At} = M_t$ and $N_{Bt} = 0$. w_{At} is then chosen to max out the volatility limit, yielding $w_{At} = \sqrt{\frac{\kappa_t}{M_t}}$.

Similarly, for $M_t < \bar{M}_{1t}$, there is another corner solution in which the hedge fund invests into all newly and previously mispriced stocks, $N_{At} = M_t$ and $N_{Bt} = M_{t-1}$. Finding the optimal w_{At} and w_{Bt} involves solving the first-order-conditions implied by the following Lagrangian:

$$\mathcal{L}(w_{At}, w_{Bt}, \lambda) \equiv W_t [M_t w_{At} + M_{t-1} w_{Bt} (1 - \delta)] \Delta - c(M_t + M_{t-1}) - \lambda (M_t w_{At}^2 + M_{t-1} w_{Bt}^2 - \kappa_t) .$$

The unique solution is given by

$$w_{At} = \sqrt{\frac{\kappa_t}{M_t + M_{t-1}(1 - \delta)^2}}, w_{Bt} = \sqrt{\frac{\kappa_t (1 - \delta)^2}{M_t + M_{t-1}(1 - \delta)^2}}, \text{and } \lambda = \frac{\Delta}{2} \sqrt{\frac{M_t + M_{t-1}(1 - \delta)^2}{\kappa_t}} > 0 . \blacksquare$$

The optimal trading rule has intuitive properties. When M_t is very large, the hedge fund only invests in some of the newly mispriced stocks. The exact number of newly mispriced stocks into which it invests is increasing in the fund's wealth W_t, the level of the mispricing $|\Delta|$, the volatility limit κ_t, and decreasing in the monitoring cost c. For a lower M_t, there is first a range in which the hedge fund only invests in all newly mispriced stocks, but not in previously mispriced ones. As M_t gets lower still, the hedge fund also starts investing into previously mispriced stocks, where the number of such positions is an increasing function of wealth W_t, mispricing $|\Delta|$, decay factor δ, volatility limit κ_t, and decreasing in monitoring cost c. Finally, when M_t and M_{t-1} are very low, the hedge fund invests into all newly and previously mispriced stocks.

3) Life-cycle of a round-trip trade

We now describe the life-cycle of a round-trip trade—i.e., its *opening*, the *rebalancing* and its *closure*. Consider a new mispricing in stock i occurring in period t. In that period, the hedge fund *opens* the trade by investing $W_t \times w_{At}$ of risk capital into that stock.[20] Depending on whether this is an under- or overpricing, this would take the form of either a long or a short position. The hedge fund *closes* its position after either one or two periods, depending on how many newly mispriced stocks there will be in the next period (*t+1*). All intermediate trades are defined as *rebalancing* trades.[21] (These rebalancing trades will typically result in a gradual downscaling of the position concomitant to the decay in alpha.)

4) Empirical predictions

Let N_{At-1} be the number of positions in stocks that became mispriced in *t-1* ($N_{At-1} \leq M_{t-1}$) and let N_{Bt-1} be the number of positions in stocks that became mispriced in *t-2* ($N_{Bt-1} \leq M_{t-2}$).

In period *t*, the hedge fund closes all the N_{Bt-1} positions in stocks that become misprised in *t-2* (because they stop being mispriced). In addition, the hedge fund may need to close some (and perhaps all) of its N_{At-1} positions in stocks that become misprised in *t-1*. Specifically, out of the N_{At-1} positions, it will only be able to hold on to N_{Bt} positions, where typically $N_{Bt} < N_{At-1}$.[22] Each of these prematurely closed positions is followed by a positive expected return ($\Delta(1-\delta)$). As such, the average return after closing trades in period t is given by $X_t\Delta(1-\delta)$, where X_t is defined as

$$X_t \equiv \frac{(\mathrm{Max}\{N_{At-1} - \mathrm{N}_{Bt}, 0\})w_{At-1}}{(\mathrm{Max}\{N_{At-1} - \mathrm{N}_{Bt}, 0\})w_{At-1} + N_{Bt-1}w_{Bt-1}}.$$

Note that X_t is a fraction; i.e., $0 \leq X_t \leq 1$. The fraction becomes zero if $N_{At-1} \leq N_{Bt}$, which should be the exception rather than the rule (see footnote 6). Otherwise it will be strictly positive. Moreover, as long as N_{Bt-1} is not zero, fraction X_t is strictly less than one, in which case it is decreasing in N_{Bt}.

[20] When there are many newly mispriced stocks, the hedge fund may not be able to invest into all of them. For this paragraph, we simply assume that the stock under consideration is one of the N_{At} newly mispriced stocks in which the hedge fund does invest.

[21] Note that, with this definition, only positions that are open for two periods can have a rebalancing trade (in the intermediate period).

[22] To see why typically $N_{Bt} < N_{At-1}$, note that the hedge fund always prioritizes newly mispriced stocks (because of the alpha decay in previously mispriced stocks). Thus, as long as the number of open positions $N_{Pt} = N_{At} + N_{Bt}$ does not drastically increase from one period to the next, the hedge fund ends up closing some positions in previously mispriced stocks to shift the risk capital into newly mispriced stocks.

Finally, note that all terms entering X_t except for N_{Bt} are pre-determined (i.e., depend on parameters from period *t-1*). Thus, only N_{Bt} matters for the description of the relationship between contemporaneous characteristics (such as M_t or W_t) and post-closure returns.

The following empirical predictions follow immediately:

Prediction 1*: The opening of a trade is more predictive of future returns than the closing of a trade.*

Proof: Opening trades in any period *t* are followed by an average return close to Δ.[23] Closing trades are followed by an average return of $X_t\Delta(1-\delta)$, where $0 \leq X_t \leq 1$ (see above). ■

Prediction 2*: The closing of a trade is followed by future returns in the opposite direction of the closing trade. In other words, the difference in post-closure returns between closed long and short positions is positive—implying that the hedge fund "leaves money on the table".*

Proof: For underpriced stocks ($\Delta_{it}=\Delta$), the hedge fund took long positions, which require selling at closure. Yet, as seen above, the average return following such long sells is positive. For overpriced stocks ($\Delta_{it}=-\Delta$), the hedge fund took short positions, which require buying at closure. The average return following such short buys is negative. ■

Prediction 3*: The return difference between closed long and short positions should be higher in periods when lots of new stock mispricings occur (and thus when lots of new positions are opened).*

Proof: X_t is decreasing in N_{Bt}, which in turn is decreasing in M_t. ■

Prediction 4*: The return difference between closed long and short positions should be higher after periods in which the hedge fund has had low returns.*

Proof: X_t is decreasing in N_{Bt}, which in turn is increasing in r_{Pt} (through W_t). ■

Prediction 5*: The return difference between closed long and short positions should be higher in periods when stocks are more volatile.*

Proof: X_t is decreasing in N_{Bt}, which is increasing in κ_t and thus decreasing in σ_t. ■

The intuitions for these predictions are straightforward. Prediction 1 follows from the fact that the hedge fund opens positions when the mispricing has just occurred and is thus the biggest, whereas it closes its positions when the mispricing has (partially or fully) decayed. Prediction 2 says that the hedge fund "leave money on the table"; i.e., it could have made additional profits from holding on to its positions for longer. This result naturally follows from the fund's desire to limit total position monitoring costs, as it may induce the fund to close positions in partially mispriced stocks when better investment opportunities become available. Finally, predictions 3 to 5 say that such position closures of still partially mispriced stocks occur more often when there are more new mispricings, when the fund has suffered from poor returns, or when the volatility constraint becomes more binding due to an increase in stock return volatility.

[23] Occasionally, it can occur that a new position is opened in a previously mispriced stocks. Specifically, when the hedge fund has had a phenomenally high return, it chooses to open many new positions, which may entail opening a position in a previously mispriced stock that the fund had not yet invested in. Since such position openings will be rare, the average post-opening return will be strictly larger than $\Delta(1-\delta)$.

Appendix C: Additional robustness checks

Table C.1: Robustness check – Only trades where holding and trade data agree

This table shows a robustness check in which we remove all trades from our data for which the change in the holdings data does not exactly match the trade data. In Panel A, we show robustness checks for Tables 2 to 4. Regressions 1 and 2 are run on opening orders and provide robustness to Table 2. Regressions 3 and 4 are run on closing orders and provide robustness to Table 3. Regressions 5 and 6 are run on both closing and opening orders and provide robustness to Table 4 Panel C. In Panel B, we display robustness checks for the sample splits in Tables 5 to 7. Regressions 1 and 2 splits the sample based on the change in number of positions in the 5 days prior to the order. Regressions 3 and 4 split the sample based on whether the fund return in the 5 days prior to the order was positive. Regressions 5 and 6 split the sample by whether fund volatility in the month of the order increased relative to the previous month. Details on variable constructions can be found in Appendix A.1. We include fund fixed effects and month fixed effects (based on the month of the last day of the order), except for regressions 5 and 6 in Panel A which have fund×month fixed effects instead. 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: Robustness for Tables 2-4

Sample:	Opening Orders		Closing Orders		Opening and Closing Orders	
Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.81***	-2.68***	-0.73**	-1.38***		
	(-5.65)	(-5.51)	(-2.13)	(-2.60)		
D(Opening)					0.48**	0.54*
					(2.39)	(1.76)
Observations	11337	10799	8588	8160	19925	18959
Adjusted R^2	0.06	0.09	0.07	0.09	0.02	0.03
Fund Fixed Effects	Yes	Yes	Yes	Yes	No	No
Month Fixed Effects	Yes	Yes	Yes	Yes	No	No
Fund×Month F.E.	No	No	No	No	Yes	Yes

Panel B: Robustness for Tables 5-7 (sample splits)

Dependent Variable:	Excess Return t+1, t+125					
Sample	More Positions	Less Positions	Positive Fund Return	Negative Fund Return	Higher Volatility	Lower Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.60**	-1.09	-0.55	-2.61***	-1.50**	-1.07
	(-2.06)	(-1.53)	(-0.84)	(-3.26)	(-2.12)	(-1.44)
Observations	3849	4311	4506	3654	4212	3780
Adjusted R^2	0.09	0.10	0.07	0.13	0.09	0.13
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table C.2: Robustness check – Exclude trades with stock prices below $1

This table shows a robustness check in which we remove all trades of stocks with a price below USD 1. In Panel A, we show robustness checks for Tables 2 to 4. Regressions 1 and 2 are run on opening orders and provide robustness to Table 2. Regressions 3 and 4 are run on closing orders and provide robustness to Table 3. Regressions 5 and 6 are run on both closing and opening orders and provide robustness to Table 4 Panel C. In Panel B, we display robustness checks for the sample splits in Tables 5 to 7. Regressions 1 and 2 splits the sample based on the change in number of positions in the 5 days prior to the order. Regressions 3 and 4 split the sample based on whether the fund return in the 5 days prior to the order was positive. Regressions 5 and 6 split the sample by whether fund volatility in the month of the order increased relative to the previous month. Details on variable constructions can be found in Appendix A.1. We include fund fixed effects and month fixed effects (based on the month of the last day of the order), except for regressions 5 and 6 in Panel A which have fund×month fixed effects instead. 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: Robustness for Tables 2-4

Sample:	Opening Orders		Closing Orders		Opening and Closing Orders	
Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.90***	-2.67***	-0.76***	-1.54***		
	(-6.67)	(-6.18)	(-2.60)	(-3.46)		
D(Opening)					0.55***	0.67***
					(3.41)	(2.75)
Observations	12776	12141	11679	11058	24455	23199
Adjusted R^2	0.06	0.09	0.07	0.10	0.03	0.03
Fund Fixed Effects	Yes	Yes	Yes	Yes	No	No
Month Fixed Effects	Yes	Yes	Yes	Yes	No	No
Fund×Month F.E.	No	No	No	No	Yes	Yes

Panel B: Robustness for Tables 5-7 (sample splits)

Dependent Variable:	Excess Return t+1, t+125					
Sample	More Positions	Less Positions	Positive Fund Return	Negative Fund Return	Higher Volatility	Lower Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-2.31***	-0.79	-0.77	-2.56***	-2.04***	-1.13*
	(-3.53)	(-1.33)	(-1.46)	(-3.77)	(-3.38)	(-1.87)
Observations	4961	6084	6196	4862	5697	5138
Adjusted R^2	0.10	0.10	0.08	0.12	0.10	0.12
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table C.3: Robustness check – Exclude trades of stocks outside stock universe

This table shows a robustness check in which we remove all trades of stocks which are not within the stock universe (e.g. region information is missing, book value data is missing or negative, etc.). In Panel A, we show robustness checks for Tables 2 to 4. Regressions 1 and 2 are run on opening orders and provide robustness to Table 2. Regressions 3 and 4 are run on closing orders and provide robustness to Table 3. Regressions 5 and 6 are run on both closing and opening orders and provide robustness to Table 4 Panel C. In Panel B, we display robustness checks for the sample splits in Tables 5 to 7. Regressions 1 and 2 splits the sample based on the change in number of positions in the 5 days prior to the order. Regressions 3 and 4 split the sample based on whether the fund return in the 5 days prior to the order was positive. Regressions 5 and 6 split the sample by whether fund volatility in the month of the order increased relative to the previous month. Details on variable constructions can be found in Appendix A.1. We include fund fixed effects and month fixed effects (based on the month of the last day of the order), except for regressions 5 and 6 in Panel A which have fund×month fixed effects instead. 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: Robustness for Tables 2-4

Sample:	Opening Orders		Closing Orders		Opening and Closing Orders	
Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.64***	-2.17***	-0.58*	-1.32***		
	(-5.64)	(-4.88)	(-1.96)	(-2.93)		
D(Opening)					0.55***	0.51**
					(3.35)	(2.02)
Observations	11732	11222	11037	10453	22769	21675
Adjusted R^2	0.06	0.09	0.07	0.10	0.03	0.03
Fund Fixed Effects	Yes	Yes	Yes	Yes	No	No
Month Fixed Effects	Yes	Yes	Yes	Yes	No	No
Fund×Month F.E.	No	No	No	No	Yes	Yes

Panel B: Robustness for Tables 5-7 (sample splits)

Dependent Variable:	Excess Return t+1, t+125					
Sample	More Positions	Less Positions	Positive Fund Return	Negative Fund Return	Higher Volatility	Lower Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.73***	-0.88	-0.64	-2.24***	-1.94***	-0.76
	(-2.67)	(-1.42)	(-1.19)	(-3.22)	(-3.13)	(-1.21)
Observations	4703	5740	5852	4601	5344	4899
Adjusted R^2	0.10	0.10	0.08	0.12	0.10	0.13
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table C.4: Robustness check – Exclude returns from Analytics

This table shows a robustness check in which we remove all return data that was provided by Analytics and only base the analyses on return data provided by Datastream. In Panel A, we show robustness checks for Tables 2 to 4. Regressions 1 and 2 are run on opening orders and provide robustness to Table 2. Regressions 3 and 4 are run on closing orders and provide robustness to Table 3. Regressions 5 and 6 are run on both closing and opening orders and provide robustness to Table 4 Panel C. In Panel B, we display robustness checks for the sample splits in Tables 5 to 7. Regressions 1 and 2 splits the sample based on the change in number of positions in the 5 days prior to the order. Regressions 3 and 4 split the sample based on whether the fund return in the 5 days prior to the order was positive. Regressions 5 and 6 split the sample by whether fund volatility in the month of the order increased relative to the previous month. Details on variable constructions can be found in Appendix A.1. We include fund fixed effects and month fixed effects (based on the month of the last day of the order), except for regressions 5 and 6 in Panel A which have fund×month fixed effects instead. 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: Robustness for Tables 2-4

Sample:	Opening Orders		Closing Orders		Opening and Closing Orders	
Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.77***	-2.43***	-0.72**	-1.51***		
	(-6.17)	(-5.59)	(-2.45)	(-3.40)		
D(Opening)					0.53***	0.55**
					(3.32)	(2.25)
Observations	12526	11991	11698	11077	24224	23068
Adjusted R^2	0.06	0.09	0.07	0.10	0.03	0.03
Fund Fixed Effects	Yes	Yes	Yes	Yes	No	No
Month Fixed Effects	Yes	Yes	Yes	Yes	No	No
Fund×Month F.E.	No	No	No	No	Yes	Yes

Panel B: Robustness for Tables 5-7 (sample splits)

Dependent Variable:	Excess Return t+1, t+125					
Sample	More Positions	Less Positions	Positive Fund Return	Negative Fund Return	Higher Volatility	Lower Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-2.25***	-0.84	-0.74	-2.51***	-2.06***	-1.03*
	(-3.43)	(-1.44)	(-1.39)	(-3.72)	(-3.43)	(-1.70)
Observations	4980	6084	6214	4863	5687	5169
Adjusted R^2	0.11	0.10	0.08	0.12	0.10	0.13
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes